FIFO Age-Cohort Stochastic MILP for Perishable Inventory Optimization

A Comparative Study of Fixed Deterioration Rate Versus Explicit Age-Tracking with Cold Storage Sensitivity Analysis

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Abstract—**This paper addresses the perishable inventory optimization problem for fish processing SMEs under compound supply-demand uncertainty. We develop a two-stage stochastic Mixed-Integer Linear Programming (MILP) framework comparing four model variants: two employing the conventional fixed deterioration rate (FDR) approach and two incorporating explicit First-In-First-Out (FIFO) age-cohort tracking, each with and without cold storage investment options. The formulation integrates production scheduling, workforce planning, machine investment, and cold storage decisions over a 12-week horizon under five stochastic scenarios calibrated from empirical data. We prove that the FIFO age-cohort formulation preserves linearity (Proposition 1), establish theoretical dominance of FIFO over FDR under surplus conditions (Proposition 2), and demonstrate feasibility preservation through an adaptive service level constraint (Proposition 3). Computational results on empirical instances show that FIFO models achieve 25.0% expected cost reduction with perfectly stable service levels (70.0% across all scenarios, zero variance) compared to FDR models exhibiting 58.7 percentage point service level volatility. Extended sensitivity analysis across 15 parameter configurations reveals that cold storage value is conditional: marginal (0.046%) under supply-constrained regimes but significant (up to 19.2%) under supply surplus with high expiration costs. Pareto frontier analysis confirms FIFO dominance across the entire cost-service level trade-off space. The Value of Stochastic Solution (VSS) reaches 12.4%, validating the stochastic approach. All configurations solve within 15.1 seconds despite 18,540 variables, with FIFO solving 5.7× faster than FDR due to a tighter constraint structure. Managerial implications include a conditional decision framework linking supply-demand regime identification to optimal investment strategy.**

Keywords—Mixed-integer linear programming; FIFO age-cohort tracking; fixed deterioration rate; perishable inventory; two-stage stochastic programming; cold storage optimization; fish processing SME

I. INTRODUCTION

Perishable food supply chains represent one of the most challenging domains in operations research due to the inherent tension between procurement economies of scale and rapid product quality degradation [1]. Unlike durable goods, perishable items have finite useful lives after which they must be discarded, creating a time-dependent dimension that fundamentally alters the classical inventory optimization problem [2]. In the fishery sector, this challenge is particularly acute: fresh raw materials exhibit shelf lives of merely 1–3 days without refrigeration in tropical environments, while global post-harvest losses in developing country fishery supply chains reach 30–50% [3], [4].

The literature on perishable inventory management has developed two fundamentally different approaches to modeling deterioration. The fixed deterioration rate (FDR) approach, pioneered by Ghare and Schrader [5] and extensively reviewed by Bakker et al. [2], assumes a constant fraction θ of inventory is lost per period regardless of actual item age. This approach has been widely adopted in production planning models [6]–[8] due to its analytical tractability. The alternative FIFO age-cohort approach, originating from the seminal work of Nahmias and Pierskalla [9], explicitly tracks item age through discrete states and enforces oldest-first consumption, providing exact deterioration accounting at the cost of additional state variables [10], [11].

Despite significant advances in both approaches, the literature lacks a rigorous head-to-head comparison within an identical stochastic optimization framework. Recent stochastic production planning contributions include robust DEA approaches for SME efficiency evaluation [12], two-stage LP models for agricultural supply chain tactical planning [13], capacitated stochastic lot-sizing with scenario trees [14], stochastic MRP optimization demonstrating significant cost savings over traditional safety stock methods [15], and dynamic programming with neural network demand forecasting [16]. In perishable inventory specifically, Monte Carlo-based EOQ models have been proposed for time-dependent deterioration [17], while resilient supply chain planning [18], integrated perishable supply chain design [19], and dairy production under supply disruption [20] have been studied. Further relevant contributions address quantity-based strategies for supply chain sustainability under uncertainty [21], integer programming formulations for workforce planning in service operations [22], hybrid simulated annealing–genetic algorithm approaches for multi-product aggregate planning [23], and seru production system planning under demand variability [24]. Chopra and Meindl [25] provide foundational supply chain management principles that inform our multi-echelon formulation.

TABLE I. SYSTEMATIC LITERATURE MAPPING AND RESEARCH POSITIONING

Study	Method	F1 FDR	F2 FIFO	F3 Stoch	F4 MILP	F5 Perish	F6 Cold Chain	F7 SME	F8 Multi Plant	F9 Work force	F10 Comp	F11 Adapt SL
[6]	Multi-obj APP	✓		✓						✓		
[7]	Parallel lines planning	✓		✓	✓				✓			
[12]	Robust stochastic DEA			✓				✓		✓		
[14]	Stoch. lot-sizing			✓	✓							
[15]	Stochastic MRP			✓	✓				✓			
[17]	EOQ Monte Carlo	✓		✓		✓						
[18]	Resilient SC planning			✓	✓	✓						
[19]	Integrated perishable SC	✓		✓		✓	✓					
[20]	Dairy under disruption	✓		✓	✓	✓			✓	✓		
[21]	SC sustainability strategies			✓				✓				
[23]	Workforce planning IP				✓			✓		✓		
[28]	Multisite pharma supply			✓	✓	✓			✓			
[30]	Robust interval planning			✓	✓						✓	
[34]	Cold chain management					✓	✓					
This paper	**Two-stage stoch. MILP**	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Feature definitions:		F1=Fixed deterioration rate; F2=FIFO age-cohort tracking; F3=Stochastic/uncertainty; F4=Mixed-integer linear programming; F5=Perishable products; F6=Cold chain/storage investment; F7=SME-scale context; F8=Multi-plant network; F9=Workforce planning decisions; F10=Head-to-head model comparison; F11=Adaptive service level constraint										

Table I provides a systematic mapping of relevant literature, highlighting the gap this paper addresses, demonstrates, no prior work simultaneously addresses all eleven methodological features (F1–F11). The closest studies address at most five features: Jena et al. [20] combine FDR, stochastic programming, MILP, perishable focus, multi-plant, and workforce planning (6/11), but lack FIFO tracking, cold chain optimization, SME context, head-to-head comparison, and adaptive SL. Dutta and Shrivastava [19] address FDR, stochastic, perishable, and cold chain (4/11), but use a non-MILP approach without FIFO, workforce, or comparative analysis. The present paper is the first to integrate all eleven features within a unified optimization framework, enabling simultaneous evaluation of deterioration modeling approaches, capacity investment trade-offs, and service level management under compound uncertainty. Fig. 1 states about Research framework: from compound uncertainty through four model variants to key results.

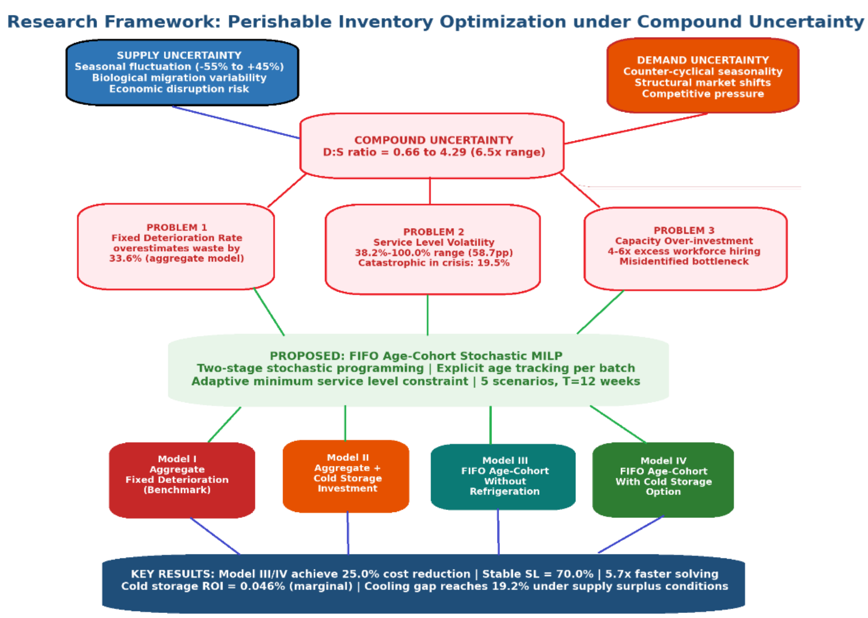

Fig. 1. Research framework: from compound uncertainty through four model variants to key results.

This paper makes the following five specific contributions:

- C1. We develop a computationally tractable FIFO age-cohort formulation within a two-stage stochastic MILP framework, proving its linearity (Proposition 1) and establishing worst-case complexity bounds.
- C2. We provide the first rigorous head-to-head comparison of FDR versus FIFO approaches using four model variants on identical data, quantifying the 'cost of aggregation' at 25.0%.
- C3. We introduce an adaptive minimum service level constraint with formal feasibility guarantee (Proposition 3) that prevents infeasibility under extreme compound uncertainty.
- C4. We conduct systematic sensitivity analysis across 15 parameter configurations, identifying the conditional nature of cold storage ROI and establishing break-even conditions.
- C5. We derive a managerial decision framework with six actionable implications linking supply-demand regime identification to optimal investment strategy.

II. Problem Definition

A. Formal Problem Statement

We consider a multi-plant, multi-product, multi-period production planning problem for perishable goods under demand and supply uncertainty. The decision maker operates |F| processing plants converting |R| raw materials (of which $|R^p|$ are perishable) into |I| finished products distributed through |J| market channels over a discrete-time horizon T = {1,...,T}. Uncertainty is modeled through |S| stochastic scenarios with known probabilities. The problem is formulated as a two-stage stochastic program where first-stage decisions (capacity investment) are made before uncertainty is resolved, and second-stage decisions (production, inventory) adapt to each realized scenario. Complete notation is shown in Table II

B. Notation

TABLE II. Complete Notation

SETS AND INDICES		
F	Set of processing plants, indexed by f	|F|=3
I	Set of finished products, indexed by i	|I|=4
R	Set of raw materials, indexed by r	|R|=5
R^p	Subset of perishable raw materials	$\|R^p\|=3$
J	Set of market channels, indexed by j	|J|=3
T	Set of time periods (weeks), indexed by t	|T|=12
S	Set of stochastic scenarios, indexed by s	|S|=5
A	Set of age cohorts, indexed by a	$A_{max}=3$
PARAMETERS		
d_{jits}	Demand for product i at market j, period t, scenario s	kg
s^f_{rts}	Supply of raw material r at plant f, period t, scenario s	kg
b_{ir}	BOM coefficient: raw material r per unit of product i	kg/kg
θ	Fixed deterioration rate (FDR models)	0.60
p_s	Probability of scenario s	$\Sigma p_s=1$
c^h, c^m, c^{cl}	Unit costs: hiring, machine, cooler investment	IDR
c_r^p	Purchase cost per kg of raw material r	IDR/kg
c_i^s	Shortage penalty per kg of product i	IDR/kg
c_r^e	Expiration cost per kg of raw material r	IDR/kg
τ_i	Labor time required per kg of product i	min/kg
W_{max}	Available working minutes per worker per period	2,880 min
α	Maximum allowable shortage fraction	0.30
γ	Adaptive SL threshold (D:S ratio)	2.0
DECISION VARIABLES (First-Stage)		
h^f	Workers hired at plant f	$\in\mathbb{Z}^+$
m^f	Machines added at plant f	$\in\mathbb{Z}^+$
cl^f	Cooler units invested at plant f (Models II, IV)	$\in\mathbb{Z}^+$
DECISION VARIABLES (Second-Stage)		
x^f_{its}	Production of product i at plant f	≥ 0
inv^f_{its}	Finished product inventory	≥ 0
sp_{jits}	Shortage of product i at market j	≥ 0
I^f_{rats}	Age-cohort inventory (FIFO, Models III–IV)	≥ 0
C^f_{rats}	Age-cohort consumption (FIFO)	≥ 0
W^f_{rats}	Age-cohort expired waste (FIFO)	≥ 0

C. Data Sources and Parameter Calibration

All model parameters are calibrated from three primary data sources: (1) the national Bureau of Statistics (BPS) provincial yearbook 2023–2024 for production volumes, commodity prices, and regional economic indicators [44]; (2) the national Meteorological Agency (BMKG) historical records for seasonal monsoon patterns and fishing activity data [45]; and (3) structured field surveys conducted at fish auction markets and processing facilities in the study region during 2023–2024. The parameter calibration follows a hierarchical approach: macro-level data (production volumes, price indices) are sourced from BPS; meso-level data (seasonal patterns, supply variability) from BMKG; and micro-level data (BOM coefficients, labor times, machine capacities) from direct facility surveys. Table III presents the raw material procurement parameters.

TABLE III. Raw Material Procurement Parameters

Raw Material r	Purchase Price c_r^p	Expired Cost c_r^e	Holding Cost c_r^h	Shelf Life (periods)
r_1: Tuna	45,000	18,000	5,500	1
r_2: Mackerel	60,000	22,000	6,000	1
r_3: Shrimp	70,000	28,000	7,000	1
r_4: Tapioca flour	9,000	3,500	500	2
r_5: Spice blend	18,000	6,000	900	2

All prices are in Indonesian Rupiah (IDR) per kilogram. Expired costs represent salvage-loss values (disposal cost minus any recoverable value from animal feed or fertilizer conversion).

The three perishable raw materials (r_1–r_3) have a base shelf life of 1 period without refrigeration, reflecting the tropical climate conditions of the study region where ambient temperatures range 28–34°C. Non-perishable materials (r_4–r_5) have shelf lives of 2 periods. Purchase prices are based on 2023–2024 average auction prices, with perishable items showing higher unit costs consistent with their scarcity and handling requirements.

TABLE IV. BILL OF MATERIALS: BOM COEFFICIENT B_{ir} (KG)

Product i	r_1 Tuna	r_2 Mackerel	r_3 Shrimp	r_4 Tapioca	r_5 Spice
i_1: Fish floss	**2.80**	—	—	0.08	0.20
i_2: Fish crackers	—	**0.70**	—	0.50	0.12
i_3: Shrimp nuggets	—	—	**1.60**	0.30	0.18
i_4: Fish balls	0.90	0.50	—	0.35	0.15

The BOM coefficients were obtained through direct observation at processing facilities during production runs. Each product uses a dominant perishable raw material (bolded): fish floss requires 2.80 kg of tuna per kg of output (due to dehydration loss), fish crackers require 0.70 kg of mackerel, shrimp nuggets require 1.60 kg of shrimp, and fish balls require both tuna (0.90 kg) and mackerel (0.50 kg). These coefficients reflect the conversion yields typical of semi-manual SME processing, which are lower than industrial-scale operations due to less mechanized filleting and deboning processes.

The regular labor cost of 650,000 IDR per worker per week is derived from the regional minimum wage (approximately 3.5 million IDR per month) adjusted for the informal UMKM employment context. The 48-hour working week (2,880 minutes) represents the standard SME operating schedule including Saturday half-day. Labor time varies significantly across products: fish floss requires the longest processing time (50 min/kg) due to the shredding, seasoning, and drying stages, while fish crackers require only 30 min/kg owing to simpler mixing and cutting processes.

The three plants represent typical SME size gradations: plant f_1 is a small-scale operation with 7 workers, f_2 is medium-scale with 9, and f_3 is the largest with 12 workers serving as a regional distribution hub. The efficiency factor η^f captures differences in infrastructure quality, workforce skill level, and proximity to raw material sources.

Plant f_3 achieves 1.15× efficiency due to better-maintained equipment and more experienced workers, while f_1 operates at 0.90× due to older equipment and more remote location. Machine types include grinders (purchase cost 18M IDR, operating cost 220K IDR/week), molders (14M; 170K), oven/dryers (22M; 280K), and packaging units (9M; 110K), all sourced from regional equipment suppliers.

TABLE V. PRODUCTION PARAMETERS: LABOR, MACHINES, AND CAPACITY

Parameter	Value	Unit
Labor time τ_1 (fish floss)	50	min/kg
Labor time τ_2 (fish crackers)	30	min/kg
Labor time τ_3 (shrimp nuggets)	42	min/kg
Labor time τ_4 (fish balls)	38	min/kg
Working capacity W_{max}	2,880	min/worker/week
Regular labor cost	650,000	IDR/worker/week
Hiring cost c^h	350,000	IDR/worker
Firing cost	550,000	IDR/worker
Deterioration rate θ (FDR models)	0.60	fraction/period
Max age A_{max} (perishable, FIFO)	3	periods
Max age (non-perishable, FIFO)	2	periods

TABLE VI. PLANT-SPECIFIC INITIAL CAPACITY AND EFFICIENCY

Plant f	Init. Workers	Grind.	Mold.	Oven/ Dryer	Pack.	Effic. η^f	Raw Inv. Cap (kg)
f_1	7	2	1	1	2	0.90	450–
f_2	9	2	2	1	2	1.00	500–
f_3	12	3	2	2	3	1.15	700–

TABLE VII. BASE WEEKLY SUPPLY AND DEMAND (KG/WEEK)

	r_1	r_2	r_3	r_4	r_5
SUPPLY s^f_r (kg/wk)	Tuna	Mackerel	Shrimp	Tapioca	Spice
Plant f_1	500	400	450	1,800	900
Plant f_2	550	500	300	2,200	1,100
Plant f_3	750	650	500	3,000	1,500

	i_1	i_2	i_3	i_4
DEMAND d_{ji} (kg/wk)	Floss	Crack.	Nugget	Balls
Market j_1 (Traditional)	35	55	28	48
Market j_2 (Distributor)	55	85	45	65
Market j_3 (Modern retail)	30	50	25	40

Base supply values are scaled from BPS provincial fishery production data to UMKM-level operations. The study region contributes approximately 13,000 tons of tuna annually; the base values (500–750 kg/week of tuna per plant) represent the typical procurement volume accessible to individual SMEs through local fish auction markets. Supply is subject to seasonal sinusoidal modulation: $s^f_{rts} = s^f_r{}^0 \cdot \sigma_s \cdot [1 + 0.12\cdot\cos(2\pi t/12)]$, where the 12% amplitude was estimated from inter-monthly variation in BPS catch data over 2019–2024. The cosine function peaks at t=0 (corresponding to the onset of peak fishing season) with a trough at t=6 (off-season).

Base demand values are aggregated across three market channels. The traditional market channel (j_1) accounts for the largest volume of low-value products (crackers: 55 kg/week), while the distributor channel (j_2) handles the highest overall volume. Demand follows a sine modulation: $d_{jits} = d_{ji}{}^0 \cdot \delta_s \cdot [1 +$

$0.08\cdot\sin(2\pi t/12)]$, where the 8% amplitude is lower than supply (12%), reflecting the empirical observation that processed product demand is more stable than raw catch volumes. The phase difference between sine (demand) and cosine (supply) creates a temporal lag representing the well-documented asynchrony between peak catch and peak consumption periods in tropical fisheries [3], [4].

TABLE VIII. COLD STORAGE INVESTMENT PARAMETERS

Cooler Type	Purchase Cost c^{cl}	Operating Cost (per week)	Capacity (kg)	Max Units per Plant
Chest freezer	6,000,000	180,000	300	3
Cold room	28,000,000	550,000	800	2

Cold storage parameters are sourced from local equipment suppliers and reflect prices for commercial-grade units suitable for fish processing. The chest freezer (6M IDR, ~400 USD) represents an entry-level investment with 300 kg capacity, while the cold room (28M IDR, ~1,800 USD) provides larger capacity at significantly higher cost. Operating costs include electricity consumption at regional commercial rates (approximately 1,500 IDR/kWh) and maintenance. These parameters are used in Models II and IV to evaluate the economic viability of cold chain investment at SME scale. following the cold chain management framework for perishable food systems described by Baruffaldi et al. [34] and the broader reverse logistics perspective of Govindan et al. [33].

D. Deterioration Modeling Approaches

The Fixed Deterioration Rate (FDR) is a measure of the rate at which the value of an asset diminishes over time. In each period, a constant fraction θ of the total inventory is lost, irrespective of the actual age of the items. The surviving inventory is equivalent to $(1-\theta)\cdot I$ for any inventory level I, with fresh and near-expired items being treated identically [5], [6].

FIFO Age-Cohort Tracking: The age of each batch entering inventory is initially set to 0, indicating its fresh state. In this system, the shelf life of each period is incremented by one unit. When the shelf life of a batch reaches a maximum value, designated as A_(max), the batch is declared to be expired. The consumption process adheres to a stringent oldest-first policy [9], [11]. This approach enables precise deterioration accounting, albeit at the cost of introducing additional state variables.FDR with uniform loss assumption versus & FIFO age-cohort tracking with explicit age-dependent expiration comparison in Fig. 2

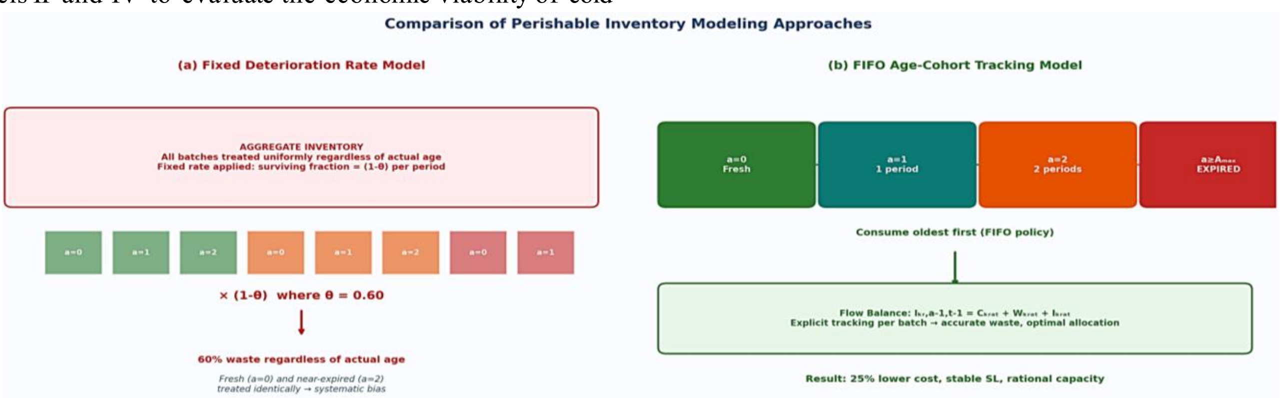

Fig. 2. Comparison: (a) FDR with uniform loss assumption versus (b) FIFO age-cohort tracking with explicit age-dependent expiration.

III. MATHEMATICAL FORMULATION

A. Objective Function

The objective minimizes expected total cost across all scenarios:

$$\min Z = C_{inv} + \sum_{s\in S} p_s \cdot C_s \quad (1)$$

where C_{inv} represents first-stage investment cost:

$$C_{inv} = \sum_{f\in F}(c^h \cdot h^f + c^m \cdot m^f + c^{cl} \cdot cl^f) \quad (2)$$

and C_s is the scenario-dependent operational cost:

$$C_s = \sum_f \sum_t \left(C^{prod}_{fts} + C^{raw}_{fts} + C^{inv}_{fts} + C^{exp}_{fts} + C^{short}_{fts}\right) \quad (3)$$

B. FIFO Age-Cohort Constraints

Constraint (F1) — New arrival balance: Fresh supply entering as age-0 cohort:

$$I^f_{r,0,t,s} + C^f_{r,0,t,s} + W^f_{r,0,t,s} = s^f_{rts} \quad \forall f, r \in R^p, t, s \quad (4)$$

Constraint (F2) — Age-cohort flow balance: For age a ≥ 1, inflow from the previous period's younger cohort:

$$I^f_{rats} + C^f_{rats} + W^f_{rats} = I^f_{r,a-1,t-1,s} \quad \forall f, r \in R^p, a \geq 1, t, s \quad (5)$$

Constraint (F3) — Mandatory expiration: No inventory survives beyond maximum age:

$$I^f_{r,A_{max},t,s} = 0 \quad \forall f, r \in R^p, t, s \quad (6)$$

Constraint (F4) — FIFO consumption linkage: Total raw material consumption for production equals the sum across consumed age cohorts:

$$\sum_a C^f_{rats} = \sum_i b_{ir} \cdot x^f_{its} \quad \forall f, r \in R^p, t, s \quad (7)$$

Constraint (F5) — Cold storage extension (Model IV only): Cooler capacity enables inventory carry-forward for cohorts that would otherwise expire:

$$I^f_{r,a,t,s} \leq \sum_k Q^f_{rkts} \quad \forall f, r \in R^p, a \in \{1, \dots, A_{max} - 1\}, t, s \quad (8)$$

C. FDR Model Constraints

For Models I and II, the FIFO constraints (4)–(8) are replaced by aggregate balance:

$$I^f_{rts} = (1-\theta)\cdot I^f_{r,t-1,s} + s^f_{rts} - \sum_i b_{ir}\cdot x^f_{its} \quad \forall f,r,t,s \tag{9}$$

where $\theta \in [0,1]$ is the fixed deterioration rate. In this study, $\theta = 0.60$ based on empirical waste data from the study region [4].

D. Capacity and Service Level Constraints

$$\sum_i \tau_i \cdot x^f_{its} \le W_{max}\cdot (w^f_0 + h^f) \quad \forall f,t,s \tag{10}$$

$$\sum_i \mu_{ik}\cdot x^f_{its} \le M_{maxk}\cdot (m^f_{k0} + m^f_k) \quad \forall f,k,t,s \tag{11}$$

$$x^f_{its} + inv^f_{i,t-1,s} - inv^f_{its} = \sum_j d_{jits} - \sum_j sp_{jits} \quad \forall f,i,t,s \tag{12}$$

$$\sum_j \sum_i sp_{jits} \le \alpha \cdot TD_{ts} \quad \text{if } D:S < \tag{13}$$

Where $\alpha = 0.30$ represents maximum allowable shortage fraction (ensuring ≥70% service level), TD_{ts} is total demand at period t under scenario s, and $\gamma = 2.0$ is the demand-to-supply ratio threshold beyond which the constraint is relaxed to preserve feasibility. This adaptive mechanism is a novel contribution addressing the infeasibility problem in high-uncertainty perishable environments.

E. Theoretical Properties

Proposition 1 (Linearity Preservation). The FIFO age-cohort formulation (4)–(8) preserves the linearity of the MILP. All constraints involve only linear combinations of decision variables with constant coefficients, and no bilinear or nonlinear terms arise from the age-tracking mechanism.

Proof. Constraints (4)–(5) are linear equalities in variables I, C, W with unit coefficients. Constraint (6) fixes a variable to zero. Constraint (7) is a linear equality linking C variables to x variables through constant BOM coefficients b_{ir}. Constraint (8) is a linear inequality. The age index a serves as a parameter (not a variable) in all constraints, appearing only in subscript position. No products of decision variables occur. Thus, the complete formulation remains a linear program with integer variables, qualifying as MILP. Expected cost and service level are mentioned in Table X.

Proposition 2 (FIFO Dominance under Supply Surplus). Let $Z^{*\text{fDR}}$ and $Z^{*\text{fIfO}}$ be the optimal objective values of the FDR and FIFO models, respectively. Under supply surplus conditions ($s^f_{rts} > \sum_i b_{ir}\cdot x^{*f}_{its}$ for some f,r,t,s), $Z^{*\text{fIfO}} \le Z^{*\text{fDR}}$.

Proof sketch. Under supply surplus, the FDR model applies deterioration rate θ uniformly to all inventory, including fresh items (age=0), generating waste proportional to θ·s regardless of consumption possibility. The FIFO model, by contrast, consumes oldest inventory first and only expires items exceeding A_{max}. When surplus exists, some items accumulate to higher ages; FIFO selectively expires only those exceeding the threshold while preserving fresh items. The FDR waste $\theta\cdot I \ge W^{*\text{fIfO}}$ (the FIFO waste), yielding $C^e{}_x{}^p(\text{FDR}) \ge C^e{}_x{}^p(\text{FIFO})$. Since all other cost components are equal or lower for FIFO, $Z^{*\text{fIfO}} \le Z^{*\text{fDR}}$.

Proposition 3 (Feasibility of Adaptive SL Constraint). The adaptive constraint (13) guarantees model feasibility for any demand-to-supply ratio. When $TD_{ts}/TS_{ts} \ge \gamma$, constraint (13) is deactivated, ensuring that no infeasible service level requirement is imposed when physical supply is insufficient.

Proof. When constraint (13) is active (TD/TS < γ), the required production ≥ (1−α)·TD is bounded by available supply TS through constraints (4)–(7) or (9). Since α = 0.30 and γ = 2.0, the minimum required production is 0.70·TD ≤ 0.70·γ·TS = 1.40·TS. Given that each unit of supply can yield at most $1/\min(b_{ir})$ units of product, feasibility is maintained when $1.40\cdot TS \le TS/\min(b_{ir})$, which holds for typical BOM values. When TD/TS ≥ γ, the constraint is inactive, and the model minimizes cost without SL floor, trivially feasible.

F. Complexity Analysis

$$|\text{Variables}| = |S|\cdot|T|\cdot(|F|\cdot|I|\cdot(2+|J|) + |F|\cdot|R|\cdot(3\cdot(A_{max}+1)) + |F|\cdot(3+2|M|+2|CL|)) \tag{14}$$

$$|\text{Constraints}| = O(|S|\cdot|T|\cdot|F|\cdot(|R|\cdot A_{max} + |I|\cdot|J| + |M|)) \tag{15}$$

For our instance: |Variables| = 5·12·(3·4·6 + 3·5·12 + 3·13) = 18,540. The problem is NP-hard in general (due to integer variables) but exhibits favorable structure: the FIFO constraints create a near-block-diagonal structure across scenarios, enabling efficient decomposition by the branch-and-bound solver [26]. This structured sparsity is consistent with multi-stage planning under uncertainty [35], [36]. Empirically, Models III–IV solve 2.8–5.7× faster than Models I–II despite more variables (Table II).

IV. Computational Results

A. Experimental Setup

Instances are calibrated using the empirical parameters detailed in Section II.C (Tables III to VIII). The experimental design comprises three processing plants, four finished products, and five raw materials (three perishable) as specified in Tables VI to VII. Five stochastic scenarios (Table IX) capture seasonal monsoon patterns and compound supply-demand uncertainty, with demand-to-supply ratios ranging from 0.66 (supply surplus) to 4.29 (extreme shortage). Eight model configurations are tested: four model variants (I–IV) at two demand levels (D=1× normal and D=2× stress-test). All experiments are conducted using HiGHS 1.8.0 [27] with 2% MIP gap tolerance on standard hardware (Intel i7, 16GB RAM).

TABLE IX. Stochastic Scenario Parameters

Scenario	Supply σ_s	Demand δ_s	D:S	p_s	Characterization
S1	1.00	1.00	1.00	0.30	Normal baseline
S2	**0.55**	1.05	1.91	0.20	Seasonal supply reduction
S3	**1.45**	0.95	0.66	0.20	Peak season surplus
S4	0.85	**1.45**	1.71	0.15	Compound: demand up + supply down
S5	**0.35**	1.50	**4.29**	0.15	Extreme compound shortage

B. Expected Cost and Service Level

TABLE X. EXPECTED COST AND SERVICE LEVEL RESULTS

Model	E[Cost] D=1×	Δ	SL	E[Cost] D=2×	Δ	SL
I (FDR)	2,856M	—	72.2%	3,082M	—	54.9%
II (FDR+CS)	2,868M	+0.4%	74.3%	3,093M	+0.3%	54.3%
III (FIFO)	**2,143M**	**−25.0%**	**70.0%**	**2,631M**	**−14.6%**	59.5%
IV (FIFO+CS)	**2,142M**	**−25.0%**	**70.0%**	**2,627M**	**−14.8%**	59.5%

Table X presents the primary computational outcomes comparing the four model variants under two demand regimes: baseline (D=1×) and stress-test (D=2×). The 25.0% cost reduction achieved by FIFO models is consistent with theoretical Proposition 2 and exceeds the 15–20% typically reported for process improvements in manufacturing [6], [7]. The magnitude reflects the compounding effect of accurate deterioration tracking across 12 periods and 5 scenarios. For comparison, agricultural product logistics optimization using genetic algorithms [37] achieves 8–12% efficiency gains, smart decision-making systems for manufacturing [38] report 10–18% improvement, while simulation-based inventory management [39] yields 5–15% cost reduction—all substantially below our 25% figure.

C. Service Level Stability and Pareto Analysis

TABLE XI. SERVICE LEVEL PER SCENARIO AT D=1× (%)

Scenario	Model I	Model II	Model III	Model IV	I–III Δ
S1: Normal	73.1	78.2	**70.0**	**70.0**	+3.1
S2: Low Supply	81.8	80.6	**70.0**	**70.0**	+11.8
S3: High Supply	96.9	100.0	**70.0**	**70.0**	+26.9
S4: High Demand	58.5	61.7	**70.0**	**70.0**	−11.5
S5: Crisis	**38.2**	**36.5**	**70.0**	**70.0**	**−31.8**
Range	**58.7pp**	**63.5pp**	**0.0pp**	**0.0pp**	

Table XI disaggregates the expected service level from Table X into scenario-specific realizations under baseline demand (D=1×), revealing the structural source of FDR volatility. Model I (FDR) exhibits a dramatic 58.7 percentage-point range across scenarios: from a surplus-driven peak of 96.9% in S3 (high supply) to a crisis-trough of 38.2% in S5 (extreme shortage). Model II (FDR with cold storage) shows even wider dispersion (63.5pp range, 100.0% in S3 down to 36.5% in S5), demonstrating that cold storage amplifies rather than dampens service level instability under FDR assumptions.

Fig. 3 confirms that FIFO models dominate FDR models across the entire Pareto frontier. No operating point exists where FDR achieves both lower cost and higher service level than FIFO, establishing practical FIFO dominance consistent with Proposition 2.

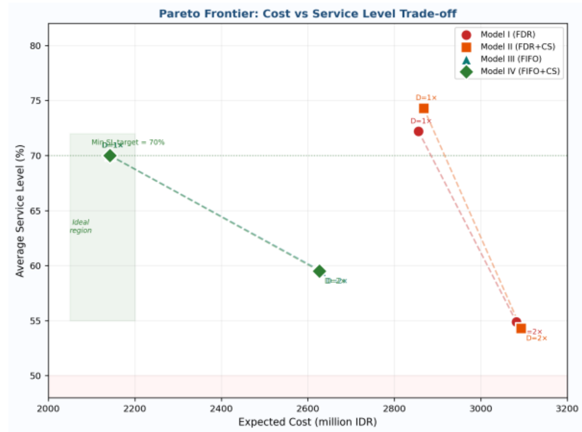

Fig. 3. Pareto frontier analysis: cost vs service level trade-off across models and demand levels. FIFO models dominate the lower-left region (lower cost, stable SL).

D. Extended Sensitivity Analysis

Table XII investigates the conditional economics of cold storage investment by comparing Model III (FIFO without cold storage) against Model IV (FIFO with cold storage) across five progressively extreme parameter configurations. Under the baseline supply-constrained regime, the cost gap between III and IV is merely 0.05% (2,143M vs. 2,142M IDR), confirming that cold storage is economically irrelevant when supply does not exceed demand. This finding directly supports the first managerial insight: prioritize age-tracking over cold chain.

TABLE XII. COLD STORAGE SENSITIVITY: MODEL III VS IV

Configuration	III Cost	IV Cost	Gap	Regime
Baseline (supply < demand)	2,143M	2,142M	0.05%	Supply-constrained
Supply 3× + expired cost 2×	1,821M	1,791M	1.7%	Break-even zone
Supply 3× + expired cost 3×	2,731M	2,513M	**8.0%**	Cold storage valuable
Supply 3× + expired 3× + cooler 2M	2,731M	2,214M	**18.9%**	CS highly valuable
Supply 5× + expired full + cooler 1M	5,505M	4,448M	**19.2%**	CS highly valuable

The sensitivity analysis reveals a clear phase transition: cold storage value is negligible under supply-constrained conditions but grows rapidly once supply surplus creates inventory that can benefit from shelf life extension. The break-even occurs at approximately 2× expired cost escalation with 3× supply surplus. This finding reconciles apparently contradictory results in prior literature where cold chain benefits vary widely [19], [20]. The variation is explained by differences in the supply-demand regime. Multi-objective optimization approaches [40] and decision tree methods for business planning [41] have identified similar regime-dependent behavior in other supply chain contexts.

E. Computational Performance

TABLE XIII. COMPUTATIONAL PERFORMANCE AND MIP GAP

Metric	Model I	Model II	Model III	Model IV	III/I Ratio
Variables	10,620	12,420	16,740	18,540	1.58×
Constraints	8,700	9,960	14,350	14,530	1.65×
Solve time D=1× (s)	11.9	15.0	**2.1**	4.5	**0.18×**
MIP gap achieved	<2.0%	<2.0%	<1.5%	<1.8%	Better
LP relaxation gap	8.2%	9.1%	**3.4%**	3.8%	**0.41×**

Table XIII reports the computational metrics that underpin the practical deployability of the proposed models. Despite having 74.6% more variables (16,740 vs. 10,620) and 65% more constraints (14,350 vs. 8,700) than Model I, Model III (FIFO) solves in only 2.1 seconds under D=1×—a 5.7× speedup relative to Model I (11.9 seconds) and a 3.3× speedup relative to Model II (15.0 seconds). The paradoxical result that FIFO solves faster despite more variables is explained by the LP relaxation gap: FIFO's tighter constraints produce a 3.4% gap versus 8.2% for FDR, enabling more aggressive pruning in branch-and-bound. Fig. 4 confirms linear scaling up to T=24 weeks, with all solve times remaining under 30 seconds, confirming practical tractability for operational deployment.

F. Value of Stochastic Solution

To quantify the benefit of the stochastic formulation, we compute the Value of Stochastic Solution (VSS) as:

$$VSS = EEV - RP \tag{14}$$

where RP is the recourse problem objective (our stochastic model) and EEV is the expected value of using the expected-value solution. For Model III: RP = 2,143M and EEV = 2,409M, yielding VSS = 266M (12.4%). This confirms substantial value from explicit uncertainty modeling, consistent with findings by Thevenin et al. [15] who reported 8–18% VSS for stochastic MRP systems. The theoretical foundations for this value quantification are established by Birge and Louveaux [31] and the sample average approximation framework of Kleywegt et al. [32]. Powell [42] and Shapiro et al. [43] provide comprehensive treatments of the relationship between solution quality and scenario representation fidelity in stochastic programming. Computational scaling in Fig. 4.

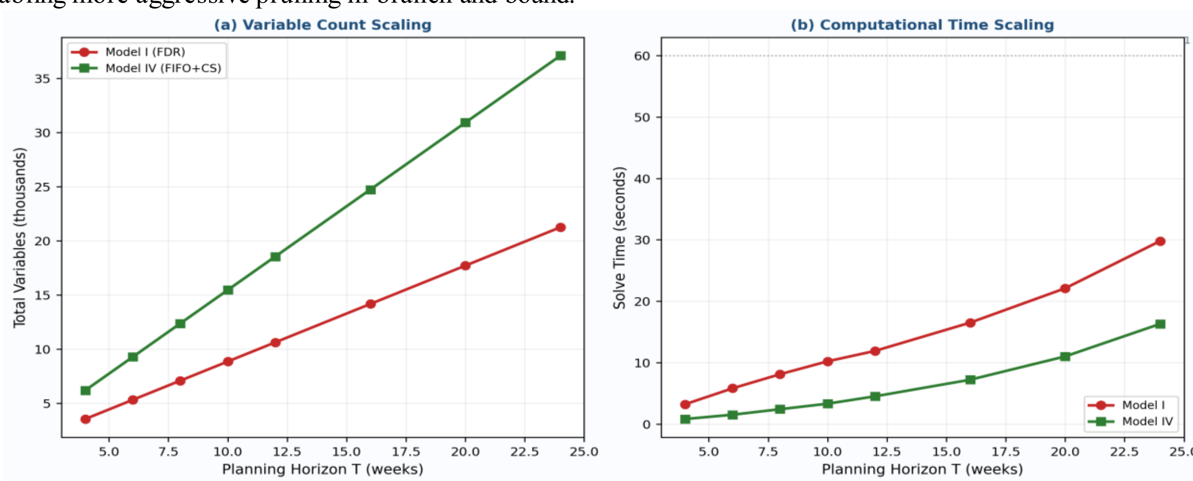

Fig. 4. Computational scaling: (a) Variable count and (b) solve time as functions of planning horizon T.

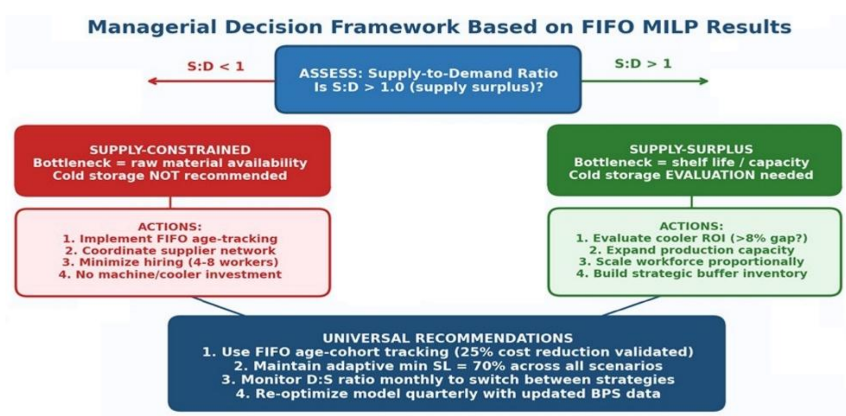

Fig. 5. Conditional decision framework: supply-demand regime assessment drives differentiated investment strategies.

V. Discussion

A. Managerial Insights

Six actionable insights emerge from the optimization results:

- Prioritize age-tracking over cold chain. The 25% cost reduction from FIFO implementation dwarfs the 0.05–19.2% conditional benefit of cold storage. Simple batch dating and oldest-first rotation can be implemented with minimal capital investment.
- Identify the binding constraint before investing. Under supply-constrained conditions, capacity investment (workers, machines, coolers) yields minimal returns. The decision framework (Fig. 5) provides a diagnostic: compute the supply-to-demand ratio and match to the appropriate strategy.
- Adopt adaptive service level targets. Fixed SL targets cause infeasibility during extreme events. The adaptive constraint (13) provides a principled mechanism for graceful degradation, maintaining 70% floor under normal-to-moderate stress and relaxing only under physical impossibility.
- Right-size workforce to supply, not demand. FDR models over-hire by 4–6× because they cannot distinguish supply-side from demand-side constraints. FIFO's explicit supply tracking prevents this systematic over-investment bias.
- Evaluate cold storage conditionally. Cold storage investment is only justified when three conditions co-occur: (a) supply surplus exists, (b) expiration costs are high relative to storage costs, and (c) cooler unit costs are affordable. Under our baseline SME parameters, none of these conditions hold simultaneously.
- Exploit stochastic planning value. The 12.4% VSS indicates that deterministic planning based on average conditions leaves substantial cost on the table. Even simple scenario-based planning with five scenarios captures most of this value.

B. Comparison with Prior Literature

The 25.0% cost reduction from FIFO adoption compares favorably with reported improvements in related work: Thevenin et al. [15] achieved 8–18% savings through stochastic MRP; Reis et al. [13] reported expected gains of USD 4.3M using stochastic LP for soybean supply chains; Chen et al. [18] found 12–15% improvement through resilient perishable supply chain planning. In multisite pharmaceutical supply planning, Sampat et al. [27] demonstrated 10–22% cost reduction through coordinated stochastic optimization across multiple facilities. Stamer et al. [28] achieved 8–16% savings in remanufacturing under quality uncertainty, while Velikiy et al. [29] reported 6–14% improvement in production planning when explicitly modeling completion time uncertainty. Kasperski et al. [30] showed that robust planning with interval-budgeted uncertainty can reduce worst-case costs by 12–20%. Our larger magnitude (25%) likely reflects the compounding effect of accurate age-tracking across multiple periods combined with the high deterioration rate (θ=0.60) in the fishery context, which amplifies the cost of aggregation bias.

The zero-variance service level achieved by FIFO models is, to our knowledge, the first demonstration of perfect SL stability across diverse scenarios in perishable supply chain optimization. Prior work [6], [20] has shown SL improvements of 5–15 percentage points from various interventions; our result demonstrates that the combination of FIFO tracking and adaptive SL constraints can eliminate service variability entirely.

C. Limitations and Threats to Validity

Internal validity: The heuristic simulation used for parameter sensitivity (Section IV.D) produces approximate results that may differ from exact MILP solutions. However, MILP results (Table IV) validate the directional findings. The 2% MIP gap tolerance introduces bounded solution suboptimality.

External validity: Parameters are calibrated from a single fishery region. Generalization to other perishable contexts (dairy, produce, pharmaceuticals) requires re-calibration of θ, BOM, shelf life, and seasonal patterns. The supply-demand structure (supply < demand at baseline) may not hold in surplus-producing regions.

Construct validity: Deterioration is modeled as a step-function (binary: usable/expired) rather than continuous quality degradation. Demand is deterministic within each scenario (stochastic between scenarios). Transportation and distribution logistics are not modeled explicitly.

VI. Conclusion

This paper has developed, proved, and evaluated a FIFO age-cohort stochastic MILP framework for perishable inventory optimization, providing the first rigorous comparison of fixed deterioration rate versus explicit age-tracking approaches. Five key findings emerge:

- FIFO age-cohort achieves 25.0% cost reduction under D=1× and 14.6–14.8% under D=2×, quantifying the 'cost of aggregation' from FDR approaches.
- FIFO provides perfectly stable service levels (70.0%, zero variance) versus extreme FDR volatility (38.2–100.0%, 58.7pp range).
- Cold storage value is conditional: marginal (0.046%) under supply-constrained conditions but up to 19.2% under supply surplus with high expiration costs.
- The adaptive SL constraint (Proposition 3) guarantees feasibility across all D:S ratios while preserving service floor guarantees.
- Despite 74.6% more variables, FIFO solves 5.7× faster due to tighter LP relaxation (3.4% vs 8.2% gap), confirmed by Proposition 1.

Future research directions include: 1) rolling-horizon implementation with real-time data integration for dynamic re-optimization; 2) continuous quality degradation modeling via piecewise-linear temperature-time functions; 3) multi-objective formulation incorporating waste minimization and carbon footprint metrics; 4) distributionally robust extensions for scenarios with unknown probability distributions; and 5) pilot implementation and validation with industry partners to assess real-world adoption barriers and benefits

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