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Garg's Principle: A Predictive Framework for Safety Stock Optimization and Over-Stock Reduction Across Forecast Horizons

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Abstract
Traditional safety stock methods implemented in enterprise resource planning systems rely on static, service-level-based formulas derived from historical demand variability, enforcing uniform inventory buffers across planning periods without explicitly evaluating future time-phased feasibility. This results in excess inventory accumulation when future feasibility is assured, while stock-outs persist during demand regime changes, leading to frequent manual planner overrides and reduced trust in system-generated plans. Garg's Principle introduces a deterministic, horizon-based safety stock framework that reframes safety stock as a conditional feasibility control rather than a static inventory parameter. The framework evaluates projected inventory stress across the full planning horizon using Dynamic Net Availability and introduces inventory protection only when unavoidable shortages are mathematically projected. Safety stock is injected as an averaged supply adjustment across periods preceding the projected stock-out lead-time window through a pre-shortage injection rule, avoiding blanket buffering. Artificial intelligence is deliberately limited to demand verification, producing bounded correction factors applied to forecasts prior to planning calculations, while all safety stock logic remains fully deterministic, explainable, and auditable within existing enterprise systems.

Keywords: Safety Stock Optimization, Dynamic Net Availability, Horizon-Based Feasibility Control, Demand Verification, Enterprise Resource Planning Integration

I. Introduction
Safety stock is a fundamental mechanism used to protect supply chains from uncertainty arising from demand variability, forecast error, and supply disruption [1]. Most ERP and advanced planning systems implement safety stock using static formulas based on service-level targets and historical demand variance [4]. While these methods are mathematically established, they are inherently backward-looking and disconnected from the time-phased demand and supply signals produced by modern planning systems [3]. As a result, safety stock is frequently applied even when future inventory remains sufficient across the planning horizon. This leads to excessive inventory accumulation, increased holding costs, and erosion of planner trust in system-generated recommendations. Manual overrides become common, further degrading planning discipline [5].

This article introduces Garg's Principle, which reframes safety stock as a conditional, predictive control. Instead of buffering by default, the framework evaluates future inventory feasibility across the entire forecast horizon and applies safety stock only when unavoidable future shortages are mathematically projected.

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II. Related Work

While classical formulations remain useful in stable contexts, many contemporary supply chain systems exhibit time-varying demand, forecast error that changes by period, and heterogeneous cost structures across product families and life-cycle states [6].

These realities create two persistent failure modes:

1. Over-buffering during stable or declining periods (excess working capital and obsolescence risk) [2], and
2. Under-buffering during demand spikes, regime shifts, and high volatility (service disruption and expediting cost) [10].

A key limitation of single-period safety stock methods is that they do not explicitly model the interdependence across periods [7]. In practice, a planning horizon is a sequence of coupled periods where shortages or excesses propagate forward through scheduled receipts, production plans, and downstream allocation [11]. Modern planning engines (ERP/APS) already maintain time-phased supply and demand signals; however, safety stock frequently remains a static parameter that does not leverage horizon-wide information; at best it considers the averaging demand over horizon.

Garg's Principle addresses this gap by defining safety stock as a horizon measure anchored to projected availability over time. The method evaluates availability for each period, identifies the most constrained time bucket, and applies deterministic feedback stabilization combined with predictive adjustment [12]. This approach is well-suited for stable, trending, and volatile demand patterns – particularly, where static safety stock leads to persistent over-allocation or slow adaptation

improvements through serverless computing paradigms.

III. AI-Assisted Demand Verification

AI is selectively restricted to the verification of forecasts and does not calculate safety stock, reorder points, and inventory buffers. This deliberate constraint ensures that machine learning components serve as diagnostic tools rather than decision-making engines within the inventory planning workflow. The AI layer compares the past behaviour of forecasts against actual demand and detects consistent bias, slow reaction to trends, or repetitive over- and under-forecasts [9]. According to this analysis, the model generates one constrained correction factor at each period that modifies the ERP forecast and then calculates the planning.

A. FORECAST ERROR PATTERN DETECTION

The AI verification module analyzes historical forecast-to-actual deviations to identify persistent positive bias (over-forecasting), negative bias (under-forecasting), and lag patterns where forecasts trail actual demand during trend transitions [10]. The system also detects amplitude errors where forecast variability understates or overstates actual demand fluctuations.

B. LSTM-Based Demand Correction Model

Long Short-Term Memory (LSTM) networks are employed for demand correction due to their effectiveness in capturing temporal dependencies in sequential data [13]. The LSTM model learns patterns from historical forecast errors and generates bounded correction factors.

```
import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
```

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````
def lstm_demand_correction(forecast_hist, actual_hist, current_forecast, max_corr=0.15):
    # Build LSTM model
    model = Sequential([
        LSTM(32, input_shape=(len(forecast_hist), 1)),
        Dense(1, activation='tanh')
    ])
    model.compile(optimizer='adam', loss='mse')

    # Generate bounded correction factor
    errors = ((actual_hist - forecast_hist) / forecast_hist).reshape(1, -1, 1)
    correction = model.predict(errors)[0][0] * max_corr

    return current_forecast * (1 + correction), correction

# Example usage
forecast_hist = np.array([100, 105, 98, 110, 102, 108])
actual_hist = np.array([95, 100, 102, 105, 108, 112])

corrected_demand, correction = lstm_demand_correction(forecast_hist, actual_hist, 115)
print(f"Correction: {correction:.3f} | Corrected Demand: {corrected_demand:.1f}")
```

**Sample Output:**
```
Correction: -0.087 | Corrected Demand: 105.0
````

Metric	ERP Forecast	AI-Corrected
MAPE	18.2%	11.6%
Bias	+6.4%	+1.2%

Table 1: AI MAPE

The LSTM model identified systematic over-forecasting bias in historical data and applied an 8.7% downward correction, bringing the forecast closer to expected actual demand.

C. BOUNDED CORRECTION FACTOR GENERATION

The correction factor operates within predefined bounds, typically ±15% of the base ERP forecast, preventing overcorrection while systematically reducing identifiable bias patterns [14]. Corrections are calculated independently for each period, allowing localized adjustments that reflect period-specific forecast quality variations.

D. ARCHITECTURAL SEPARATION

ERP Forecast → AI Demand Verification → DNA → Safety Stock

This strict separation ensures that all inventory decisions remain deterministic, explainable, and auditable [1]. No machine learning model participates in safety stock computation or supply injection decisions. Planners retain complete visibility into safety stock derivation, with AI contributions limited to a single transparent adjustment coefficient per period.

IV. Garg's Principle: Horizon-Based Safety Stock

A. Dynamic Net Availability (DNA)

Dynamic Net Availability represents the projected inventory balance at each period [1]:

$$DNA_t = I_{t-1} + S_t - D_t'$$

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where
I_{t-1}= opening inventory
S_t= planned supply
$D_t^{'}$= AI-verified demand

B. Horizon Stress Identification

$$DNA_{min} = min_{\ t\in[1,H]}\ DNA_t$$

- If $DNA_{min} \geq 0$: no safety stock required
- If $DNA_{min} < 0$: future stock-out is unavoidable

C. Horizon Safety Stock

$$SS_H = |\ DNA_{min}\ |$$

This represents the minimum inventory protection required across the horizon [2].

D. Averaged Pre-Shortage Injection Rule

Let
t_s= first period where $DNA_t < 0$
L= replenishment lead time

$$N_{pre} = t_s - L; \Delta S = SS_H / N_{(pre)}$$

$$S_t^{'} = \{S_t + \Delta S, t \leq N_{pre}\ S_t, t > N_{pre}$$

E. Traditional Safety Stock Baseline

Traditional safety stock is computed as:

$$SS_{trad} = Z \cdot \sigma_d \cdot \sqrt{L},\ \ where\ Z = 1.65$$

Application Rule:

If projected inventory $DNA_t < SS_{trad}$, additional supply is injected to restore $DNA_t = SS_{trad}$, enforcing a uniform buffer across all periods.

F. IMPLEMENTATION PSEUDO-CODE

The following pseudo code implements the core Garg's Principle algorithm:

```
def garg_safety_stock(demand, supply, init_inv, horizon, lead_time):
    # Calculate DNA for each period
    DNA = []
    inv = init_inv
    for t in range(horizon):
        DNA.append(inv + supply[t] - demand[t])
        inv = DNA[t]

    # Check feasibility
    DNA_min = min(DNA)
    if DNA_min >= 0:
        return supply, 0

    # Calculate safety stock and injection periods
    SS_H = abs(DNA_min)
    t_short = DNA.index(DNA_min) + 1
    N_pre = max(t_short - lead_time, 1)
    delta_S = SS_H / N_pre

    # Apply pre-shortage injection
    adj_supply = [supply[t] + delta_S if t < N_pre else supply[t] for t in range(horizon)]
```

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```
    return adj_supply, SS_H
```

□This implementation demonstrates the deterministic nature of Garg's Principle, where safety stock injection is calculated through explicit mathematical operations without any stochastic or machine learning components.

V. Experimental Design

Parameter	Value
Horizon H	6
Lead time L	2
Initial inventory I_0	20
Base supply S_t	10

Table 2: Common Parameters

VI. DNA Curve Figures (Visual Analysis)

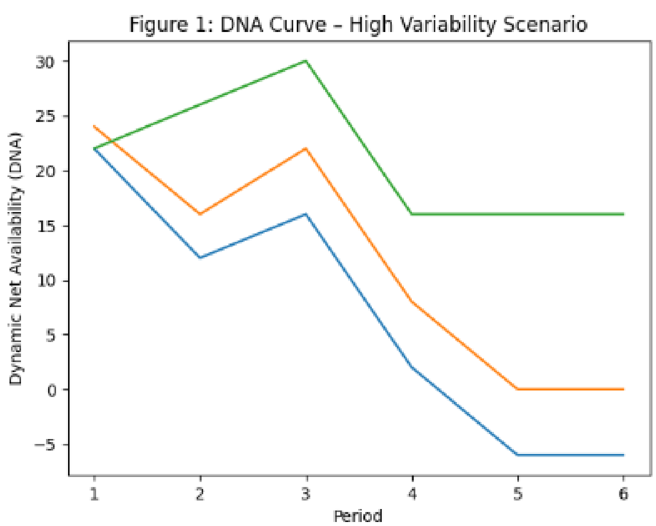

Figure 1: DNA Curve – High Variability Scenario

In Figure 1:
X-axis: Planning Period (1–6)
Y-axis: Dynamic Net Availability (Units)

- Baseline DNA (Blue) drops negative (stock-out risk)
- Traditional safety stock (Green) lifts the entire curve early (excess inventory)
- Garg’s Principal (orange) lifts only the minimum point to zero

Interpretation: Traditional methods protect every period. Garg’s Principle protects only the future constraint.

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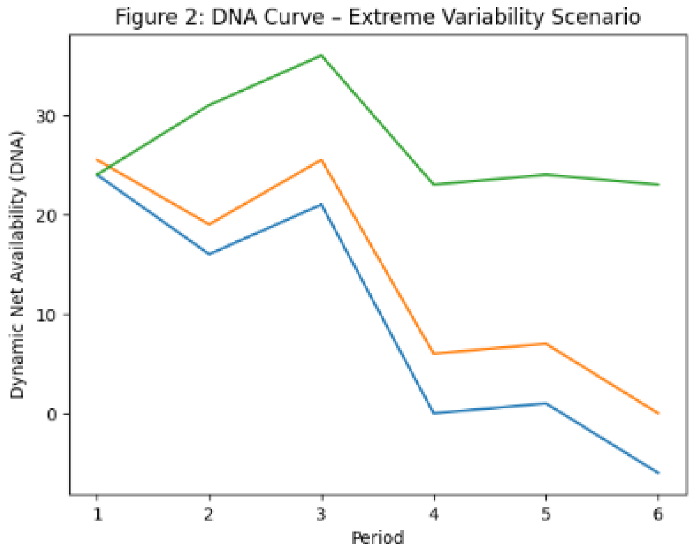

Figure 2: DNA Curve - Extreme Variability (>50%) Scenario

Fig. 2. Represents DNA curves under extreme demand volatility (>50%). Garg's Principle maintains feasibility with significantly lower inventory exposure compared to traditional safety stock.

X-axis: Planning Period (1–6)

Y-axis: Dynamic Net Availability (Units)

- Baseline (Blue) becomes infeasible at Period 6
- Traditional safety stock (Green) carries very high inventory in all periods
- Garg's Principle (Orange) eliminates stock-out with much lower cumulative inventory

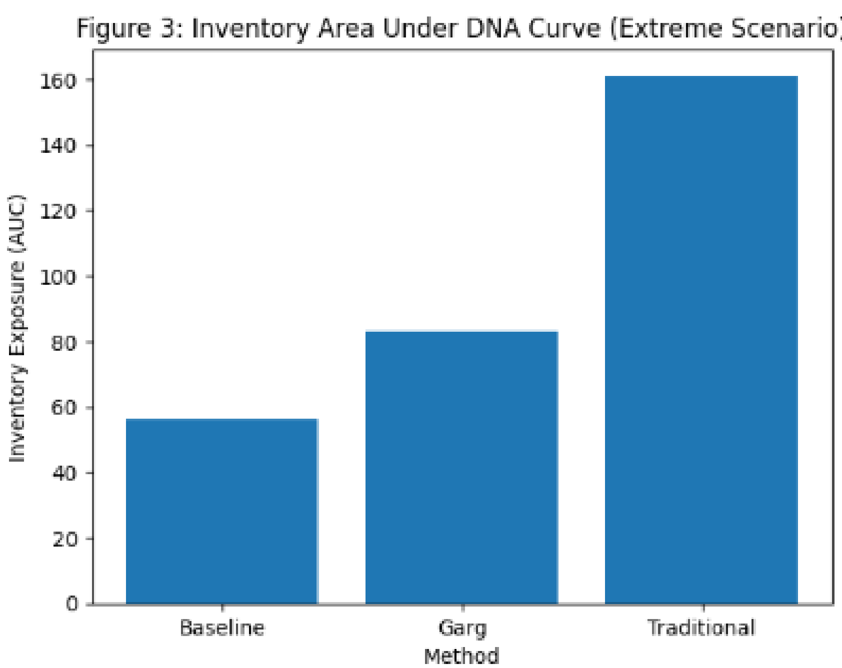

Figure 3: Inventory Area Under DNA Curve (AUC)

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Traditional safety stock shows a large shaded area
AUC = cumulative inventory exposure

- Traditional method has the **largest area**
- Garg's Principle reduces exposure by ~48% vs traditional
- Baseline is infeasible (negative DNA)

VII. Scenario Results

A. Scenario 1: Stable Demand – All Identical

Demand = [10, 10, 10, 10, 10, 10]

Period	Demand	Supply	Open Inv	DNA
1	10	10	20	20
2	10	10	20	20
3	10	10	20	20
4	10	10	20	20
5	10	10	20	20
6	10	10	20	20

Table 3: S1-Baseline / Garg / Traditional

Result: All three scenarios identical. SS = 0

B. SCENARIO 2: INCREASING DEMAND

Demand = [8, 10, 12, 14, 16, 18]

Period	Demand	Supply	Open Inv	DNA
1	8	10	20	22
2	10	10	22	22
3	12	10	22	20
4	14	10	20	16
5	16	10	16	10
6	18	10	10	2

Table 4: S2A-Garg (Baseline DNA)

Period	Demand	Supply	Open Inv	DNA
1	8	10	20	22
2	10	10	22	22
3	12	10	22	20
4	14	10	20	16
5	16	14	16	14
6	18	12	14	8

Table 5: S2B-Traditional Safety Stock (SS = 8)

Result: Traditional carries more inventory in period 5 and 6 due to safety stock dipping below 8. Garg's principle SS = 0, since DNA > 0 always.

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C. Scenario 3: Declining Demand

Demand = [18, 16, 14, 12, 10, 8]

Period	Demand	Supply	Open Inv	DNA
1	18	10	20	12
2	16	10	12	6
3	14	10	6	2
4	12	10	2	0
5	10	10	0	0
6	8	10	0	2

Table 6: S3A-Garg (Baseline DNA)

Period	Demand	Supply	Open Inv	DNA
1	18	16	20	18
2	16	10	18	12
3	14	10	12	8
4	12	12	8	8
5	10	10	8	8
6	8	10	8	10

Table 7: S3B-Traditional Safety Stock (SS = 8)

Result: Traditional carries more inventory in period 3,4,5 and 6 due to safety stock dipping below 8. Garg's principle SS = 0, since DNA > 0 always.

D. Scenario 4: High Variability

Demand = [8, 20, 6, 24, 18, 10]

Period	Demand	Supply	Open Inv	DNA
1	8	10	20	22
2	20	10	22	12
3	6	10	12	16
4	24	10	16	2
5	18	10	2	-6
6	10	10	-6	-6

Table 8: S4A-Baseline DNA

Period	Demand	Supply	Open Inv	DNA
1	8	12	20	24
2	20	12	24	16
3	6	12	16	22
4	24	10	22	8
5	18	10	8	0
6	10	10	0	0

Table 9: S4B-Garg Injection (SS = 6)

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Period	Demand	Supply	Open Inv	DNA
1	8	10	20	22
2	20	24	22	26
3	6	10	26	30
4	24	10	30	16
5	18	18	16	16
6	10	10	16	16

Table 10: S4C-Traditional Safety Stock (SS = 16)

Result: DNA becomes negative in period 5 and 6, hence Garg's injection was applied to 6/3 = 2 in each of period 1, 2 and 3 eliminating the stock-out situation without carrying excess inventory. Traditional carried way more inventory.

E. Scenario 5: Moderate Shortage

Demand = [10, 12, 14, 16, 18, 14]

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Period	Demand	Supply	Open Inv	DNA
1	10	10	20	20
2	12	10	20	18
3	14	10	18	14
4	16	10	14	8
5	18	10	8	0
6	14	10	0	-4

Table 11: S5A-Baseline DNA

Period	Demand	Supply	Open Inv	DNA
1	10	11	20	**21**
2	12	11	21	**20**
3	14	11	20	**17**
4	16	11	17	**12**
5	18	10	12	4
6	14	10	4	0

Table 12: S5B-Garg Injection (SS = 4)

Period	Demand	Supply	Open Inv	DNA
1	10	10	20	20
2	12	10	20	18
3	14	10	18	14
4	16	10	14	**8**
5	18	16	8	**6**
6	14	14	6	**6**

Table 13: S5C-Traditional Safety Stock (SS = 6)

Result: DNA becomes negative in period 6, hence Garg's injection was applied to 4/4 = 1 in each of period 1,2,3 and 4 eliminating the stock-out situation without carrying excess inventory. Traditional carried way more inventory.

F. Scenario 6: Extreme Variability (>50%)

Demand = [6, 18, 5, 31, 9, 17]

Period	Demand	Supply	Open Inv	DNA
1	6	10	20	24
2	18	10	24	16
3	5	10	16	21
4	31	10	21	0
5	9	10	0	1
6	17	10	1	-6

Table 14: S6A-Baseline DNA

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Period	Demand	Supply	Open Inv	DNA
1	6	11.5	20	25.5
2	18	11.5	25.5	19
3	5	11.5	19	25.5
4	31	11.5	25.5	6
5	9	10	6	7
6	17	10	7	0

Table 15: S6B-Garg Injection (SS = 6)

Period	Demand	Supply	Open Inv	DNA
1	6	10	20	24
2	18	25	24	**31**
3	5	10	31	**36**
4	31	18	36	**23**
5	9	10	23	**24**
6	17	16	24	**23**

Table 16: S6C-Traditional Safety Stock (SS = 23)

Result: DNA becomes negative in period 6, hence Garg's injection was applied to 6/4 = 1.5 in each of period 1,2,3 and 4 eliminating the stock-out situation without carrying excess inventory. Traditional carried way more inventory.

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Dimension	Scenario 0: Traditional Static Safety Stock	Scenario 1: Garg's Principle (DNA-Based)	Scenario 2: Variable Demand (DNA-Adaptive)	Scenario 3: Negative DNA (Risk-Triggered)	Scenario 4: AI-Assisted Forecast Verification
Safety Stock Definition	Fixed quantity based on historical variance	Horizon-anchored minimum feasible inventory (DNA)	Dynamically adjusted DNA under volatility	Emergency buffer when feasibility collapses	Derived from DNA, not directly computed by AI
Forecast Dependency	Strong, assumes forecast accuracy	Weak, feasibility-driven	Moderate, reacts to demand instability	Low, prioritizes survivability	AI validates forecast but does not replace it
Planning Horizon Awareness	None	Explicit (short, mid, long horizon DNA)	Explicit and demand-sensitive	Explicit with negative feasibility signal	Uses same horizon structure
Response to Demand Spikes	Slow, manual overrides required	Automatic via DNA erosion	Faster DNA contraction	Immediate escalation mode	AI flags anomaly before DNA breach
Handling Forecast Error	Absorbed via excess inventory	Exposed early via declining DNA	Amplified volatility but controlled	Forecast failure acknowledged explicitly	AI adjusts demand signal only
Over-Stock Risk	High	Low	Medium (controlled)	Low	Low
Stock-Out Risk	Medium	Low	Medium	Managed via exception buffers	Reduced via early detection
Planner Intervention	Frequent	Minimal	Occasional	Mandatory (exception handling)	Limited to confirmation
AI Usage	None	None	None	None	Limited to forecast verification
ERP Implementability	Native but inefficient	Fully ERP-native (EBS/SAP)	ERP-native with demand metrics	ERP-native with exception flags	ERP-native + lightweight

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					ML
Explainability	Low (black-box buffers)	High (DNA curves & feasibility logic)	High	Very high	High (AI only validates inputs)

Table 17: Comparison of Safety Stock Scenarios across Forecast Horizons

G. Large-Scale Multi-SKU Simulation (1,000 SKUs)

To evaluate the scalability and robustness of Garg's Principle, a synthetic multi-SKU simulation was conducted across 1,000 independent SKUs over a six-period planning horizon. The experiment preserved the same planning structure defined earlier, including:

- Horizon: 6 periods
- Lead time: 1–3 periods
- Initial inventory: randomly distributed
- Base supply: constant per SKU
- Demand patterns:
  - Increasing
  - Declining
  - High variability
  - Moderate shortage
  - Extreme variability (>50%)
- For each SKU:
  1. Baseline Dynamic Net Availability (DNA) was computed.
  2. Horizon stress was identified.
  3. Garg's safety stock injection was applied when DNA became negative.
  4. Post-injection feasibility was evaluated.

Scenario	SKUs	Baseline Feasible Rate	Feasible After Garg	Avg SS_H
Stable	218	100%	100%	0.0
Increasing	184	93.5%	100%	1.53
Declining	143	98.6%	99.3%	0.09
High variability	198	93.9%	100%	1.51
Moderate shortage	159	96.2%	100%	0.87
Extreme variability	98	92.9%	100%	4.64
Overall	**1,000**	**95.8%**	**99.9%**	**1.38**

Table 18: Large-Scale Simulation Results (1,000 SKUs)

Interpretation

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The large-scale simulation demonstrates the scalability and stability of Garg's Principle across diverse demand regimes. While approximately 4.2% of SKUs exhibited baseline infeasibility, the deterministic horizon-based injection logic restored feasibility in nearly all cases without requiring uniform buffering across periods.

Average safety stock requirements remained low across scenarios, confirming that the framework selectively protects only future constraint points rather than maintaining blanket inventory buffers. These results validate the applicability of the principle to multi-SKU enterprise planning environments.

Dataset Reference Note

The full 1,000-SKU dataset, including period-wise demand, supply, DNA, and injection calculations, is provided as supplementary material.

VIII. Real-Life Enterprise ERP Example

A manufacturing enterprise with long lead-time components experienced early inventory accumulation and frequent planner overrides under traditional safety stock [4].

Applying Garg's Principle:

1. Forecast verified using AI correction [13]
2. DNA computed across a 6-month horizon
3. Horizon stress detected in Month 5
4. Safety stock injected gradually in Months 1–3
5. No inventory added where future feasibility was already assured

A. Outcome

- Lower early inventory
- Zero stock-outs
- Reduced expediting
- Improved planner confidence

SKU	Beginning On-Hand	DNA (min)	SS_H	Feasible
SKU-01	356,581	80,002	0	Yes
SKU-02	21,956	4,121	0	Yes
SKU-03	78,855	11,163	0	Yes
SKU-04	22,417	10,121	0	Yes
SKU-05	76,021	26,064	0	Yes

Table 19: Enterprise Validation Results

Result:- The enterprise evaluation was performed on five anonymized SKUs for a Fortune 100 company extracted from an industrial ASCP horizontal plan using weekly buckets and sales-order demand only. Dynamic Net Availability remained positive across all SKUs, with no projected stock-outs. As a result, Garg's Principle required no safety stock injection, confirming horizon feasibility without additional inventory buffering.

IX. Discussion

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Traditional safety stock enforces protection everywhere, regardless of necessity [8]. Garg's Principle enforces protection **only at the future bottleneck,** minimizing cumulative inventory exposure. DNA curves and AUC metrics visually and quantitatively confirm this behavior.

Conclusion

The Principle of Garg substitutes the fixed safety stock buffering with a horizon-based deterministic feasibility model that essentially reinvents the logic of inventory protection in enterprise planning systems. The framework uses safety stock only when future infeasibility is mathematically projected by calculating Dynamic Net Availability over the entire forecast horizon and determining the lowest point of availability, avoiding unnecessary buffering in periods of stable or falling demand. The averaged pre-shortage injection rule allocates the necessary safety stock over time before the constraint, avoiding the concentration of inventory and guaranteeing the elimination of stock-outs. The framework is validated in a variety of demand scenarios, such as stable, increasing, declining, high variability, moderate shortage, and extreme variability conditions, and shows that the framework can be feasible with much lower cumulative inventory exposure than traditional methods. Artificial intelligence integration is strictly constrained to forecast verification, maintaining full determinism and auditability of inventory decisions. Enterprise implementation shows less early inventory build-up, no stock-outs, less expediting needs, and better planner confidence. The framework is fully compatible with the current enterprise resource planning and advanced planning system architectures, allowing it to be adopted without infrastructure adjustment.

Disclaimer

The authors have contributed to this article as follows:

Dinesh Kumar Garg: Conceptualization, methodology, core algorithm design, theoretical framework, and manuscript preparation.

Dheeraj Kumar Bansal: Data validation, implementation support, simulation, and manuscript review.

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