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A Hybrid Inventory Planning Framework Using Croston Forecasting and Safety Stock Optimization for Intermittent Automotive Spare Parts Demand

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Abstract - Automotive aftermarket spare parts inventory planning presents significant challenges due to intermittent and irregular demand patterns, long procurement lead times, and high service-level expectations. Traditional forecasting techniques such as moving averages and exponential smoothing frequently fail to provide reliable planning outputs for low-frequency demand items, resulting in excess inventory accumulation or critical stock-outs.

This study presents a practical implementation of a hybrid inventory planning framework integrating Croston forecasting methodology with safety stock optimization and lead-time-based inventory control within an automotive aftermarket spare parts distribution environment operating across GCC and African markets. The proposed framework combines intermittent demand forecasting, buffer stock management, ABC classification, and lead-time coverage planning to improve service-level performance for irregular-demand spare parts.

The implemented methodology was applied across a portfolio of 63 intermittent-demand automotive spare parts across 6 automotive brands, characterized by sporadic sales patterns and extended zero-demand intervals — with an average of 64.8% zero-demand periods across the SKU portfolio. Results demonstrated significant operational improvement, achieving approximately 93–95% stock availability while maintaining controlled inventory exposure and reducing stock-out frequency.

The findings indicate that integrating Croston forecasting with operational inventory planning controls can substantially improve spare parts availability and inventory stability in automotive aftermarket supply chains. The proposed framework offers scalable applicability for automotive aftermarket distributors, heavy equipment spare parts businesses, and industrial maintenance inventory environments.

Keywords — *Croston Forecasting, Intermittent Demand, Inventory Planning, Automotive Spare Parts, Safety Stock, Supply Chain Management, Service Level Optimization.*

1. INTRODUCTION

Inventory planning for automotive aftermarket spare parts remains one of the most complex functions within supply chain management due to highly irregular demand behaviour, long procurement lead times, and high customer service expectations. Unlike fast-moving consumer products, spare parts frequently exhibit intermittent demand characteristics where demand occurs irregularly with long periods of zero consumption.

Traditional forecasting methods such as moving averages and simple exponential smoothing are generally unsuitable for intermittent demand items because they fail to accurately capture demand occurrence intervals. This often results in either overstocking or critical stock shortages, both of which impose significant operational and financial costs on distributors.

In automotive aftermarket distribution environments, maintaining high inventory availability is essential due to the urgent nature of spare parts requirements. Simultaneously, organizations must minimize excess inventory investment and dead stock accumulation — particularly in multi-market operations spanning diverse demand geographies such as the GCC and African regions.

This study presents a practical industrial implementation of a hybrid inventory planning framework combining Croston forecasting methodology with safety stock optimization and lead-time coverage planning. The research evaluates the operational effectiveness of this approach within an automotive aftermarket spare parts distribution business operating across GCC and African markets, applied to a dataset of 63 SKUs across 6 automotive brands over a 13-month period (June 2025 – June 2026).

The primary objective is to demonstrate how intermittent demand forecasting integrated with operational inventory planning controls can improve service-level performance for irregular-demand automotive spare parts while maintaining inventory efficiency.

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2. LITERATURE REVIEW

Intermittent demand forecasting has received significant attention in inventory management research due to the limitations of traditional forecasting methods for low-frequency demand items. The foundational challenge lies in the dual uncertainty inherent in intermittent demand: uncertainty about when demand will occur and uncertainty about how large the demand will be when it does occur (Syntetos & Boylan, 2005).

John Croston introduced the Croston forecasting method in 1972 specifically for intermittent demand forecasting. Unlike conventional forecasting methods, the Croston approach separately estimates demand size and demand interval using exponential smoothing on each component. This separation allows the model to handle extended zero-demand periods more accurately than methods that treat all observations uniformly.

The Croston forecasting equation is represented as:

$$\hat{y}t = \dot{z}t / \hat{p}t$$

Where: $\dot{z}t$ = Estimated demand size per non-zero demand period; $\hat{p}t$ = Estimated interval between demand occurrences.

Syntetos and Boylan (2001, 2005) identified a systematic positive bias in the original Croston methodology and proposed the Syntetos-Boylan Approximation (SBA), which applies a correction factor of $(1 – \alpha/2)$ to the demand rate estimate. Their work has become foundational in intermittent demand forecasting literature, and their classification scheme — based on demand interval and demand variability — helps practitioners select appropriate forecasting methods.

Willemain et al. (2004) proposed a bootstrapping approach for generating lead-time demand distributions for intermittent items, demonstrating superior performance over Croston in certain spare parts environments. Teunter et al. (2011) further advanced the field by introducing demand classification frameworks that distinguish between erratic, lumpy, slow-moving, and smooth demand patterns, each warranting different inventory policies.

Silver et al. (2017) emphasize that forecasting accuracy alone is insufficient for effective inventory management. Safety stock planning, lead-time coverage, service-level targets, and procurement constraints must also be integrated into a holistic planning framework. This perspective aligns with the hybrid framework proposed in the current study.

In automotive aftermarket contexts, several studies have documented the unique challenges of spare parts inventory management including long replenishment lead times, high SKU proliferation, and the critical consequences of stock-outs (Cavalieri et al., 2008; Bacchetti & Saccani, 2012). However, limited empirical research exists on long-term practical implementation of Croston-based frameworks within automotive aftermarket distribution operations in emerging markets such as the GCC and Africa.

This study contributes to existing literature by presenting a practical, data-driven implementation of a hybrid inventory planning model integrating Croston forecasting with operational safety stock optimization in a real-world automotive aftermarket environment, supported by 13 months of actual demand data across 63 SKUs.

3. RESEARCH OBJECTIVES

The objectives of this research are:

- To evaluate the applicability of Croston forecasting methodology for intermittent-demand automotive spare parts across GCC and African markets.
- To develop a hybrid inventory planning framework integrating intermittent demand forecasting and safety stock optimization.
- To improve inventory service levels and reduce stock-out occurrences for irregular-demand spare parts.
- To analyze the operational effectiveness of Croston forecasting within automotive aftermarket inventory planning using 13 months of real transactional data.
- To provide a scalable forecasting and inventory optimization framework suitable for spare parts distribution businesses.

4. PROBLEM STATEMENT

Traditional inventory forecasting approaches used for automotive spare parts planning often fail to manage intermittent demand behaviour effectively. Frequent zero-demand periods and irregular consumption intervals result in poor forecast reliability when conventional forecasting methods are applied.

The organization involved in this study — an automotive aftermarket spare parts distributor operating across the GCC and African regions — experienced several operational challenges including frequent stock-outs, inconsistent service levels, excess inventory accumulation, inaccurate replenishment planning, high planner intervention requirements, and inefficient inventory investment allocation.

Analysis of the 63-SKU dataset revealed that 64.8% of all monthly demand observations were zero, with the average SKU recording demand in only 4.6 out of 13 observed months. This extreme intermittency rendered conventional moving average and exponential

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smoothing techniques ineffective, as these methods consistently over-smoothed zero-demand periods and generated unreliable replenishment signals.

The primary problem addressed in this research was the development of an inventory planning framework capable of improving stock availability for intermittent-demand spare parts while maintaining inventory control and operational efficiency across a multi-brand, multi-market distribution environment.

5. RESEARCH METHODOLOGY

5.1 Research Environment

This research was conducted within an automotive aftermarket spare parts distribution environment operating across GCC and African regions. The operational environment parameters are summarized in Table 1.

Parameter	Value
SKU Count Analyzed	63 intermittent-demand SKUs
Number of Brands	6 automotive brands
Operational Markets	GCC & Africa
Planning Frequency	Monthly
Study Period	June 2025 – June 2026 (13 months)
Average Lead Time	2 months
ABC Classification	CA: 14 SKUs | CB: 23 SKUs | CC: 26 SKUs

Table 1: Research Environment Parameters

5.2 Inventory Classification

Inventory items were classified based on ABC classification (revenue contribution), demand frequency, and sales movement patterns. All 63 SKUs in this study were identified as intermittent-demand items using the following criteria:

- Low sales frequency (demand occurring in fewer than 8 of 13 months)
- Sporadic consumption patterns with extended zero-demand intervals
- Average inter-demand interval exceeding 2 months

Demand Class	Description	Criteria
Fast Moving	Consistent monthly demand	Demand in 10+ of 13 months
Medium Moving	Regular but not monthly	Demand in 6–9 of 13 months
Irregular	Sporadic demand occurrence	Demand in < 6 of 13 months
Non-Moving	No recent sales	No demand in 12+ months

Table 2: Demand Classification Framework

5.3 Croston Forecasting Methodology

Croston forecasting methodology was implemented for all 63 irregular-demand spare parts. The forecasting process separately estimated the average demand size and the average interval between non-zero demand occurrences using exponential smoothing with a smoothing factor of $\alpha = 0.1$.

The Croston forecasting equation applied was:

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$$\textbf{Forecast} = \textbf{Demand Size } (\dot{z}) \, / \, \textbf{Demand Interval } (\hat{p})$$

Parameter	Value
Historical Data Period	13 months (June 2025 – June 2026)
Forecast Frequency	Monthly
Smoothing Factor (α)	0.10
Forecast Review Cycle	Monthly
Initialization Method	First non-zero demand observation

Table 3: Croston Forecasting Parameters

5.4 Safety Stock Optimization

To improve service-level performance, Croston forecast outputs were integrated with safety stock calculations and lead-time coverage logic. Safety stock levels were differentiated by ABC classification to balance service-level targets against inventory investment.

$$\textbf{Safety Stock} = Z \times \sigma d \times \sqrt{LT}$$

Where: Z = Service-level factor; σd = Standard deviation of non-zero demand observations; LT = Supplier lead time (months).

Inventory Class	Target Service Level	Z-Score Applied	Avg Safety Stock (units)
CA (High Value)	98%	1.65	18.7
CB (Medium Value)	95%	1.28	5.9
CC (Low Value)	90%	1.04	2.8

Table 4: Service Level Policy by ABC Class

5.5 Reorder Point Logic

The reorder point calculation integrated Croston forecast demand and safety stock requirements to generate replenishment triggers:

$$\textbf{ROP} = \textbf{Lead Time Demand} + \textbf{Safety Stock} = (\textbf{Croston Forecast} \times \textbf{LT}) + \textbf{Safety Stock}$$

This logic ensured replenishment orders were triggered at the point where expected demand during the supplier lead time plus buffer stock requirements reached current available inventory levels.

5.6 Hybrid Inventory Planning Framework

The proposed hybrid inventory planning framework integrated: demand classification; Croston intermittent demand forecasting; safety stock optimization; lead-time coverage planning; procurement constraints (MOQs); and service-level monitoring.

$$\textbf{Final Planning Quantity} = \textbf{Croston Forecast Demand} + \textbf{Safety Stock} + \textbf{Lead-Time Coverage}$$

6. RESULTS AND DISCUSSION

6.1 Dataset Characteristics

The 63 SKU dataset spanned 6 automotive brands across 13 months, recording a total demand of 2,859 units. The dataset exhibited strong intermittency characteristics: the average SKU recorded demand in only 4.6 of 13 months (35.2% of months), meaning 64.8% of all monthly demand observations were zero. CA-class SKUs showed the highest activity at 7.0 active months on average, while CC-class SKUs averaged only 2.1 active months out of 13.

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6.2 Croston Forecast Outputs

Croston forecasting generated monthly demand estimates for all 63 SKUs. The average forecast across the portfolio was 6.47 units per SKU per month. CA-class items showed a higher average forecast of 10.67 units/month reflecting their higher demand activity, while CB and CC classes averaged 4.90 and 5.58 units/month respectively.

ABC Class	SKUs	Avg Croston Forecast (units/month)	Avg Non-Zero Months	Avg Safety Stock (units)	Avg ROP (units)
CA	14	10.67	7.0 / 13	18.7	40.0
CB	23	4.90	5.9 / 13	5.9	15.7
CC	26	5.58	2.1 / 13	2.8	14.0
Overall	63	6.47	4.6 / 13	7.5	20.5

Table 5: Croston Forecast Results by ABC Class

6.3 SKU Case Studies

Three representative SKUs from the highest-demand tier are presented to illustrate the framework's application:

Parameter	SKU 1111112 (Brand C, CA)	SKU 1111137 (Brand C, CA)	SKU 1111140 (Brand C, CB)
13-Month Total Demand	675 units	143 units	133 units
Active Months	9 / 13 (69%)	7 / 13 (54%)	7 / 13 (54%)
Zero-Demand Months	4 / 13 (31%)	6 / 13 (46%)	6 / 13 (46%)
Croston Forecast	42.08 units/month	9.40 units/month	14.73 units/month
Safety Stock	101 units	23 units	22 units
Reorder Point (ROP)	185 units	42 units	51 units
Service Level Target	98% (CA class)	98% (CA class)	95% (CB class)

Table 6: SKU Case Studies — Croston Framework Application

SKU 1111112 represents the most extreme case in the dataset: despite high total demand (675 units over 13 months), it exhibited a highly volatile demand pattern with spikes of 230 units in June 2026 and 130 units in February 2026 separated by multiple zero-demand months. The Croston methodology successfully smoothed this volatility to generate a stable monthly forecast of 42.08 units, enabling a structured ROP of 185 units to protect against demand surges.

6.4 Service-Level Improvement

The implemented framework demonstrated significant operational improvements compared to the previous conventional forecasting approach. Key performance indicators before and after framework implementation are summarized in Table 7.

KPI	Before Implementation	After Implementation	Improvement
Stock Availability	~72%	93-95%	+21-23 percentage points
Stock-Out Frequency	High (unplanned)	Significantly reduced	Structured ROP-based triggers
Fill Rate	Variable	Consistent (class-based)	ABC-differentiated targets met

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KPI	Before Implementation	After Implementation	Improvement
Emergency Procurement	Frequent	Rare / exception-based	Reduced expediting cost
Planner Intervention	High (manual overrides)	Reduced	Systematic ROP triggers
Inventory Stability	Inconsistent	Stable	Safety stock buffers active

Table 7: KPI Comparison Before and After Framework Implementation

6.5 Discussion

The study demonstrated that Croston forecasting methodology performs effectively for intermittent-demand automotive spare parts when integrated with operational inventory controls. The 64.8% zero-demand rate observed in this dataset confirmed that conventional forecasting methods would have systematically underestimated or misaligned inventory replenishment timing.

The differentiated safety stock policy by ABC classification proved particularly effective. CA-class items, which warranted a 98% service level and Z-score of 1.65, carried significantly higher safety stock buffers (average 18.7 units) than CC-class items (average 2.8 units at 90% service level). This differentiation prevented the common failure mode of applying uniform safety stock rules across items of vastly different criticality and value.

A key insight from the case studies was that Croston's separation of demand size from demand interval estimation enabled more stable planning signals even during extended zero-demand periods — a capability that moving average methods fundamentally lack. The practical implementation highlighted that forecasting accuracy alone is insufficient; procurement cycles, supplier lead-time variability, MOQ constraints, and service-level targets must be co-integrated into the planning logic.

7. CONCLUSION

This study demonstrated the successful implementation of a hybrid inventory planning framework integrating Croston forecasting methodology with safety stock optimization for intermittent-demand automotive spare parts across a real-world GCC and African distribution environment.

Applied to a dataset of 63 SKUs across 6 automotive brands over 13 months, the framework achieved 93–95% stock availability from a baseline of approximately 72%, while reducing stock-out frequency, emergency procurement incidents, and planner intervention requirements. The 64.8% zero-demand rate observed in the dataset validated the necessity of intermittent-demand-specific forecasting methods over conventional approaches.

The findings confirm that combining Croston intermittent demand forecasting with differentiated safety stock policies, ABC classification, and reorder point logic can significantly improve operational performance in spare parts supply chains. The framework provides scalable applicability for automotive aftermarket distributors, heavy equipment spare parts businesses, and industrial maintenance inventory environments operating in multi-market, multi-brand contexts.

Future research may evaluate machine-learning-based intermittent demand forecasting models — such as Neural Network approaches or the Temporal Fusion Transformer — and compare their performance against Croston-based frameworks. Additionally, extending the framework to incorporate supplier lead-time variability modeling and dynamic safety stock recalculation could further improve planning precision.

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