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Research Article

A Consumption-Based Forecasting Framework for Automotive Spare Parts Inventory Optimization: A Case Study of CFAO Mobility Nigeria

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Abstract

Effective spare-parts inventory management requires balancing parts availability with the financial risks of excess and obsolete stock. This study develops a Consumption-Based Forecasting (CBF) framework for optimizing Suzuki spare-parts inventory at CFAO Mobility Nigeria. Using after sales inventory and consumption records covering August 2025 to April 2026, the study applies a quantitative case-study approach integrating average monthly consumption, demand-velocity classification, stock inactivity assessment, usable inventory estimation and forecast-based replenishment decisions. The results show that total inventory value declined by 8.5%, from NGN 444.32 million to NGN 406.39 million, while the reported provision-stock ratio increased from 51% to 60%. SKU-level analysis further revealed contrasting inventory positions: an oil filter recorded average monthly consumption of 95.3 units and a forecast stock requirement of +665 units, indicating a replenishment need, whereas a fuel filter recorded average monthly consumption of 1.7 units and a surplus of 232 units. These findings demonstrate the coexistence of replenishment needs and excess stock within the same after sales inventory system. The proposed framework provides a structured basis for differentiated procurement, surplus-stock control and inventory-risk monitoring. Its predictive performance and operational effectiveness require further validation through chronological back-testing and implementation.

Keywords: Spare-parts inventory management; Consumption-Based Forecasting; demand classification; intermittent demand; inventory optimization; automotive after sales.

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Introduction

Inventory management in automotive after sales systems requires balancing spare-parts availability with the cost of holding inventory. Excess stock increases holding costs and obsolescence risk, while insufficient stock can delay repairs, reduce workshop productivity and result in lost sales. Effective inventory planning therefore depends on reliable demand estimation, replenishment control and stock monitoring [1].

This challenge is particularly evident in spare-parts environments, where demand is often intermittent, with extended periods of zero demand followed by occasional requirements. Croston [2] addressed this pattern by estimating demand size and occurrence intervals separately. Subsequent studies examined the accuracy and stock-control performance of intermittent-demand methods Syntetos and Boylan [3-4], while Teunter et al. [5] linked demand patterns to inventory obsolescence. These studies highlight the importance of considering both consumption history and SKU inactivity in inventory decisions.

Inventory policies must also reflect differences in item value, demand variability and movement. A high-volume service filter, for example, requires a different control strategy from an expensive body panel or specialised electronic component. Inventory classification methods, including ABC-XYZ-FSN, support differentiated replenishment and stock-management decisions [1,6,7].

In emerging markets, dependence on imported parts, variable replenishment lead times, foreign-exchange fluctuations and fragmented procurement can further complicate inventory planning. Decisions based solely on physical stock may encourage unnecessary replenishment of dormant items, while indiscriminate purchasing restrictions may create shortages. Consequently, inventory models should distinguish total physical stock, aged inventory and stock considered usable for meeting forecast demand, without automatically treating all aged stock as unusable.

This study examines Suzuki spare-parts inventory managed by CFAO Mobility Nigeria, using records from August 2025 to April 2026. The reported provision exposure increased from approximately 51% to 60% of total inventory value during this period. To address this challenge, the study develops a Consumption-Based Forecasting (CBF) framework integrating SKU-level consumption, inactivity measurement, aged-stock classification and net forecast stock requirements. The framework provides a mathematical basis for differentiated replenishment and inventory-risk decisions while avoiding the double-counting of aged stock.

Materials and Methods

Study Design and Data

This quantitative case study develops a consumption based framework for spare parts inventory management using Suzuki after sales records from CFAO Mobility Nigeria (August 2025 to April 2026; sourcing streams JP, IN, ID, FR and EU). The unit of analysis is the stock keeping unit (SKU), indexed by $i=1,2,\ldots,N$.

Records comprise SKU identifiers, dated consumption transactions, stock quantities and values, last movement dates and sourcing streams, with supplier lead times where available. Returns, cancellations and non demand movements are excluded where identifiable. A common observation window is applied to all SKUs so that zero demand periods are retained. Quantities and values were checked for consistency. The records do not state the SKU count, transaction volume, extraction procedure or valuation basis for every stock category; these must be supplied by the data owner for full reproducibility.

Model Formulation

Let Q_i be the qualifying consumption of SKU i over an observation window of T months. Average monthly consumption is

$$\mu_i = \frac{Q_i}{T}, T = max\left(\frac{t_{end} - t_{start}}{30.44}, 1\right) \quad (1)$$

where dates are measured in days. Inactivity, the time since the last qualifying demand at review date t_a, is

$$\tau_i = \frac{t_a - t_i}{30.44} \quad (2)$$

where t_i is the date of the last qualifying movement. With S_i the physical stock, stock is assigned to inactivity class A (six to twelve months) or class B (more than twelve months):

$$S_i^A = S_i 1\{6 \le \tau_i \le 12\}, S_i^B = S_i 1\{\tau_i > 12\} \quad (3)$$

These classes measure SKU level inactivity, not the physical age of units; receipt or batch records should be used where available. Let $\alpha_A, \alpha_B \in [0, 1]$ be the proportions of class A and class B stock unavailable for immediate fulfilment, set from documented condition assessments or management rules. Usable stock is

$$S_i^u = S_i - \alpha_A S_i^A - \alpha_B S_i^B \quad (4)$$

which prevents aged stock from being deducted twice in the replenishment calculation. Where demand variability and lead time data are sufficient, safety stock is

$$SS_i = z\sigma_i\sqrt{L_i} \quad (5)$$

where z is the standard normal quantile for the chosen service level, σ_i is the standard deviation of monthly demand and L_i is supplier lead time in months. Equation (5) assumes independent monthly demand and fixed lead time; otherwise a simulation based or alternative statistical method is used, or SS_i is set as a management input. For a target coverage period C_i (months), the net forecast stock requirement is

$$FS_i = \mu_i C_i + SS_i - S_i^u \quad (6)$$

where $FS_i > 0$ indicates a replenishment need, $FS_i = 0$ a balanced position and $FS_i < 0$ a surplus.

Classification and Decision Rules

SKUs are assigned to five demand velocity classes by average monthly consumption:

$$V_i = \begin{cases} 1(\text{fast}), & \mu_i \geq 10 \\ 2(\text{medium}), & 5 \leq \mu_i < 10 \\ 3(\text{slow}), & 1 \leq \mu_i < 5 \\ 4(\text{very slow}), & 0 < \mu_i < 1 \\ 5(\text{dormant}), & \mu_i = 0 \end{cases} \tag{7}$$

These thresholds are the operational classes of the case framework and are not assumed to be statistically optimal; they should be checked against the observed demand distribution. With a management defined overstock tolerance $\phi_i > 0$, the action for each SKU is

$$A_i = \begin{cases} \text{clearance review}, & \mu_i = 0, S_i > 0 \\ \text{replenish}, & FS_i > 0 \\ \text{monitor}, & FS_i = 0 \\ \text{freeze replenishment}, & -\phi_i \leq FS_i < 0 \\ \text{stock reduction review}, & FS_i \leftarrow \phi_i \end{cases} \tag{8}$$

with the dormant condition evaluated first and ϕ_i specified by SKU class, inventory value or purchasing policy. The preliminary replenishment quantity is

$$Q_i^r = max(0, FS_i) \tag{9}$$

and is subsequently adjusted for minimum order quantities, pack sizes, budget and purchasing cycles.

Provision Exposure and Validation

Provision exposure is the share of inventory value held in inactivity classes A and B:

$$PR = \frac{\sum_{i=1}^{N} W_i^p}{\sum_{i=1}^{N} W_i} \times 100\% \tag{10}$$

where W_i is the stock value of SKU i and W_i^p the value of its class A and B stock, on a consistent valuation basis and SKU inclusion rule across review dates. PR is a financial exposure indicator, distinct from the physical quantity unavailable for fulfilment.

Forecast performance is evaluated on a chronological holdout, estimating on earlier periods and testing on later ones, using mean absolute error (MAE) and root mean squared error (RMSE). Mean absolute percentage error is interpreted cautiously where actual demand is zero. For intermittent demand SKUs the proposed method is benchmarked against Croston type methods [2-4]. Conclusions on predictive performance or operational improvement are drawn only after this back testing.

Results and Discussion

Historical Inventory Provision Exposure

Analysis of stock records from August 2025 to April 2026 revealed increasing inventory provision exposure despite a decline in total stock value. As shown in Table 2, total inventory value decreased from NGN 444.32 million to NGN 406.39 million (8.5%), while provision value increased from NGN 226.62 million to NGN 243.76 million. Consequently, the provision-stock ratio rose from 51% to 60%.

Table 2. Temporal evolution of inventory provision exposure (August 2025–April 2026).

Audit period	Total stock value (NGN)	Provision value (NGN)	Provision ratio
18-Aug-2025	444,321,885.00	226,621,442.00	51%
28-Sep-2025	427,122,289.04	221,941,703.39	52%
31-Oct-2025	414,123,840.65	220,113,669.91	53%
07-Nov-2025	414,786,254.25	244,370,055.13	59%
30-Jan-2026	425,241,527.41	240,204,630.51	56%
06-Mar-2026	409,623,217.63	246,303,974.16	60%
10-Apr-2026	406,387,031.43	243,757,916.81	60%

The nine-percentage-point increase in provision exposure indicates that reducing aggregate inventory value did not necessarily improve inventory quality. The sharp increase between October and November 2025, followed by a return to 60% in March 2026, further suggests persistent weaknesses in replenishment and inventory-aging control. These findings reflect the challenges identified in spare-parts management, where intermittent demand, product variety and obsolescence complicate inventory decisions [8-9]. They highlight the need for SKU-level assessment rather than reliance on aggregate stock values.

Demand Classification and SKU-Level Stock Imbalances

Application of the proposed demand classification model differentiated inventory into fast-, medium-, slow-, very-slow-moving and dormant categories according to average monthly consumption. This classification, combined with the inactivity measures in Equations (2) and (3), provides complementary indicators of demand velocity and stock aging.

The Suzuki India (IN) sourcing stream revealed contrasting inventory positions. The oil filter (16510M68K20-000) recorded average monthly consumption of 95.3 units and a positive forecast stock requirement of (FS_i =+665), indicating a replenishment need. Conversely, the fuel filter (15410M53M00-000) recorded average monthly consumption of 1.7 units and (FS_i =-232), indicating excess inventory relative to its estimated requirement.

The Suzuki Japan/Europe (JP/EU) streams also exhibited concentrations of dormant or potentially obsolete references, particularly body panels and specialized electronic components. These findings demonstrate that inventory shortages and surpluses can coexist within the same sourcing system, making uniform replenishment policies inappropriate.

The results are consistent with Bacchetti and Saccani [8], who emphasize differentiated classification and forecasting in spare-parts inventory management. Furthermore, Croston [2] and Syntetos and Boylan [3-4] demonstrate the importance of accounting for intermittent demand when estimating spare-parts requirements. Accordingly, the observed differences support SKU-specific replenishment decisions based on consumption, usable stock and supplier lead time.

Forecasting and Inventory Control Implications

The proposed replenishment model integrates average consumption, target stock coverage, safety stock and usable inventory to determine net forecast stock requirements. Positive values of (FS_i) indicate replenishment needs, whereas negative values indicate surplus positions. This provides a basis for prioritizing high-demand components while restricting additional procurement of overstocked items.

The adjustment for aged stock further distinguishes recorded inventory from stock considered suitable for immediate fulfilment. However, inactivity does not necessarily imply physical obsolescence, particularly for specialized components with infrequent but continuing service demand. Installed-base information and component criticality should therefore complement historical consumption when determining clearance decisions. Dekker et al. [10] similarly highlight the value of installed-base information in spare-parts demand estimation.

For intermittently demanded items, Croston-type methods provide relevant forecasting benchmarks because they separately estimate demand occurrence and demand size. The proposed chronological holdout validation using MAE and RMSE will establish the predictive performance of the framework relative to these methods. Predictive superiority cannot, however, be established until the back-testing results are available.

Proposed Inventory Optimization Strategy

The diagnostic findings support differentiated procurement and clearance interventions. SKUs with positive forecast stock requirements should receive replenishment priority, subject to purchasing constraints, while negative forecast positions should trigger replenishment restrictions or stock reduction reviews. Dormant items with available stock should undergo clearance and obsolescence assessments.

Table 3. Inventory optimization decision framework.

Inventory condition	Decision rule	Recommended action
Dormant with stock	($\mu_i = 0$ and $S_i > 0$)	Clearance review
Replenishment requirement	($FS_i > 0$)	Replenish
Balanced position	($FS_i = 0$)	Monitor
Moderate surplus	($-\varphi \leq FS_i < 0$)	Freeze replenishment
Significant surplus	($FS_i < -\varphi$)	Stock reduction review

Existing excess inventory may be monetized through promotional bundling, business-to-business sales to fleet operators and independent workshops, and vendor reciprocity arrangements. These interventions complement procurement restrictions by addressing existing surplus while limiting further accumulation. Such differentiated control is consistent with the integrated spare-parts management approach discussed by [8-9].

Performance Targets and Overall Discussion

The proposed performance indicators provide measurable criteria for evaluating the framework over a six-to-twelve-month implementation period.

Table 4. Proposed inventory optimization key performance indicators.

Performance metric	Baseline (April 2026)	Target	Monitoring frequency
Provision-stock share	60%	Below 40%	Monthly
Overstocked SKU reduction	To be established	50% reduction	Weekly
Parts availability fill rate	Below 75%	Above 90%	Weekly

OTC sales growth	To be established	25–40% increase	Monthly
Emergency local purchases	High	20–60% reduction	Monthly
Forecast-model accuracy	Unmeasured	Above 85%	Weekly

The targets address four dimensions of inventory performance: financial exposure, stock availability, commercial recovery and forecasting reliability. In particular, reducing provision-stock share to below 40% while maintaining a fill rate above 90% would indicate improved working-capital utilization without compromising aftersales service. Forecast performance should be evaluated using the chronological holdout procedure, with the proposed accuracy target operationally defined through appropriate error measures such as WAPE, alongside MAE and RMSE.

Overall, the findings indicate that the principal inventory challenge is the misalignment between stock investment and actual consumption requirements. The proposed framework addresses this through the integration of demand classification, inactivity assessment, forecast stock requirements and differentiated procurement decisions. Its contribution lies in connecting SKU-level demand characteristics with operational and financial inventory controls.

Nevertheless, the study is constrained by the observation period, incomplete supplier lead-time information and management-defined classification thresholds. Furthermore, the proposed performance targets have not yet been validated through implementation. Subsequent chronological back-testing and longitudinal operational monitoring are therefore necessary to establish the predictive and practical effectiveness of the framework.

Conclusion

This study presents a consumption-based mathematical and managerial framework for optimizing automotive spare parts inventory at CFAO Mobility. By integrating demand-velocity classification, stock inactivity assessment and forecast-based replenishment decisions, the framework provides a systematic alternative to reactive purchasing practices. Its application offers a basis for identifying replenishment needs, controlling surplus inventory and managing provision exposure while maintaining parts availability. Implementation, supported by periodic data validation and performance monitoring, could improve inventory efficiency, reduce tied-up working capital and support workshop productivity and over-the-counter sales. Further validation using historical demand data and operational performance indicators is required to establish its predictive accuracy and practical effectiveness.

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