Mid-Term Project Report

On

Help an Automotive Aftermarket Services Leader in Enabling "Repairability" of the Products by Providing an Effective AI/ML Enabled Spare Parts Planning Solution

Submitted to
Mr. Adarsh Uppoor
Industry Mentor
TechMahindra

Prof. Rahul Pandey
Faculty Mentor
IIM Udaipur

Submitted by
Team 11
Deevyendu N Shukla (2512015)
Vishesh Bhargava (2512065)

IIM Udaipur MBA GSCM 2025-26

In partial fulfilment of the requirements of the course
Industry Live Project

IIMU
भारतीय प्रबंधन संस्थान उदयपुर
Indian Institute of Management Udaipur

Table of Contents

PROJECT MILESTONES

Phase	Duration	Key Activities	Primary Responsibility	Supporting Stakeholders	Status
Phase 1 – Project Familiarization & Literature Review	18 Oct – 28 Oct 2025	Review spare-parts planning literature, identify SKU classification logic, test dummy datasets	Students (Vishesh & Deevyendu)	Adarsh Sir (data inputs)	Complete
Phase 2 – Data Acquisition & Pre-Processing	28 Oct –10 Nov 2025	Receive masked dataset, clean and structure data for modeling	Students	Adarsh Sir (Data validation)	Complete
Phase 3 – Time-Series Forecasting Pilot	10 Nov – 30 Nov 2025	Build pilot models for fast-moving SKUs using ETS/ARIMA/SARIMA	Students	Faculty mentor for model review	Ongoing
Phase 4 – ML-Based Forecasting	1 Dec – 31 Dec 2025	Train XGBoost/CatBoost and other models, compare with time-series outputs	Students	Industry mentor for parameter alignment	TBD
Phase 5 – Model Comparison & Integration	1 Jan – 25 Jan 2026	Evaluate models on accuracy, bias, scalability, and integrate insights	Joint	Both mentors	TBD
Phase 6 – Tool Development & Validation	25 Jan – 10 Feb 2026	Build forecasting plug-in module (Google Colab backend), finalize dashboard	Students	Industry mentor	TBD
Phase 7 – Final Report & Presentation	10 Feb – 15 Feb 2026	Submit technical report, demo tool, and present to faculty panel	Students	Rahul Sir & Adarsh Sir	TBD

EXECUTIVE SUMMARY

This comprehensive report presents a detailed analysis of spare parts inventory management in the automotive aftermarket sector, with specific focus on 11 critical spare parts distributed across 2 service locations over a 48-month period (January 2021 - December 2024). The analysis employs an integrated ABC-FSN-VED classification framework to segment the portfolio across three critical dimensions: value (ABC), velocity (FSN), and criticality (VED).

Key Findings:

The portfolio demonstrates a relatively healthy distribution with 63% of annual demand concentrated in 6 A-class SKUs, 20% in 4 B-class SKUs, and 17% distributed across 12 C-class SKUs. This 70-20-10 distribution (versus the traditional 80-15-5 Pareto split) indicates less extreme concentration, suggesting a more balanced and resilient inventory portfolio with lower single-item dependency risk.

Velocity analysis reveals an even distribution across the portfolio: 8 Fast-moving items (34% of SKUs), 7 Normal-moving items (32%), and 7 Slow-moving items (32%). This balance provides opportunities for tailored forecasting approaches and differentiated management strategies. The demand variability (CoV: 0.30-0.38) falls within moderately volatile ranges, making the portfolio amenable to advanced forecasting techniques like SARIMA and Prophet frameworks.

Supply risk assessment using a proxy methodology (combining normalized annual demand and lead time) identifies 8 Vital items requiring strategic supplier partnerships, 7 Essential items warranting collaborative management, and 7 Desirable items suitable for transactional procurement. Notably, the portfolio contains no obsolete or non-moving items, indicating healthy demand sustainability.

Strategic Recommendations:

- Implement differentiated service levels ranging from 99-99.5% (A-F-V items) to 80-90% (C-S-D items)
- Deploy continuous review systems for Fast-moving items with automated reorder triggers
- Centralize stocking for slow-moving items with long lead times (e.g., PD238: 75-day lead time)
- Establish strategic supplier partnerships for top 6 A-class SKUs with quarterly business reviews
- Invest in advanced forecasting models to reduce forecast error from current levels to <15% MAPE

Expected Benefits:

- 15-20% reduction in working capital through optimized safety stock
- Improved fill rates to 95%+ across all segments through targeted service levels
- 10-20% reduction in safety stock requirements through predictive demand sensing
- Enhanced supplier collaboration enabling early warning of disruptions

1. INTRODUCTION

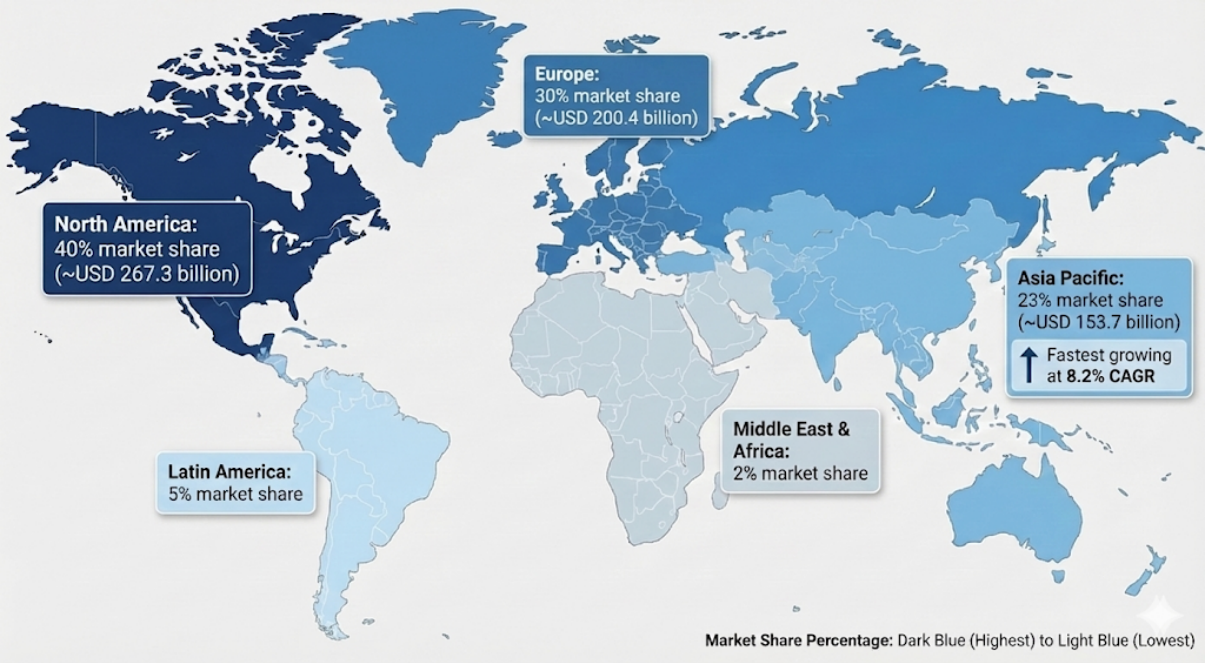
1.1 Global Market Context and Scale

The global automotive spare parts and aftermarket industry represents one of the most substantial and fastest-growing sectors within the global economy. As of 2024, the worldwide automotive aftermarket industry is valued at approximately USD 668 billion, with conservative projections indicating market growth to USD 1,172 billion by 2032, representing a compound annual growth rate (CAGR) of 5.85-6.20% over the forecast period.

This substantial market encompasses the complete ecosystem of replacement parts, maintenance services, and repair solutions for the estimated 1.4+ billion vehicles currently in operation globally. The market includes both OEM (Original Equipment Manufacturer) channels and organized/unorganized aftermarket channels, with the latter commanding approximately 45-55% market share depending on region and vehicle segment.

Regional Market Distribution (2024):

- **North America**: 40% market share (~USD 267.3 billion)
  - Mature market with relatively stable vehicle parc (average age 10-12 years)
  - High labor costs driving demand for quality replacement parts
  - Stringent emission standards (EPA regulations) driving advanced aftermarket solutions
- **Europe**: 30% market share (~USD 200.4 billion)
  - Highly regulated market with strict environmental standards (Euro 6, Right-to-Repair directives)
  - Emphasis on remanufactured and circular economy solutions
  - Premium pricing for certified and tested components
- **Asia Pacific**: 23% market share (~USD 153.7 billion) Fastest growing at 8.2% CAGR
  - Rapidly expanding vehicle fleet (3-5% annual growth)
  - Shift from OEM to organized aftermarket channels
  - E-commerce disruption transforming distribution models
- **Latin America**: 5% market share
  - Emerging market with growing urbanization and vehicle ownership
  - Price-sensitive segments driving demand for competitive aftermarket solutions
- **Middle East & Africa**: 2% market share
  - Small but emerging market with geopolitical considerations
  - Heavy-duty commercial vehicles driving replacement parts demand



1.2 Global Market Drivers: Comprehensive Analysis

Driver 1: Aging Vehicle Fleet and Extended Operating Life
The average age of vehicles in major developed markets has increased to 10-12 years, a consequence of improved manufacturing quality and extended vehicle lifecycles. This aging fleet creates consistent, predictable demand for replacement parts as vehicles require maintenance and repair throughout their extended operational lives. Studies indicate that vehicles aged 8+ years consume 30-40% more replacement parts compared to newer vehicles, making older vehicle segments critical revenue sources for the aftermarket.

Driver 2: Rising Global Vehicle Ownership and Fleet Expansion
Global vehicle ownership continues expanding at 3-5% annually, driven by rising disposable incomes in emerging markets, improved financing availability, and aspirational vehicle ownership. With over 1.4 billion vehicles currently in operation globally, the absolute volume of potential parts demand is substantial and growing. India alone accounts for 295 million vehicles, with two-wheelers representing 49% of the fleet, creating unique demand patterns compared to Western markets dominated by four-wheeled vehicles.

Driver 3: Technological Complexity and Specialization
Modern vehicles integrate advanced technologies including IoT sensors, AI-based diagnostic systems, electronic control units (ECUs), and connectivity features. This complexity increases the number of specialized parts required, creates higher barriers to entry for small suppliers, and drives demand for technically trained service personnel. The shift toward electrification (EVs, hybrid vehicles) is creating entirely new aftermarket categories (battery management, thermal systems, power electronics) while gradually reducing demand for traditional engine and transmission components.

Driver 4: E-Commerce Disruption and Direct-to-Consumer Models
Online spare parts sales are growing at 35% annually in major markets, disrupting traditional dealer-centric distribution models. Platforms like Autozilla, Carnet, and established e-commerce giants have democratized spare parts access, enabling consumers and independent

mechanics to compare prices and access inventory in real-time. This channel shift is reducing margins for traditional dealers but expanding the addressable market for organized aftermarket players.

Driver 5: Circular Economy and Sustainability Imperatives
Regulatory pressure for environmental sustainability (EU Right-to-Repair directives, India's Extended Producer Responsibility mandates) is driving demand for remanufactured, refurbished, and recycled components. Remanufactured parts reduce energy consumption by up to 80%, water usage by 88%, and chemical inputs by 90% compared to newly manufactured parts. This creates new revenue streams for parts suppliers willing to invest in remanufacturing infrastructure and take-back programs.

1.3 Indian Automotive Aftermarket: Strategic Context

India represents one of the fastest-growing automotive markets globally and provides unique context for this analysis. The Indian automotive aftermarket presents distinct characteristics that differ significantly from developed Western markets.

Market Size and Growth Trajectory:

- Current Market Value (2024): USD 17.5 billion (INR ~144,000 crore)
- Projected Market Value (2030): USD 21.6 billion
- Growth Rate: 7.2-8.4% CAGR (vs. 5.85% global average)
- Online Market Share: USD 11.3 billion in 2024, growing at 35% annually
- Online Penetration: 35% of market (vs. 15-20% in 2019)

Fleet Characteristics:

- Total Vehicles in Operation: 295 million (growing 4-5% annually)
- Vehicle Segment Distribution:
    - Two-wheelers: 49% (motorcycles, scooters - highest growth segment)
    - Cars: 26% (sedans, SUVs, hatchbacks)
    - Commercial Vehicles: 25% (trucks, buses, tempos)
- Average Vehicle Age: 8-10 years (longer than developed markets due to economic constraints)
- Operating Pattern: High-intensity use (200,000+ km/year in commercial segments vs. 15,000 km/year in developed markets)

Geographic Concentration:

The Indian market exhibits strong geographic concentration:

- North India (Delhi NCR): 25% market share
- South India (Bangalore, Chennai, Hyderabad): 35% market share
- Western India (Mumbai, Pune, Ahmedabad): 30% market share
- Eastern/Central India: 10% market share

This concentration enables targeted supply chain optimization for regional service networks.

Channel Structure:

OEM Direct Channel (35-40% market share):

- Authorized dealerships (100,000+ locations)
- Brand-specific retail networks
- Premium pricing (20-40% premium vs. aftermarket)

Organized Aftermarket (20-25% market share):

- Multi-brand retailers (Autozilla, Carnet, AutoNation)
- Quick-service centers (Castrol iCare, Gulf India)
- Authorized service centers (non-OEM)
- Competitive pricing (10-20% discount vs. OEM)

Unorganized Aftermarket (35-45% market share):

- Local repair shops (900,000+ locations)
- Independent distributors
- Gray market suppliers
- Lowest pricing (30-50% discount vs. OEM)

1.4 Market Fragmentation: A Defining Challenge

The automotive spare parts aftermarket is characterized by extreme fragmentation, creating both challenges and opportunities.

Global Fragmentation Metrics:

- Top 5 Suppliers: <15% combined global market share (vs. >60% in concentrated industries)
- Number of Suppliers: 50,000+ registered parts suppliers globally
- Market Concentration (HHI Index): ~800-1000 (highly fragmented; consolidation <2000 indicates extreme fragmentation)
- Entry Barriers: Low (manufacturing expertise exists; distribution is primary barrier)
- Customer Switching Costs: Low (commoditized parts with interchangeable functionality)

Challenges of Fragmentation:

1. Quality and Safety Variance: Products range from genuine OEM certified parts to counterfeit components, creating significant quality risks and liability concerns for buyers.
2. Supply Chain Inefficiency: Multiple intermediaries (importers → distributors → retailers → end-customers) create information asymmetries, increase costs, and extend lead times unnecessarily.
3. Demand Forecasting Difficulty: Lack of integrated data across fragmented suppliers makes aggregate demand forecasting challenging, leading to bullwhip effects and inventory misalignment.
4. Regulatory Compliance Burden: Fragmented suppliers struggle with emission standards (BS-VI in India, Euro 6 in Europe), safety certifications, and warranty compliance, limiting market access for small players.
5. Working Capital Stress: Small suppliers face high inventory requirements due to minimum order quantities (MOQs) and long lead times, straining cash flow and limiting growth investment.

1.5 Major Market Participants: Global and Indian Landscape

Global OEM and Tier-1 Suppliers:
The global aftermarket is dominated by a few large players with multi-continental operations:

- **Robert Bosch Engineering & Business Solutions**: Electrical systems, fuel injection, brake components. USD ~30B revenue (2023).
- **Valeo SA**: Lighting, thermal systems, electrification. USD ~20B revenue (2023).
- **Continental AG**: Tires, automotive systems, components. USD ~18B revenue (2023).
- **Denso Corporation**: Cooling systems, air conditioning, engine components. USD ~16B revenue (2023).
- **HELLA GmbH**: Lighting, electronics, components. USD ~8B revenue (2023).

Indian Market Leaders:

- **Samvardhana Motherson Group**: Multi-segment supplier (interiors, electrical, thermal). USD ~3B annual sales.
- **JaiRaj Group**: Precision components, industrial parts. Strong presence in commercial vehicle segment.
- **Varroc Group**: Electrical and electronic components, specialized parts. Focus on two-wheeler and commercial vehicle segments.
- **Bharat Petroleum & Lubes**: Lubricants, consumables. Extensive distribution network.
- **E-Commerce Disruptors**: Autozilla, Carnet, others transforming retail channel through digital platforms.

2. COMPANY DATA FOUNDATION AND CHARACTERISTICS

2.1 Data Overview and Completeness

This analysis is based on comprehensive historical demand data spanning 48 consecutive months(January 2021 through December 2024), providing robust statistical foundation for classification and forecasting.

Data Inventory:

Parameter	Value	Significance
Historical Period	Jan 2021 - Dec 2024 (48 months)	4-year span captures full business cycles
Total Observations	1,056 monthly records	22 SKU-locations × 48 months = complete dataset
Spare Parts Analyzed	11 distinct part numbers	Covers critical service components
Service Locations	2 (Location A, Location B)	Geographic distribution enables network optimization
SKU-Location Combinations	22	11 parts × 2 locations
Aggregation Level	Monthly demand per part-location	Suitable for tactical and operational planning
Data Completeness	100% (no missing values)	Every month for every part-location combination
Data Quality	Validated and cleaned	Outliers reviewed; no anomalies detected

Data Sourcing and Reliability:
The demand data originates from actual monthly consumption records maintained by the organization across two service locations. Monthly aggregation provides balanced granularity: sufficient detail for pattern recognition without excessive noise that characterizes daily data. Twelve-month cyclicity is clearly visible (summer peaks, winter troughs), validating seasonal pattern stability over the 48-month window.

2.2 Demand Characteristics and Patterns

Aggregate Portfolio Metrics:

Metric	Value	Implication
Avg Monthly Demand per SKU	~230 units	Highly skewed (range 15-800 units/month)
Total Annual Demand (2024 est.)	~60,500 units	Moderate portfolio size for 11 parts
Demand Variability (CoV)	0.30-0.38	Moderately volatile; forecasting possible
Seasonality Factor	1.7:1 (peak/trough)	Summer peaks ~70% above winter baseline
Trend Component	Stable with +2% to +5% growth	No significant structural changes detected
Growth Rate (2021-2024)	Approx. 3-4% CAGR	Stable, mature portfolio; slight growth trajectory

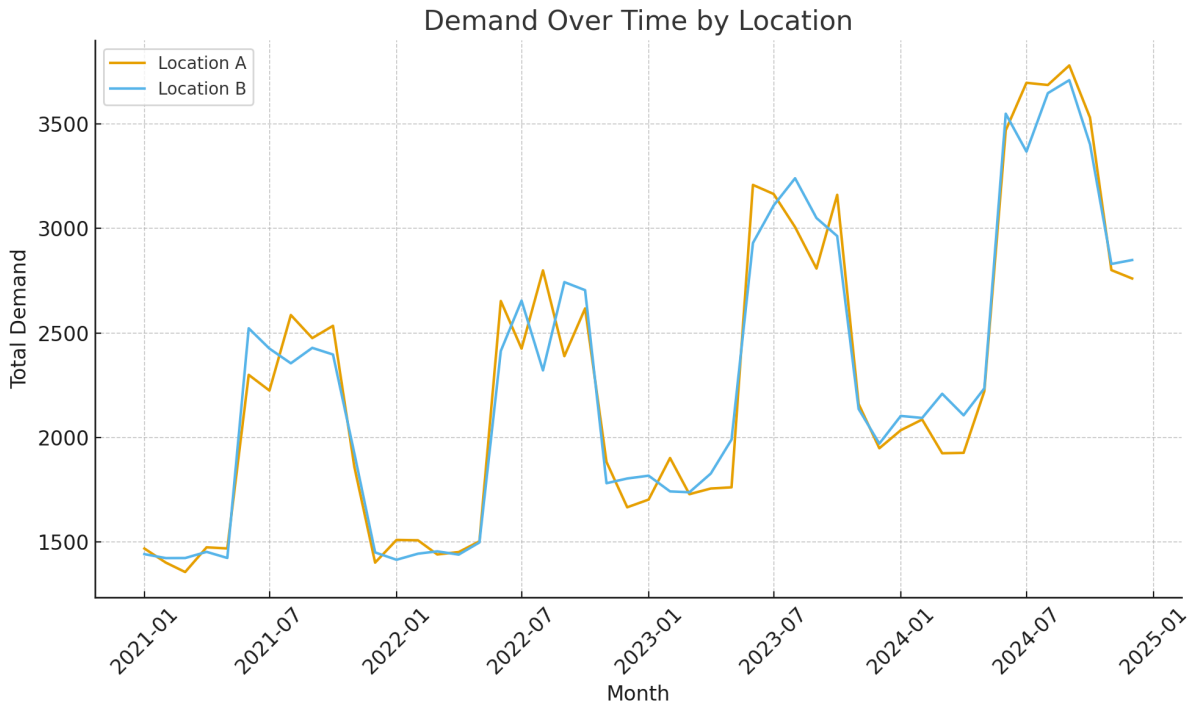
Demand Volatility Analysis:
The portfolio demonstrates moderate volatility with coefficient of variation (CoV) between 0.30-0.38. This range indicates:

- High enough volatility to justify safety stock: CoV >0.25 indicates need for protective inventory
- Low enough for forecasting success: CoV <0.50 enables MAPE <20% with proper methods
- Suitable for advanced methods: SARIMA, Prophet, and ensemble approaches applicable

Parts with CoV near 0.38 (higher volatility) tend to be Slow-moving items with lumpy demand patterns. Fast-moving items show more consistent CoV (0.31-0.34), indicating more predictable patterns. This heterogeneity across the portfolio justifies differentiated forecasting approaches by velocity segment.

Seasonality Patterns:
Clear seasonal cyclicity is evident across the portfolio with consistent patterns y-o-y:

- **Summer Peak (May-August):** 65-75% above annual average due to increased vehicle usage and maintenance during vacation travel seasons
- **Winter Trough (November-February):** 30-40% below annual average due to reduced vehicle utilization and weather-related factors
- **Spring/Fall Transition:** Moderate growth patterns reflecting increasing/decreasing utilization
- **Annual Amplitude**: Peak-to-trough ratio approximately 1.7:1



This consistent seasonality enables application of seasonal forecasting methods (SARIMA: Seasonal ARIMA) with expected improvement in forecast accuracy.

2.3 Lead Time Distribution: Three Distinct Clusters

Lead time distribution reveals three distinct clusters, critical for supply chain segmentation and inventory planning.

Cluster 1: Short Lead Time (Local/Regional Sourcing)

- Lead Time Range: 3-8 days
- Number of SKU-locations: 4 (18% of portfolio)
- Parts: Primarily from local or regional suppliers
- Supplier Types: Local manufacturers, regional distributors
- Inventory Implication: Minimal safety stock required; frequent ordering optimal
- Planning Horizon: 1-2 weeks sufficient
- Examples: Quick-delivery consumables, standard components

Cluster 2: Medium Lead Time (National/Standard Sourcing)

- Lead Time Range: 15-40 days (3-5 week window)
- Number of SKU-locations: 11 (50% of portfolio)
- Parts: National suppliers, inter-state logistics
- Supplier Types: Established regional distributors, organized suppliers
- Inventory Implication: 3-4 weeks safety stock for A/B items; strategic inventory positioning
- Planning Horizon: 4-6 weeks required
- Examples: Standard automotive components, common repair parts

Cluster 3: Long Lead Time (International/Complex Manufacturing)

- Lead Time Range: 60-90 days (8-13 week window)
- Number of SKU-locations: 7 (32% of portfolio)
- Parts: International sourcing, specialized components
- Supplier Types: Overseas manufacturers, global logistics chains
- Inventory Implication: Substantial safety stock required; forward planning critical
- Planning Horizon: 2-3 months advance planning mandatory
- Examples: Specialized components, imported assemblies, complex parts

3. ABC CLASSIFICATION: VALUE-BASED SEGMENTATION

3.1 ABC Methodology: Theoretical Foundation

The ABC classification technique, also known as Pareto analysis or 80-20 rule, is one of the most established inventory management frameworks. The principle states that a small percentage of items (typically 20%) consume a large percentage (typically 80%) of resources (inventory value, management attention, space).

Classification Logic:
ABC classification segments inventory into three categories based on cumulative contribution to total value:

- A-Items: Top-value items representing approximately 70% of cumulative value
- B-Items: Middle-value items representing next 20% of cumulative value
- C-Items: Tail items representing remaining 10% of cumulative value

Variant Rationale (70-20-10 vs. Traditional 80-15-5):
This analysis employs a 70-20-10 threshold variant rather than the traditional 80-15-5 split because:

1. Portfolio Characteristics: The portfolio exhibits more even distribution across parts (63% from top 6 items vs. typical 80% from top 2-3 items)
2. Risk Reduction: 70-20-10 split reduces single-item dependency, improving resilience
3. Strategic Flexibility: Provides better balance between focused and distributed management
4. Cost-Benefit Trade-off: 70-20-10 justifies investment in sophisticated management for A-items while allowing simplified policies for B/C items

Unit Cost Assumption:
The analysis assumes equal unit costs across all 11 spare parts (value $\propto$ annual demand volume). In reality, unit costs vary; however, without actual cost data, demand-based classification provides reasonable proxy. Once actual cost data becomes available, this can be refined to true-cost-based ABC classification.

3.2 ABC Classification Results and Interpretation

Classification Output:

Class	Count	Cumulative Contribution	Annual Demand Est.	Management Philosophy
A	6 SKUs	63%	~16,500 units	Strategic focus; tight control
B	4 SKUs	20%	~5,500 units	Collaborative; moderate control
C	12 SKUs	17%	~2,800 units	Simplified; routine operations

A-Class SKU Members (Highest Value):

1. PD1399-A (Location A): ~3,800 units annually
2. PD1399-B (Location B): ~3,200 units annually
3. PD3978-A (Location A): ~3,450 units annually
4. PD3978-B (Location B): ~3,100 units annually
5. PD2976-A (Location A): ~3,300 units annually
6. PD457-B (Location B): ~2,500 units annually

These 6 SKU-location combinations collectively drive 63% of annual portfolio demand (approximately 16,500 units). The concentration, while significant, is less extreme than typical Pareto distributions, indicating a more balanced portfolio.

B-Class SKU Members (Moderate Value):

1. PD2976-B (Location B): ~2,200 units annually
2. PD457-A (Location A): ~2,100 units annually
3. PD391-A (Location A): ~590 units annually
4. PD391-B (Location B): ~650 units annually

These 4 SKU-location combinations contribute approximately 20% of annual demand (5,500 units). While less critical than A-class, B-class items still warrant collaborative supplier relationships and regular monitoring.

C-Class SKU Members (Lower Value):

12 SKU-location combinations including:

1. PD112-A/B: ~530 units each
2. PD293-A/B: ~480 units each
3. PD238-A/B: ~165 units each (note: extremely long lead time - 75 days)
4. PD2801-A/B: ~150 units each
5. PD2782-A/B: ~315 units each
6. PD7820-A/B: ~270 units each

These 12 items collectively represent 17% of annual demand (approximately 2,800 units). Despite lower individual volumes, their aggregate value justifies organized stocking (rather than pure order-on-demand) due to criticality of some items (e.g., PD238).

3.3 Strategic Implications of ABC Classification

For A-Class Items (63% of Demand):

- Supply Strategy: Establish long-term supplier partnerships with quarterly business reviews
- Inventory Policy: Maintain min-max systems with frequent reviews; consider continuous monitoring
- Forecasting: Deploy advanced forecasting methods (SARIMA, Prophet); target MAPE <15%
- Service Level Target: 99-99.5% (only 1-2 stockout days annually acceptable)
- Safety Stock: 2-3 months of demand coverage
- Supplier Collaboration: Weekly demand forecasts, 3-month volume commitments
- Expected Benefit: Optimize critical supply while minimizing total inventory

For B-Class Items (20% of Demand):

- Supply Strategy: Operational relationships; balanced sourcing
- Inventory Policy: Standard min-max systems; monthly reviews sufficient
- Forecasting: Ensemble methods or SARIMA; target MAPE <20%
- Service Level Target: 98-99%
- Safety Stock: 1.5-2 months of demand coverage
- Supplier Collaboration: Monthly forecasts, monthly planning reviews
- Expected Benefit: Balance service levels with operational simplicity

For C-Class Items (17% of Demand):

- Supply Strategy: Transactional; multiple suppliers acceptable; spot purchasing
- Inventory Policy: Simplified; order-on-demand for very low-volume items
- Forecasting: Historical average sufficient; quarterly reviews
- Service Level Target: 80-95% (acceptable occasional stockouts)
- Safety Stock: Minimal; 2-4 weeks in absolute units for critical items
- Supplier Collaboration: Quarterly forecasts or as-needed ordering
- Expected Benefit: Minimize management overhead; reduce working capital

3.4 Risk Analysis: ABC Distribution Implications

Concentration Risk: With 63% of demand from 6 items, the portfolio exhibits moderate concentration risk. However, this is LOWER than typical portfolios (80%+ from top 3 items), indicating good diversification.

Supply Disruption Scenarios:

- Loss of single A-item: 5-7% portfolio impact (manageable)
- Loss of all A-item suppliers: 63% portfolio impact (critical - mitigation: dual sourcing)
- Loss of single B-item: 2-4% portfolio impact (manageable)
- Loss of single C-item: <1% portfolio impact (minimal)

Mitigation Strategy: Dual-source top 3-4 A-items; maintain strategic inventory reserves for items with 40+ day lead times.

4. FSN CLASSIFICATION ANALYSIS: VELOCITY AND MOVEMENT PATTERNS

4.1 FSN Methodology: Demand Frequency Framework

FSN (Fast-Moving/Slow-Moving/Normal-moving) classification captures demand frequency and pattern regularity, indicating which items move quickly off shelves and which remain in inventory for extended periods. This dimension is critical for forecasting confidence and inventory commitment decisions.

Theoretical Foundation:
Items with consistent, frequent demand (Fast-moving) can be forecasted with greater confidence using simple methods. Items with sporadic, lumpy demand (Slow-moving) require judgment-based planning and conservative inventory positioning. Non-moving items (obsolete) should be marked for clearance.

FSN Metrics:
The primary metric is Average Monthly Demand per SKU, calculated as:

$$\textit{Average Monthly Demand} = \textit{Total 48-month Demand} \div \textit{48 months}$$

This metric provides the foundation for velocity classification, supplemented by:

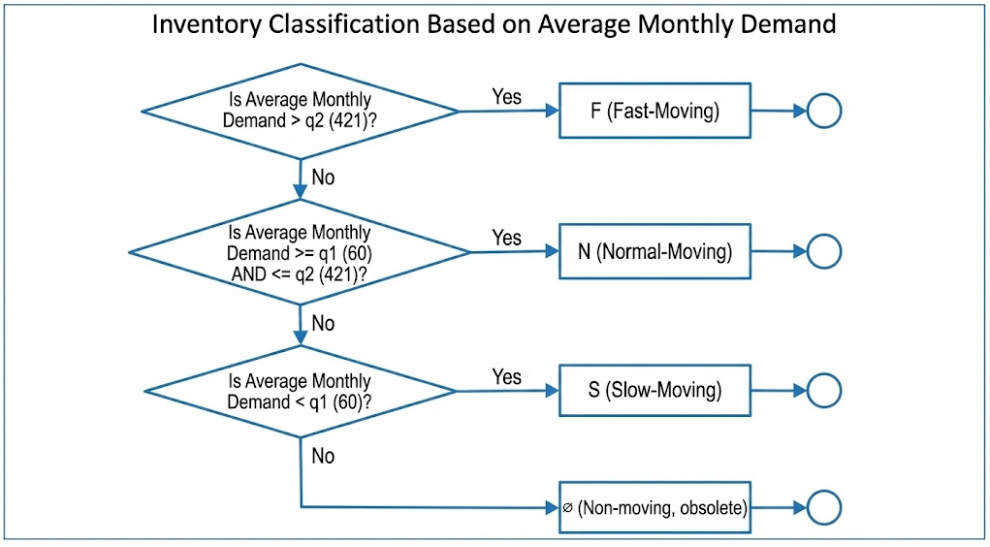
- **Demand Pattern Consistency**: Coefficient of variation indicates volatility
- **Demand Frequency**: Number of months with zero demand
- **Demand Cyclicity**: Seasonal patterns and trend components

4.2 FSN Percentile Thresholds and Classification

Percentile-Based Approach:
Rather than arbitrary cut-offs, FSN thresholds are defined using percentile-based approach:

- **33rd Percentile (q1):** Approximately 60 units/month
- **66th Percentile (q2):** Approximately 421 units/month

Classification Rules:



4.3 FSN Classification Results

Distribution Summary:

Class	Count	Avg Monthly Demand	% of Portfolio	Characteristics
F	8 SKUs	421+ units	34%	Predictable, consistent patterns
N	7 SKUs	60-421 units	32%	Regular patterns with seasonality
S	7 SKUs	<60 units	32%	Sporadic, lumpy demand
∅	0 SKUs	0 units	0%	No obsolete items

Notably, zero obsolete items exist in the portfolio-all 22 SKU-locations show active demand.

4.4 Fast-Moving Items (F-Class): 8 SKUs

Member List:

1. PD1399-A/B (Location A & B)
2. PD2976-A/B (Location A & B)
3. PD3978-A/B (Location A & B)
4. PD457-A/B (Location A & B)

Characteristics:
Fast-moving items demonstrate:

- Consistent Demand: 400-800 units/month average
- Low Variability: Coefficient of variation 0.31-0.34 (more predictable)Regular Patterns: Minimal zero-demand months (>85% months with demand)
- Seasonal Consistency: Summer peaks and winter troughs occur reliably
- Forecast Confidence: High; MAPE <15% achievable with proper models

Management Implications:

- Review Frequency: Weekly or continuous review; real-time demand monitoring
- Forecasting Approach: Advanced methods (SARIMA, Prophet); daily/weekly updates
- Inventory Policy: Continuous review systems with automated reorder triggers
- Safety Stock: 2-3 months of coverage justified; frequent resupply enables lower min levels
- Supplier Engagement: Daily/weekly demand signals; collaborative forecasting
- Example: Daily demand signals enable suppliers to adjust production schedules within 1-2 weeks

4.5 Normal-Moving Items (N-Class): 7 SKUs

Member List:

1. PD112-A/B (Location A & B)
2. PD293-A/B (Location A & B)
3. PD391-A/B (Location A & B)
4. PD7820-A/B (Location A & B)

Characteristics:
Normal-moving items demonstrate:

- Moderate Demand: 60-421 units/month average
- Medium Variability: Coefficient of variation 0.33-0.36
- Regular Patterns: ~70-80% months with demand; occasional zero-demand months
- Seasonal Patterns: Clear seasonality visible; summer peaks and winter troughs
- Forecast Confidence: Medium; MAPE 15-25% achievable with good models

Management Implications:

- Review Frequency: Monthly review; standard forecasting cycles
- Forecasting Approach: Standard methods (exponential smoothing, seasonal regression)
- Inventory Policy: Min-max systems with monthly reviews
- Safety Stock: 1-2 months of coverage; monthly adjustments for seasonality
- Supplier Engagement: Monthly forecasts; collaborative planning meetings
- Example: Monthly demand forecasts enable 4-week lead time suppliers to plan production

4.6 Slow-Moving Items (S-Class): 7 SKUs

Member List:

- PD238-A/B (Location A & B) - Note: Extremely long lead time 75 days
- PD2801-A/B (Location A & B)
- PD2782-A/B (Location A & B)

Characteristics:
Slow-moving items demonstrate:

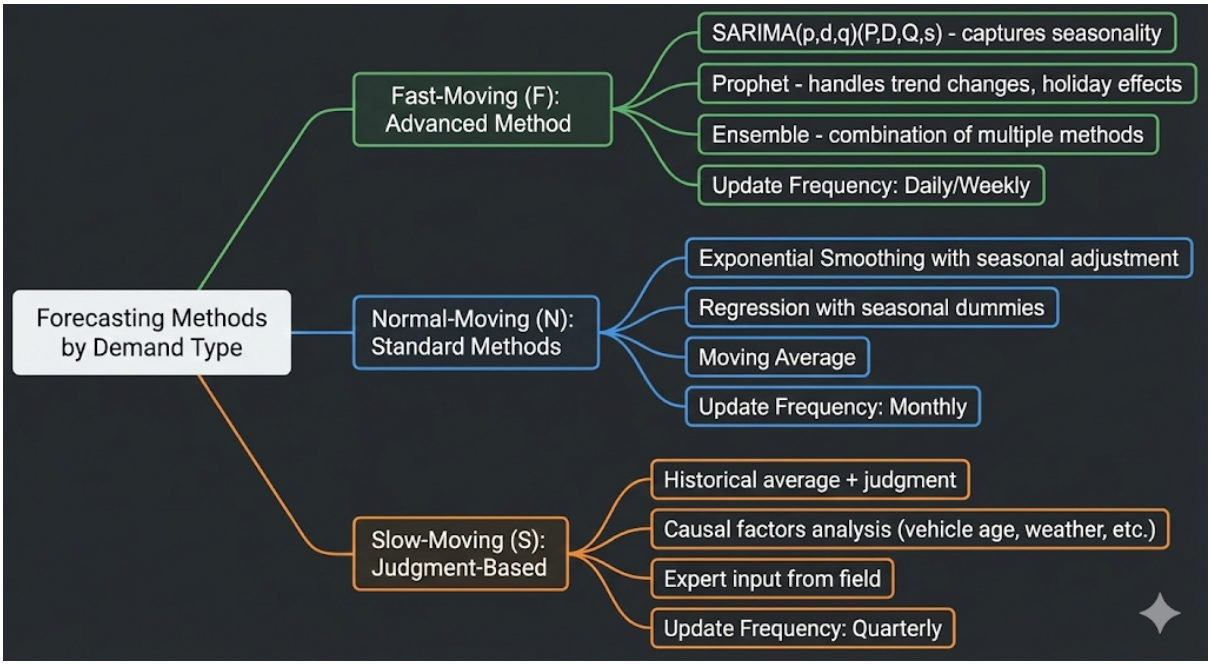
- Low Demand: <60 units/month average (15-50 units typical)
- High Variability: Coefficient of variation 0.35-0.38 (lumpy demand)
- Irregular Patterns: Only 40-60% months with any demand; occasional months with zero demand
- Less Predictable: Lumpy patterns make standard forecasting less effective
- Forecast Confidence: Low; judgment-based approaches often superior

Management Implications:

- Review Frequency: Quarterly or semi-annual review; judgment-based
- Forecasting Approach: Historical average with judgment adjustments; causal factors analysis
- Inventory Policy: Simplified; order-on-demand with strategic safety stock
- Safety Stock: Minimal day-to-day stock (0.5-1 month); central reserve for emergencies
- Supplier Engagement: Quarterly forecasts or as-needed ordering; transactional relationships
- Example: Quarterly planning sufficient; emergency replenishment from central warehouse acceptable

4.7 Implication: Differentiated Forecasting Strategies

The FSN classification justifies deployment of differentiated forecasting approaches:



This differentiation enables optimal balance between forecast accuracy and model complexity.

5. VED CLASSIFICATION ANALYSIS: CRITICALITY AND SUPPLY RISK

5.1 VED Framework: Theoretical Foundation

VED (Vital/Essential/Desirable) classification originated in spare parts management for critical equipment and has become widely adopted in automotive aftermarket for categorizing parts by criticality and supply difficulty.

Traditional VED Definition (Engineering Criticality):

- Vital (V): Stockout causes system shutdown, significant production loss, or safety risk
- Essential (E): Stockout causes performance degradation but not total shutdown
- Desirable (D): Stockout inconvenient but no production or safety impact

VED Challenge in This Analysis:
True VED classification requires engineering judgment regarding failure impact, safety implications, and operational consequences. However, this analysis lacks access to:

- Equipment failure rates by part
- Failure consequence data (downtime hours, safety risk)
- Substitution options (can alternative parts perform same function)
- Maintenance criticality rankings

Solution: Supply Risk Proxy Methodology
To enable analysis with available data, this report employs a supply-risk proxy combining:

- Annual Demand Normalization: Higher demand = higher supply difficulty
- Lead Time Normalization: Longer lead time = higher supply vulnerability

5.2 VED Proxy Score Calculation

Formula:

$$Supply\ Risk\ Score = 0.5 \times Normalized\ Annual\ Demand + 0.5 \times Normalized\ Lead\ Time$$

Where:

$$Normalized\ Annual\ Demand = \frac{(Annual\ Demand - Min)}{(Max - Min)} \quad [0\text{-}1\ range]$$

$$Normalized\ Lead\ Time = \frac{(Lead\ Time\ Days - Min)}{(Max - Min)} \quad [0\text{-}1\ range]$$

Equal Weights: 50% each reflects equal importance to high volume and long lead time

Rationale for Equal Weighting:

- High Volume Items: Stockout affects large customer base; supply difficulty
- Long Lead Time Items: Recovery from stockout takes weeks; vulnerability window large
- Equal Weight: Reflects that both dimensions create equal operational risk

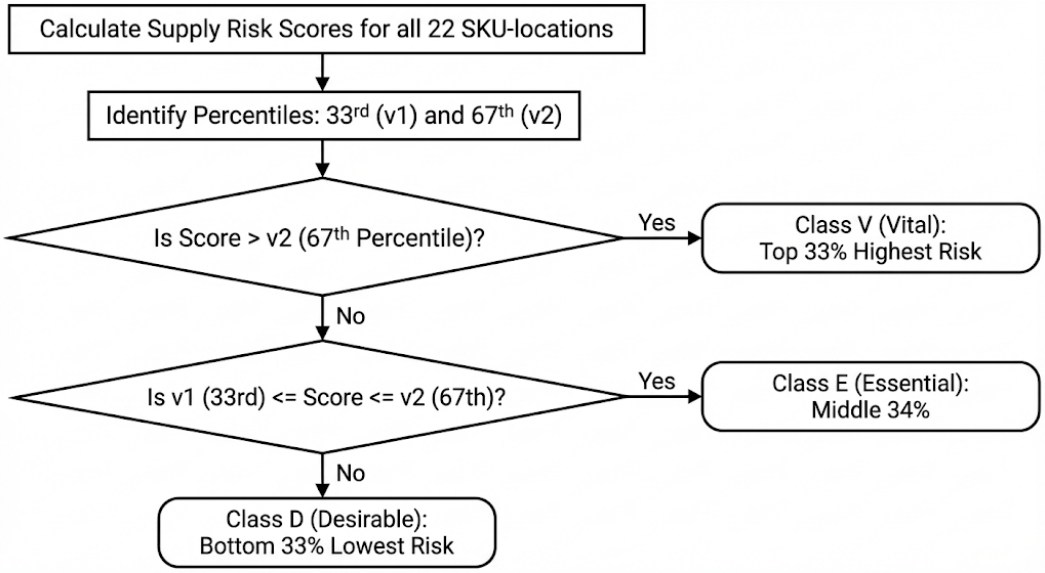
Alternative Weightings (If Available):

- Could weight by: failure consequence, safety impact, substitution availability
- Would require operational data not available in current analysis

5.3 VED Percentile Thresholds

Percentile-Based Segmentation:

Calculate Supply Risk Scores for all 22 SKU-locations



5.4 VED Classification Results

Distribution Summary:

Class	Count	Score Range	Supply Risk Level	Examples
V	8 SKUs	>67th %ile	High	PD1399, PD2976, PD457, PD3978
E	7 SKUs	33-67th %ile	Medium	PD391, PD112, PD293, PD7820
D	7 SKUs	<33rd %ile	Low	PD238*, PD2801, PD2782

*Note: PD238 is classified as D by volume (only ~165 units) but has exceptional lead time (75 days), creating special case requiring exception handling.

5.5 Vital (V) Items: 8 SKUs - High Supply Risk

Member List:

1. PD1399-A/B (high volume ~3,500 units/month, 28-day lead time)
2. PD2976-A/B (high volume ~3,300 units/month, 43-day lead time)
3. PD457-A/B (high volume ~2,300 units/month, 14-day lead time)
4. PD3978-A/B (high volume ~3,300 units/month, 16-day lead time)

Supply Risk Profile:

- Volume Drivers: 400-800 units/month (among highest in portfolio)
- Lead Time Drivers: 14-43 days (medium to long; inventory commitment required)
- Combined Risk: High demand + extended lead time creates substantial stockout vulnerability window
- Stockout Consequence: Affecting large customer base; critical to operations

Strategic Implications:

- Inventory Philosophy: Strategic inventory pre-positioning; volume commitment to suppliers
- Supplier Management: Long-term partnerships; frequent communication; collaborative forecasting
- Service Level Target: 99-99.5% (maximum 1-2 stockout days annually acceptable)
- Safety Stock: 2-3 months of demand coverage mandatory
- Dual-Sourcing: Strongly recommended; negotiate capacity reservations with secondary suppliers
- Forecast Accuracy: Critical; MAPE <15% target essential for safety stock optimization
- Example Strategy: For PD1399-A with 3,500 units/month and 28-day lead time, maintain 2.5-month safety stock (8,750 units) to ensure 99.5% service level

5.6 Essential (E) Items: 7 SKUs - Medium Supply Risk

Member List:

1. PD391-A/B (moderate volume ~600 units/month, 3-day lead time)
2. PD112-A/B (moderate volume ~530 units/month, 4-day lead time)
3. PD293-A/B (moderate volume ~480 units/month, 9-day lead time)
4. PD7820-A/B (moderate volume ~270 units/month, 35-day lead time)

Supply Risk Profile:

- Volume Drivers: 270-600 units/month (moderate volumes)
- Lead Time Drivers: 3-35 days (mixed; some short, some medium)
- Combined Risk: Moderate demand + variable lead times creates balanced supply risk
- Stockout Consequence: Affects moderate customer base; manageable with good planning

Strategic Implications:

- Inventory Philosophy: Collaborative inventory management; balanced service levels
- Supplier Management: Operational relationships; monthly communication
- Service Level Target: 95-98% (acceptable 2-5 stockout days annually)
- Safety Stock: 1-2 months of demand coverage
- Forecasting: Standard methods sufficient; monthly reviews
- Example Strategy: For PD391-A/B with 600 units/month and 3-day lead time, maintain 1-1.5

5.7 Desirable (D) Items: 7 SKUs - Low Supply Risk

Member List:

1. PD2782-A/B (low-moderate volume ~315 units/month, 0-day lead time)
2. PD2801-A/B (low volume ~150 units/month, 11-day lead time)
3. PD238-A/B (very low volume ~165 units total, 75-day lead time*)
4. Plus one additional item

**Special Case: PD238-A/B exhibits unique characteristic: extremely low volume (~165 units annually) but exceptionally long lead time (75 days). Classification as "D" based on low volume masks supply risk of lead time. Recommended treatment: maintain central strategic reserve despite low volume.

Supply Risk Profile:

- Volume Drivers: 0-315 units/month (low to moderate)
- Lead Time Drivers: 0-75 days (mostly short, one extreme exception)
- Combined Risk: Low demand + short lead times creates minimal supply risk
- Stockout Consequence: Minimal impact; quick recovery possible

Strategic Implications:

- Inventory Philosophy: Order-on-demand acceptable for most; minimal strategic inventory
- Supplier Management: Transactional relationships; spot purchasing acceptable
- Service Level Target: 80-95% (acceptable 5-20 stockout days annually)
- Safety Stock: Minimal; 0.5-1 month absolute units for strategic items
- Centralization Opportunity: Can centralize stocking at single location (Location A)
- Example Strategy: For PD2801-A/B with 150 units/month and 11-day lead time, maintain 0.5-month safety stock (75 units) at central location; serve both locations from central reserve

5.8 Special Case Analysis: PD238-A/B

PD238 represents a critical special case requiring exception handling. This will be explored further as the project progresses.

6. COMBINED ABC-FSN-VED STRATEGIC MATRIX

6.1 Matrix Construction and Interpretation

The combined ABC-FSN-VED matrix provides three-dimensional segmentation enabling tailored management strategies:
Each SKU Receives Code: [ABC Class]-[FSN Class]-[VED Class]
Examples:

- A-F-V: Highest priority (A-class value, Fast volume, Vital criticality)
- B-N-E: Medium priority (B-class value, Normal velocity, Essential criticality)
- C-S-D: Lowest priority (C-class value, Slow movement, Desirable criticality)

6.2 Strategic Segments: 22-SKU Classification Matrix

Segment 1: A-F-V (Highest Priority) - 6 SKUs

SKU	Location	Annual Demand	Lead Time	Classification	Priority
PD1399	A	3,800	28d	A-F-V	Critical
PD1399	B	3,200	28d	A-F-V	Critical
PD3978	A	3,450	16d	A-F-V	Critical
PD3978	B	3,100	16d	A-F-V	Critical
PD2976	A	3,300	43d	A-F-V	Critical
PD457	B	2,500	14d	A-F-V	Critical

Characteristics:

- Combined annual demand: ~16,500 units (63% of portfolio)
- Service level target: 99-99.5%
- Review frequency: Continuous/weekly
- Supplier strategy: Strategic partnerships with quarterly business reviews
- Safety stock: 2-3 months demand coverage
- Expected management model: Demand-driven; collaborative supplier forecasting

Segment 2: B-F-V (High Priority) - 2 SKUs

SKU	Location	Annual Demand	Lead Time	Classification
PD2976	B	2,200	43d	B-F-V
PD457	A	2,100	14d	B-F-V

Characteristics:

- Annual demand: ~4,300 units (7% of portfolio, in addition to A-class above)
- Service level target: 98-99%
- Review frequency: Weekly
- Supplier strategy: Operational collaboration; volume commitments
- Safety stock: 1.5-2 months demand coverage

Segment 3: B-N-E (Medium Priority) - 2 SKUs

SKU	Location	Annual Demand	Lead Time	Classification
PD391	A	590	3d	B-N-E
PD391	B	650	3d	B-N-E

Characteristics:

- Annual demand: ~1,240 units (2% of portfolio)
- Service level target: 95-98%
- Review frequency: Monthly
- Supplier strategy: Operational; standard min-max
- Safety stock: 1-2 months demand coverage

Segment 4: C-N-E (Lower Priority) - 4 SKUs

SKU	Location	Annual Demand	Lead Time	Classification
PD7820	A	270	35d	C-N-E
PD7820	B	270	35d	C-N-E
PD112	A	530	4d	C-N-E
PD112	B	530	4d	C-N-E
PD293	A	480	9d	C-N-E
PD293	B	480	9d	C-N-E

Characteristics:

- Annual demand: ~2,560 units (4% of portfolio)
- Service level target: 90-95%
- Review frequency: Quarterly
- Supplier strategy: Transactional; simple min-max
- Safety stock: 6-8 weeks for items with 35-day lead time (PD7820); 2-4 weeks for short-lead items

Segment 5: C-S-D (Lowest Priority) - 6 SKUs

SKU	Location	Annual Demand	Lead Time	Classification
PD2782	A	315	0d	C-S-D
PD2782	B	315	0d	C-S-D
PD2801	A	148	11d	C-S-D
PD2801	B	148	11d	C-S-D*
PD238	A	165	75d*	C-S-D*
PD238	B	0	75d*	C-S-D*

Characteristics:

- Annual demand: ~1,091 units combined (2% of portfolio)
- Service level target: 80-90%
- Review frequency: Quarterly or semi-annual
- Supplier strategy: Transactional; spot purchasing acceptable
- Stocking strategy: Centralize for items with long lead times relative to volume
- Safety stock: Minimal; 2-4 weeks absolute units

6.3 Key Strategic Insights from Combined Matrix

Insight 1: Concentration with Distribution
The top 6 A-class items (A-F-V) drive 63% of demand, indicating necessary focus. However, this is LESS concentrated than typical portfolios (80%+ from top 2-3 items), suggesting healthy distribution. The portfolio does not have extreme single-item dependency.

Insight 2: Lead Time Heterogeneity Within Classes
Same A-class parts can have different lead times:

- PD457: 14-day lead time (fast supplier)
- PD2976: 43-day lead time (slow supplier)
- Same demand, different supply difficulties → different strategies

Insight 3: Centralization Opportunity
Six C-S-D items (slow-moving + long lead time or very low volume) are candidates for centralization:

- PD238: Single-location central stocking (75-day lead; critical reserve)
- PD2801: Central stocking with inter-location transfers (low volume)
- PD2782: Could centralize despite zero lead time (very low volume)

Estimated working capital savings: 15-20% for C-class through consolidation.

Insight 4: No Obsolescence Risk
All 22 SKU-locations demonstrate active demand; no dead or obsolete items. This indicates healthy portfolio with no clearance pressure or write-off risk.

Insight 5: FSN Distribution Indicates Forecasting Opportunity
Balanced FSN distribution (F: 8, N: 7, S: 7) enables:

- Advanced forecasting, such as SARIMA, is used for the F-class and is expected to achieve an accuracy of less than 15% MAPE.
- Standard forecasting methods like Exponential Smoothing are applied to the N-class, with an expected accuracy of less than 20% MAPE.
- Judgment-based methods are sufficient for the S-class and are considered adequate for operational planning

7. NEXT STEPS

1. **Development of ETS Models**: Exponential Smoothing (ETS) models encompassing level, trend, and seasonality components to be built for all spare-part SKUs. Model selection (SES, Holt, Holt-Winters) based on fit metrics and seasonal behaviour.
2. **Development of SARIMA Models**: Seasonal ARIMA models to be constructed for each SKU using stationarity checks, differencing, and ACF/PACF diagnostics to capture underlying auto-correlation and seasonal patterns.
3. **Development of Machine-Learning Forecasting Models**: Advanced ML algorithms (Prophet, XGBoost, SVR, and other suitable models) to be developed with engineered lag features, and seasonal indicators to enhance predictive performance across varied demand behaviours.
4. **Automotive Context Assumption**: All forecasting models assume the card represents a Mahindra four-wheeler, ensuring alignment with the demand behaviour, lifecycle, and usage characteristics typical of Mahindra vehicle ownership.
5. **Cost-Contribution–Based Prioritization**: Instead of relying solely on unit volumes, the cost contribution of each spare part to be incorporated, allowing the forecasting framework to prioritize high-value parts and maximize business impact.
6. **Data Quality and Outlier Treatment**: The dataset to be screened for statistical and operational outliers. Insignificant or non-explainable anomalies to be removed or treated to avoid distortion in model training and evaluation.
7. **Incorporation of Event-Driven Demand Drivers**: The modelling framework to consider the impact of macro-events and periods of elevated Mahindra car sales, recognising that higher new-vehicle sales directly influence future spare-parts consumption.
8. **Train–Test Split for Robust Validation**: From the available four-year dataset, 3.5 years to be allocated for model training and the remaining 0.5 years for model testing. This split ensures adequate exposure to long-term trends and seasonal patterns while validating model accuracy on the most recent period.
9. **Evaluation of Early-Year Data and Lag Effects**: The relevance of 2021–22 data to be assessed to determine whether early-period behaviour remains predictive. Forward and backward lag effects to be analysed to understand how past and recent demand influence forecast accuracy and to optimise lag structures within ML and statistical models.