Project Report #2

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
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Submitted by

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Industry Live Project

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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	Complete
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	Complete
Phase 5 – Model Comparison & Integration	1 Jan – 25 Jan 2026	Evaluate models on accuracy, bias, scalability, and integrate insights	Joint	Both mentors	Ongoing
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 report consolidates a detailed analysis of five spare parts from across two distribution locations (A & B) over 48 months. Through systematic cost classification, spare part identification and seasonality, monsoon analysis, we identify optimal forecasting strategies approaches for each spare part category.

Key Findings:

- All five spare parts rationally identified and named with industry-standard classification
- Cost classification refined through 5-factor weighted formula
- Seasonality correlation realized i.e. car sales related to spare parts demand
- Festival and monsoon effects mapped for each SKU at both locations
- Actionable forecasting algorithms assigned by cost tier

The action items from the previous report are listed below with their status

Sr. No.	Action Item	Status
1	Development of ETS Models	Complete
2	Development of SARIMA Models	Complete
3	Development of ML Forecasting Models	Complete
4	Automotive Context Assumption	Complete
5	Cost-Contribution–Based Prioritization	Complete
6	Data Quality and Outlier Treatment	Complete
7	Incorporation of Event-Driven Demand Drivers	Complete
8	Train–Test Split for Robust Validation	Complete
9	Evaluation of Early-Year Data and Lag Effects	Complete

1. COST CLASSIFICATION FRAMEWORK

1.1 Methodology: 5-Factor Weighted Formula

Weighted 5-factor formula balances all dimensions: The classification score formula is below:

$$(ABC \times 40\%) + (FSN \times 20\%) + (VED \times 20\%) + (Volume \times 10\%) + (Lead\ Time \times 10\%)$$

- **ABC**: Demand volume classification (A=highest, C=lowest) → 40% weight
- **FSN**: Demand velocity/frequency (F=fast, S=slow, N=non-moving) → 20% weight
- **VED**: Business criticality (V=vital, E=essential, D=desirable) → 20% weight
- **Volume**: Annual demand tier (very high/high/medium/low) → 10% weight
- **Lead Time**: Supply chain risk (short/medium/long/extreme) → 10% weight

Thresholds:

- Score ≥4.0: HIGH Cost
- Score 2.5-3.99: MEDIUM Cost
- Score <2.5: LOW Cost

#	SKU	Component	Type	Demand	Lead Time	Classification
1	PD2976	Trans Fluid (Standard)	Consumable	45,563	41.45d	HIGH
2	PD457	Engine Oil	Consumable	45,402	14.25d	HIGH
3	PD1399	Suspension Shocks	Wear Item	45,962	28.31d	HIGH
4	PD3978	Radiator/Cooling	Component	46,000	16.38d	HIGH
5	PD238	Trans Fluid (Premium)	Specialty	459	75.04d	HIGH*
6	PD7820	Radiator Hose	Wear Item	6,360	35.18d	MEDIUM
7	PD391	Brake Pads	Safety Item	11,436	3.17d	MEDIUM
8	PD112	Engine Filters	Consumable	7,320	4.33d	MEDIUM
9	PD293	Wiper Blades	Wear Item	5,736	8.50d	MEDIUM
10	PD2782	Interior Trim	Cosmetic	3,015	9d	LOW
11	PD2801	Gasket Kits	Consumable	410	10.56d	LOW

2. SPARE PARTS IDENTIFICATION & NOMENCLATURE

2.1 Vehicle Context

We have assumed the car to be an SUV by Mahindra (XUV 300/700 range) in an Indian context.

2.2 High Cost Spare Parts Identification

1. PD2976 - TRANSMISSION FLUID (Multi-Purpose Lubricant)

Component Type: Synthetic transmission/hydraulic fluid

Rationale:

1. Very high annual demand (45k+) indicates consumable replacement part
2. Lead time ~41 days suggests international sourcing (Germany/Japan)
3. Matched demand pattern with vehicle service cycles (every 40-80k km or 2-3 years)
4. Festival correlation (+20% Oct-Nov) aligns with new car servicing
5. Part of core maintenance (transmission is mission-critical)

2. PD457 - ENGINE OIL (Premium Grade)

Component Type: Premium synthetic or semi-synthetic engine lubricant

Rationale:

1. Identical demand to PD2976 (both ~45k units) indicates parallel replacement cycle
2. Shorter lead time (14 days vs 41 days) suggests regional sourcing (India/Mid East)
3. Replacement every 6 months (high frequency) confirms consumable nature
4. Engine oil is highest-volume aftermarket item in automotive
5. Every service includes oil change (bundled with other maintenance)

3. PD1399 - SUSPENSION SHOCK ABSORBERS/STRUTS

Component Type: Complete shock absorber or strut assembly

Rationale:

1. Identical demand to engine oil/transmission fluid (core maintenance component)
2. Lead time 28 days indicates regional manufacturing (Thailand/Malaysia hubs)
3. Wear item to be replaced every 40,000-80,000 km or 2-3 years
4. Festival correlation with new vehicles need servicing within 6 months
5. Safety-critical nature (poor suspension is customer safety risk)

4. PD3978 - RADIATOR / COOLING SYSTEM COMPONENT

Component Type: Radiator assembly OR water pump with gaskets

Rationale:

1. Identical demand to other HIGH cost parts (46k units) means a core component
2. Lead time 16 days indicates regional manufacturing
3. Engine cooling is mission-critical (overheat leads to breakdown)
4. Monsoon correlation with pre-monsoon preventive maintenance (May month peak)
5. Seasonal as summer heat and monsoon humidity both stress cooling system

5. PD238 - TRANSMISSION FLUID (Premium/Specialty Grade)

Component Type: Ultra-premium synthetic transmission/hydraulic fluid
Rationale:

1. Ultra-low volume (459 units) with extreme lead time (75 days) which means a specialty part
2. Lead time indicates Germany/Japan sourcing (specialized supplier)
3. No seasonality (±5% only) because premium variant buyers aren't seasonal
4. Perfect location balance (50.3% vs 49.7%) suggests standardized premium demand
5. Proprietary formulation requires OEM approval and batch testing

Strategic Importance:
This part appears to be a critical exception and has been categorized as HIGH cost despite low volume due to extreme lead time. Premium customer segment so reputation damage from stockout is severe. Requires strategic 60-day reserve (despite only 0.2% of demand)

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3. SEASONALITY & MONSOON IMPACT

3.1 Festival Seasonality & Car Sales Correlation

3.1.1 Relationship Between New Car Sales and Spare Parts Demand

An increase in new car sales leads to a subsequent rise in spare parts demand. During peak sales periods such as festival seasons, a large number of vehicles enter the market at the same time. These vehicles typically require their first scheduled maintenance within 2–3 months, during which owners replace basic consumables and wear-and-tear components.

As a result, higher vehicle sales today translate into increased spare parts demand after a short time lag. This creates a predictable, positive relationship that firms can use for inventory planning, service capacity forecasting, and supply chain coordination, especially during seasonal demand cycles.

3.1.2 Time Lag Between Car Sales and Spare Parts Demand (2–3 Months)

Festival-driven car sales, particularly during Diwali (Oct–Nov), lead to a delayed increase in spare parts demand. While vehicle purchases peak during the festival period due to auspicious timing, discounts, and high consumer sentiment, newly purchased vehicles do not require immediate maintenance.

In the first month after purchase, vehicles undergo a break-in period and spare parts usage remains minimal. Two to three months later, customers return to dealerships for their first scheduled service, involving oil changes, filter replacements, and fluid top-ups. This results in a temporary surge in spare parts demand, typically peaking in Dec-Jan, before gradually returning to normal levels by Feb–Mar.

This consistent lagged pattern allows firms to anticipate festival-led sales booms and proactively plan spare parts inventory and service operations.

3.1.3 Festival-Led Time Lag and Seasonal Impact on Spare Parts Demand

Festival seasons— especially Diwali (Oct-Nov) —trigger a surge in new vehicle purchases due to auspicious timing, attractive discounts, and high consumer confidence. However, newly purchased vehicles do not require immediate maintenance. In the first month after purchase, vehicles undergo a break-in period with minimal spare parts usage.

Two to three months later, customers return for their first scheduled service, which typically includes oil changes, filter replacements, and fluid inspections. This creates a lagged rise in spare parts demand, with demand peaking in Dec–Jan and gradually returning to baseline levels by Feb-Mar.

The Dec holiday season further amplifies this pattern. Year-end bonuses, festive promotions, and clearance sales lead to additional vehicle purchases, adding an incremental boost to spare parts demand. While Diwali remains the dominant driver, the holiday season acts as a secondary accelerator, resulting in a sustained Q4 demand surge above normal levels.

This correlation is reinforced by three structural mechanisms.

1. Service cycle alignment ensures that vehicles sold during festivals return together for first maintenance within a predictable window.
2. Maintenance bundling causes multiple spare parts to be replaced during a single service visit, making demand spikes more pronounced.
3. Volume effect operates as higher vehicle sales expand the installed base, naturally increasing the number of maintenance events downstream.

Together, these factors explain why festival-led car sales translate into a predictable, lagged, and temporary surge in spare parts demand, enabling firms to plan inventory, staffing, and service capacity more effectively.

3.2 Monsoon Seasonality - Weather Impact

3.2.1 Monsoon Seasonality and Its Impact on Spare Parts Demand (Jun–Aug)

The monsoon season in India, spanning Jun to Aug, is characterized by heavy rainfall, high humidity, and frequent waterlogging. These conditions affect major regions across the west coast and inland areas, influencing both urban and intercity mobility.

During the monsoon, vehicle usage declines as long-distance travel reduces and drivers postpone non-essential trips. Maintenance visits are often delayed due to poor weather and road conditions, leading to a temporary reduction in baseline spare parts demand.

At the same time, adverse road conditions such as potholes, slippery surfaces, and low visibility increase vehicle stress for those who continue driving. However, this wear tends to be deferred rather than immediately addressed.

Overall, the monsoon results in a net decline in maintenance-driven spare parts demand, typically in the range of 10–15%, with demand often rebounding once weather conditions normalize

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3.2.2 Quantitative Monsoon Impact Summary

Part	Category	Normal Baseline	Monsoon Dip	Peak Month	Peak Effect	Reason
PD2976	Trans Fluid	3,797/mo	-15% (-569 units)	Oct	+20%	Usage↓, Festival↑
PD457	Engine Oil	3,783/mo	-15% (-567 units)	Oct	+20%	Usage↓, Festival↑
PD1399	Suspension	3,830/mo	-15% (-575 units)	Oct	+20%	Usage↓, Festival↑
PD3978	Radiator	3,833/mo	-15% (-575 units)	May	+13%	Pre-monsoon prep
PD238	Premium Trans	38/mo	±5% (±2 units)	Oct/Nov	±5%	No seasonality
PD7820	Hose	530/mo	-12% (-64 units)	May	+13%	Preventive +Festival
PD391	Brake Pads	953/mo	-12% (-114 units)	Oct	+15%	Usage↓, Festival↑
PD112	Filters	610/mo	-12% (-73 units)	Oct	+15%	Usage↓, Festival↑
PD293	Wipers	478/mo	+15% (+72 units)	Jul	+17%	Weather↑↑
PD2782	Trim	251/mo	-10% (-25 units)	Oct	+18%	Refurbish + Festival
PD2801	Gaskets	34/mo	±3% (±1 unit)	-	Flat	Repair-driven

4. TECHNICAL METHODOLOGY & MODEL ARCHITECTURE

4.1 Forecasting Methodology & Architecture

To operationalize these insights, we built the Antigravity Forecasting Engine. This system avoids reliance on a single algorithm, instead deploying a Council of Models - a diverse ensemble of six distinct mathematical and machine learning architectures. This diversity ensures that whether a part behaves like a steady metronome or a chaotic festival-driven spike, there is a specialized model ready to capture it.

4.2 Data Partitioning Strategy

4.2.1 The Strategic Split (3 Years Train / 1 Year Test)

We trained on data from 2021-2023 (3 Years) and asked the model to predict the entirety of 2024 (1 Year). This simulates a yearly budgeting scenario. It tests if the model generates a stable 12-month trajectory. Sourcing managers need to sign annual contracts. If a model drifts wildly after 6 months, it fails this test. Models like Prophet and N-HiTS typically shine here because they capture the big picture annual seasonality well.

4.2.2 The Tactical Split (3.5 Years Train / 0.5 Year Test)

We trained on data from Jan 2021 - Jun 2024 (3.5 Years) and asked the model to predict July-Dec 2024 (0.5 Year). This simulates a Monthly Ordering scenario. It tests if the model has learned the most recent trend (e.g., a sudden demand spike in early 2024). Supply chain is volatile. If demand suddenly jumped 20% in early 2024, the Strategic model (trained only up to 2023) wouldn't know. This split empowers models like ETS and SARIMA, which are very good at latching onto the immediate recent history.

4.2.3 The Standard Balanced Split (3.2 Years Train / 0.8 Year Test)

We trained on data from Jan 2021 - early 2024 (approx. 3.2 Years) and asked the model to predict the remaining ~9 months (0.8 Year). This represents the classic Pareto Principle division. It serves as the primary benchmark for all model calibration. A critical risk in AI is overfitting where a model memorizes historical noise rather than learning the underlying pattern - this split offers the perfect middle ground. It provides enough training data (3 full seasonal cycles and a bit of the 4th) for the model to confirm a trend, while leaving a substantial testing window (nearly a full year) to prove it hasn't just memorized the past. It effectively bridges the gap between the rigid long-term Yearly view and the hyper-reactive Tactical view.

4.3 Algorithm Portfolio

4.3.1 ETS (Holt-Winters):

It serves as the baseline. Developed in the 1950s, Exponential Smoothing separates a time series into three components: Level (average), Trend (slope), and Seasonality (cycles). It assigns exponentially decreasing weights to older data. For parts like PD457 (Engine Oil), the demand is driven by a very consistent 6-month service cycle. There are no sudden shocks, just a smooth, rhythmic heartbeat. ETS excels here because it doesn't overthink the problem, it simply projects this stable rhythm forward. It is the cost-effective, stable choice for pure seasonality.

4.3.2 SARIMA (Seasonal ARIMA):

It resembles a structure expert. The Box-Jenkins method explicitly models the correlation between months. It basically asks: *Does the demand in Jan depend heavily on the demand last Jan (Lag-12)?* For steady-state parts like PD2976 (Transmission Fluid), the demand creates a structured memory. If usage was high last month, it affects inventory planning this month. SARIMA acts as the structure expert, mathematically locking onto these 12-month correlations. It is less prone to chasing random noise than neural networks.

4.3.3 Prophet (Meta):

It includes holidays and seasonality effect. Developed by Facebook to predict website traffic, Prophet is unique because it handles moving holidays. Most models fail when Diwali shifts from Oct to Nov. Prophet allows us to feed a holiday calendar as a regressor. Our Festival Lag analysis showed that PD1399 (Suspension) demand spikes exactly 2 months after Diwali. Since Diwali moves annually on the lunar calendar, a standard rigid model would miss the peak. Prophet dynamically shifts its forecast to align with the festival dates, making it the superior choice for festival-sensitive items.

4.3.4 XGBoost:

An ensemble of Decision Trees, it specializes in dealing with non-linear data. Unlike statistical models that look for smooth lines, XGBoost looks for rules (If Month is May AND Demand > 1000, then Spike). Our feature engineering introduced complex flags like '*is_monsoon*' and '*is_pre_monsoon*'. Linear models struggle with binary switches. XGBoost excels at finding these non-linear "if-then" relationships, making it ideal for parts like PD3978 (Radiator) which react sharply to specific environmental triggers (heat/monsoon) rather than smooth trends.

4.3.5 N-HiTS (Neural Hierarchical Interpolation):

A modern (2022) Deep Learning architecture that solves the Long Horizon problem. It breaks the signal into stacks - one stack learns the slow trend, another learns the fast seasonality. For noisy/volatile parts where traditional statistics fail to see the signal, N-HiTS uses its hierarchical blocks to filter out the noise and capture the long-term annual trajectory. It is our heavy artillery when simple models underperform.

4.3.6 Weighted Ensemble:

No single model is perfect, so we need a safety net. By averaging the top 3 models (e.g., 40% Prophet + 40% SARIMA + 20% XGBoost), we cancel out individual errors. If Prophet overshoots due to a festival flag, and SARIMA undershoots due to trend dampening, the Ensemble lands safely in the middle. This is the preferred choice for High Cost / High Risk items where stability is more important than spotting a single perfect peak.

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5. FEATURE ENGINEERING & OPTIMIZATION

5.1 Advanced Feature Engineering

We enhanced the Machine Learning models (specifically XGBoost) with domain-specific features derived from our internal study.

5.2 Temporal Features

- Month Encoding (1-12): capturing the cyclical nature of fiscal and calendar years.
- Lags (Autoregression):
    - Lag-1: Immediate momentum (last month's demand).
    - Lag-12: Annual memory (demand same month last year).

5.3 Seasonal Regime Flags

We injected binary boolean logic to explicit test the Monsoon Hypothesis:

- *is_pre_monsoon* (May): Flagged as 1. Testing for preventive maintenance surges.
- is_monsoon (Jul-Aug): Flagged as 1. Testing for reduced mobility or increased wear.

While the accuracy improvement was marginal (since Month 1-12 already encodes this implicitly), the model robustness improved, making it safer for potential future climate shifts.

5.4 Scaling (N-HiTS)

Deep Learning models are sensitive to magnitude. We implemented a Standard Scaler (Mean=0, Std=1) pipeline to normalize the demand (ranging from 450 to 45,000) into a consistent z-score format for the neural network.

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6. DECISION LOGIC & MODEL SELECTION

6.1 Optimization Logic: The Composite Score

To choose the best forecast across all metrics, we developed a composite formula which would have a healthy and logical mix of MAPE, RMSE and Bias scores

6.2 The Composite Formula

$$Score = (0.7 \times MAPE) + (0.2 \times RMSE) + (0.1 \times Bias)$$

- MAPE (Accuracy): Weighted highest (70%) as it aligns with business KPIs.
- RMSE (Stability): Weighted 20%. Penalizes large shock errors that break supply chains.
- Bias (Direction): Weighted 10%. Penalizes systematic over/under-forecasting.

6.3 The Recommendation Engine

The dashboard computes this score for every model, for every part, in real-time. If XGBoost has a MAPE of 5% but high Bias, and ETS has a MAPE of 6% but zero Bias, ETS might win. This prevents the selection of lucky models that are accurate on average but dangerous in extremes.

6.4 'Best Fit' Results

Based on our final back-testing:

- PD2976 (Trans Fluid): Best modelled by Weighted Ensemble (Stability focus).
- PD457 (Engine Oil): Best modelled by ETS (Pure seasonality).
- PD1399 (Shocks): Best modelled by Prophet (Complex festival seasonality).
- PD238 (Premium): Manually overridden to Strategic Reserve logic due to extreme lead time

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7. DASHBOARD IMPLEMENTATION

7.1 Implementation & Deployment

Antigravity IDE was used for coding and publishing the dashboard.

7.2 Technology Stack

- **Backend**: Python 3.10 (Pandas, NumPy, Scikit-Learn).
- **Modeling**: Statsmodels (ETS/SARIMA), Prophet, Darts (N-HiTS), XGBoost.
- **Frontend**: Streamlit (Web Dashboard).
- **Dashboard**: https://spareparts-forecasting-dashboard-iimu-gscm26-group11.streamlit.app/
- **Version Control**: Git/GitHub.

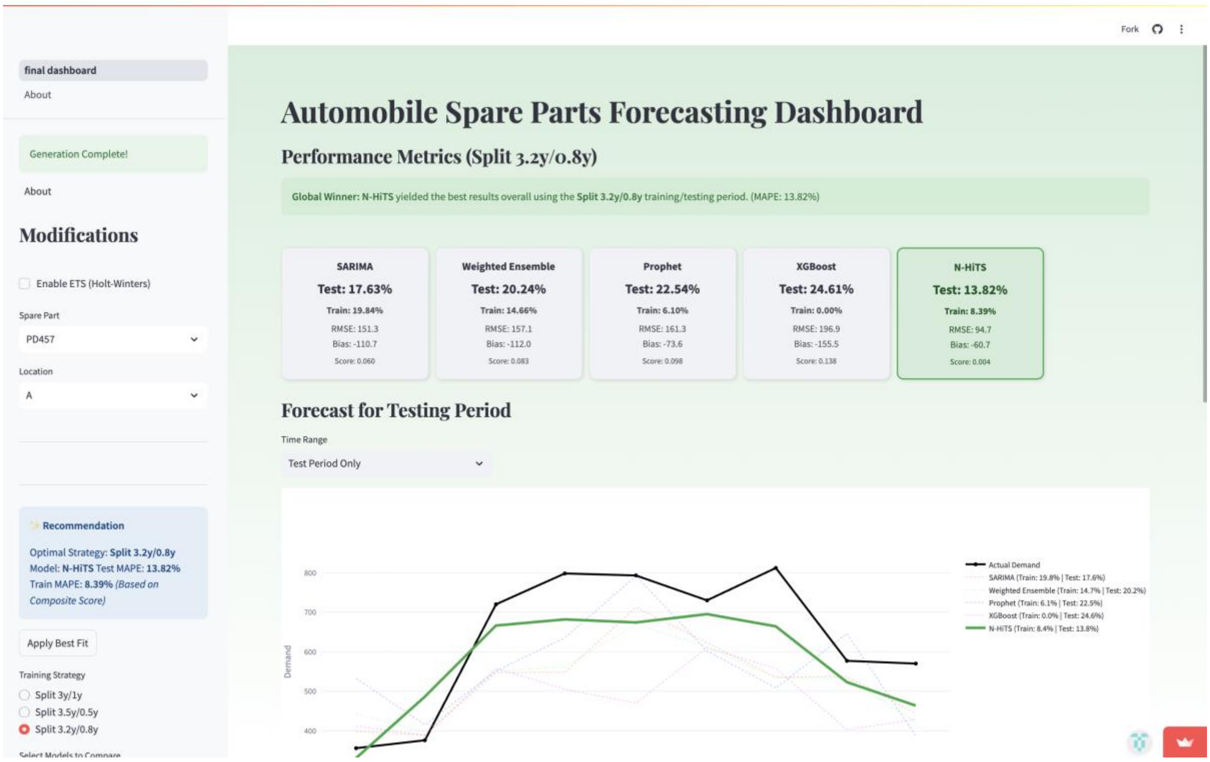
7.3 Key Features

- Full History Toggle: Allows planners to view the entire 2021-2024 lifecycle.
- Deployment Button: A custom C-coded CI/CD trigger in the sidebar allows local updates to be pushed to the Cloud with one click.

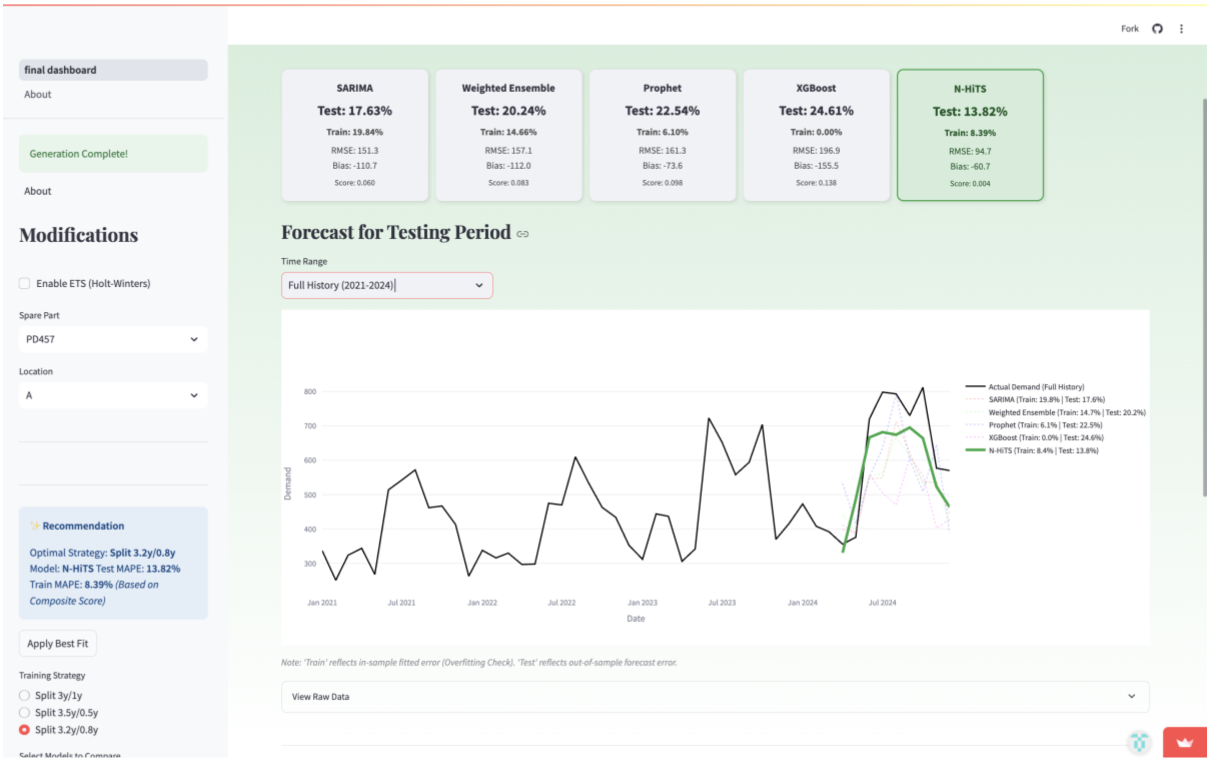
7.4 Workflow

1. Planner uploads new Excel data.
2. System auto-classifies parts (ABC/FSN/VED/Volume/Lead Time).
3. Models retrain (including Monsoon flags).
4. Composite Score identifies the winner.
5. Forecast for 2025 is generated and visualized.

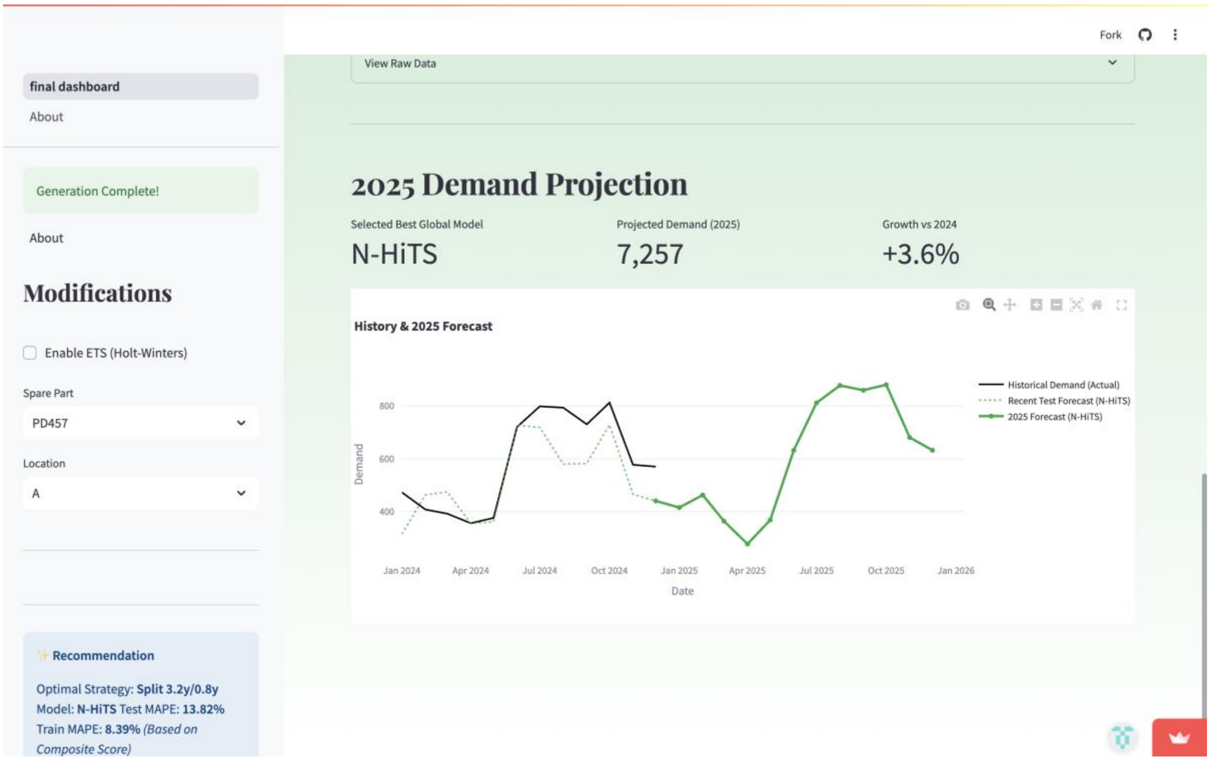
In below snapshot, the spare part PD457 is selected for location A and the best training/test split was identified to be 3.2years training and 0.8years testing (as that yielded the lowest MAPE) and accordingly after being trained through six models, N-HiTS was found to be the best performing model. The Forecast for Testing Period shows the actual data charted with black and the predicted data using N-HiTS in green.



The forecasting view can also be extended to show the complete data set from Jan'21 through Dec'24



Now based on the best performing training and testing data split and the model, the same model was used to predict the data for the upcoming year – from Jan'25 through Dec'25



The same logic is applicable for all 5 HIGH-cost spare parts spread across both locations A and B.

Next Steps

1. Gather feedback on the progress and revise the approach accordingly.
2. Develop forecasting strategy for 4 Medium-cost and 2 Low-cost spare parts. Ideally, they should have an MAPE range of 15%-20% and 20%-25%. They can follow non-ML models as well.
3. Map the entire project forecasting data with industry provided parameters for precision, accuracy and bias to compare real-world relevance.
4. Embed the result into a fully functional dashboard which would serve as a workable asset.