Optimizing Inventory Management and Business Processes for Sustainable Growth in a Manufacturing SME

A Final Report for the BDM capstone Project

Submitted by

Name**: Abhinav Jaswal**

Roll number: **22f3002782**

IITM Online BS Degree Program,

Indian Institute of Technology, Madras, Chennai

Tamil Nadu, India, 600036

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1 Executive Summary

Sterling Foods and Beverages, located in Neota, Jaipur, is a growing B2B manufacturer of packaged drinking water under the brand name Cubic. Despite rapid revenue expansion from ₹20.4 lakh in FY22–23 to ₹190.3 lakh in FY24–25, the firm continues to face operational challenges including inefficient inventory management, unstable procurement cycles, and significant working-capital lock-ups due to manual processes. These issues lead to frequent overstocking and stockouts, restricted liquidity, and reduced scalability.

This project analyses transactional business data collected between April 2022 and March 2025 across Sales, Purchases, Raw Material, and Inventory Movement sheets. After structured data cleaning and preprocessing, the analysis applies descriptive statistics, correlation and volatility analysis, ABC classification, Inventory Turnover and Days-in-Inventory (DII), cross-correlation, and exponential smoothing demand forecasting using Excel and Python. These techniques were selected to directly address the identified business problems—inventory inefficiency, cash-flow strain, and lack of automation.

The results show highly volatile procurement patterns (CV = 0.925) compared to sales (CV = 0.758), with purchases leading sales by approximately one month and causing stock build-up. Two A-class SKUs—PET forms and 1000 ml labels—constitute 65% of total raw-material value, while inventory turnover averages 7.79x (~21 DII), locking approximately ₹10.8 lakh of working capital at any time. Based on these insights, the report recommends implementing ABC-based min-max reorder controls, adopting 3–6 month rolling forecasts, synchronizing production with demand cycles, and deploying lightweight Excel/Python dashboards for real-time KPIs. These improvements are expected to reduce excess inventory by 20–30%, free ₹3.2 lakh of working capital, increase forecast accuracy (MAPE ≤15%), and build a scalable, data-driven operational foundation.

2 Detailed Explanation of Analysis Process/Method

2.1 Data Collection and Sources

Data was collected directly from Sterling Foods and Beverages' internal records for the period **April 2022 to March 2025**. The final cleaned workbook contains four sheets:

- **Sales Sheet**
    - Variables: Month, Fiscal Year (FY), Sales (₹).
    - Purpose: Analyse revenue growth, seasonality, and demand volatility to address **inefficient inventory management** and **demand–supply mismatch**.
- **Purchase Sheet**
    - Variables: Month, FY, Purchase_Value (₹).
    - Purpose: Study procurement timing, volatility, and alignment with sales to address **working-capital** and **cash-flow gaps**.
- **Raw Material Sheet**
    - Variables: Item, FY, Quantity, Rate, Value.
    - Purpose: Support **ABC value-based categorisation** and identify high-impact SKUs driving inventory cost.
- **Inventory Movement Sheet**
    - Variables: Month, FY, Manufactured Quantity/Value, Sold Quantity/Value, Remaining Quantity/Value.
    - Purpose: Analyse **manufacturing vs sales**, inventory build-up, turnover, and working capital tied in stock.

Data entry, consolidation, initial summary statistics and most of Graphical analysis were done in **Microsoft Excel**, while more advanced analysis (e.g., cross-correlation, decomposition plots) was supported in **Python (Pandas, Matplotlib, Seaborn) via Google Colab**.

2.2 Data Cleaning and Pre-processing

Consistent cleaning methods were applied across all sheets to ensure reliability of the analysis:

1. **Structural checks and consolidation**
    - Verified that all months from April 2022 to March 2025 were present in Sales and Purchase sheets (36 rows each).

- Aligned sheets on common keys **(Month, FY)** to allow combined analysis across sales, purchases, manufacturing, and inventory.

2. **Handling missing values**
   - For numerical fields (Sales, Purchase_Value, Quantity, Value), isolated missing entries and:
     - Imputed occasional internal gaps using **mean or** logical interpolation when they were clearly in-range.
     - Left structurally missing periods as true zeros where business confirmed no activity.
   - For categorical fields (e.g., Item names), missing labels were completed based on partner confirmation and consistent naming.
3. **Removing duplicates and correcting inconsistencies**
   - Checked for duplicate (Month, FY) rows and removed any repeated entries so that each period is counted once.
   - Standardized formats (e.g., "April-22", "Apr 2022") into a single month key and unified currency format (₹).
4. **Outlier detection and treatment**
   - Applied the Interquartile Range (IQR) method on Sales, Purchase_Value, and Raw Material Value to flag extreme values.
   - Outliers were **not blindly removed**; they were retained when confirmed as genuine business peaks (e.g., October festival push), and only corrected when clearly due to data entry errors.
5. **Derived fields for later analysis**
   - Created helper variables such as:
     - **Gap = Sales – Purchase_Value** (monthly sales–procurement gap).
     - **Monthly inventory turnover and DII** from Inventory Movement sheet.
     - **Annual consumption value per raw material item** for ABC analysis.

This cleaned dataset forms the foundation for all subsequent methods and ensures that patterns reflect true business behaviour rather than data noise.

2.3 Mapping Problem Statements to Analytical Methods

The **proposal** identified two **major** problem statements:

1. Inefficient inventory management.
2. Working-capital and cash-flow gaps.

Each problem is explicitly mapped to quantitative methods and tools as follows:

- **Problem 1: Inefficient Inventory Management**
    - Methods:
        - Descriptive statistics of Sales, Purchases, Manufactured and Sold Values.
        - Time-series plots and seasonal decomposition of Sales.
        - Inventory Turnover and Days-in-Inventory (DII).
        - Manufacturing vs Sold vs Remaining analysis from Inventory Movement.
    - Tools & Data: Excel pivot tables and charts; Python line plots and decomposition on Sales and Inventory Movement sheets.
- **Problem 2: Working Capital and Cash-Flow Gaps**
    - Methods:
        - Calculation of **working capital tied in inventory** using Remaining Value.
        - ABC Analysis of Raw Material Value to identify cost-concentrated SKUs.
        - Cross-correlation between Sales and Purchase_Value to detect lead–lag behaviour.
    - Tools & Data: Excel formulas, Python correlation functions on Purchase, Raw Material, and Inventory Movement sheets.

2.4 Specific Quantitative Methods Used

This subsection describes how each major analysis in Section 3 was carried out.

2.4.1 Procurement and Supply Chain Analysis

1. **Objective:** Understand whether procurement magnitude and timing align with sales.

2. **Data used:** Sales and Purchase sheets aggregated by Month and FY.
3. **Steps:**
    1. Calculated monthly totals of Sales and Purchase_Value.
    2. Computed **coefficient of variation (CV)** for both series:

$$CV = \frac{\sigma}{\mu}$$

    3. Computed **Pearson correlation coefficient (ρ)** between monthly Sales and Purchase_Value:

$$r_{xy} = \frac{Cov(x, y)}{\sigma_x \sigma y}$$

    4. Generated line charts (Sales vs Purchases) and clustered bar charts to visualize gaps.
    5. Compute **cross-correlation** at different lags (–2 to +2 months) to check if purchases lead or lag sales.

This analysis feeds directly into **Sections 3.2 and 3.3** (procurement dynamics and lead–lag behaviour).

2.4.2 Value-Based Categorization (ABC Analysis)

- Objective: Identify high-value raw materials that require tight control.
- **Data used:** Raw Material sheet (Item, Quantity, Rate, Value).
- **Steps:**
    1. For each Item, computed annual consumption value:

$$Annual\ Consumption\ Value_i = \sum_{months} Qunatity_i \times Rate_i$$

    2. Sorted items in descending order of consumption value and computed the **cumulative percentage** contribution.
    3. Classified items as:
        - **A-class:** Top ~65–70% of value.
        - **B-class:** Next ~20–25%.
        - **C-class:** Remaining ~5–10%.

4. Visualised results using a **Pareto chart** showing cumulative percentage and bar plots across years.

This method underpins **Section 3.4 (ABC Analysis and Strategic Raw Material Management)** and the recommendations around PET forms and labels.

2.4.3 Manufacturing and Stock Movement Analysis

- **Objective:** Examine whether production is aligned with sales and how much stock remains each month.
- **Data used:** Inventory Movement sheet.
- **Steps:**
  1. For each month, extracted **Manufactured Quantity/Value, Sold Quantity/Value, Remaining Quantity/Value**.
  2. Created stacked area and bar charts of Manufactured vs Sold vs Remaining.
  3. Calculated **manufacturing efficiency**:

$$Manufacturing\ Efficienty = \frac{Sold\ Value}{Manufactured\ Value} \times 100\%$$

  4. Identified months where production greatly exceeded sales, signalling inventory build-up.

Results appear in **Section 3.5** and support Problem 1 (inventory inefficiency).

2.4.4 Inventory Turnover and Working Capital Utilization

- **Objective:** Quantify how quickly inventory is converted into sales and how much capital is tied up.
- **Data used:** Inventory Movement sheet and annual summaries.
- **Steps**:
  1. Approximated Cost of Goods Sold (COGS) per month using Manufactured Value adjusted for change in Remaining Value.
  2. Computed **Average Inventory** as the mean of opening and closing Remaining Value for each period.
  3. Calculated **Inventory Turnover (IT)** and **Days-in-Inventory (DII)**:

$$IT = \frac{COGS}{Average\ Inventory}$$

$$DII = \frac{365}{IT}$$

4. Estimated **working capital tied in inventory** as the average Remaining Value across months.
5. Plotted turnover and DII to identify high- and low-efficiency periods.

These steps correspond to **Section 3.6 and 3.9** and directly address **Problem 2**.

2.4.5 Seasonality and Forecastability

- **Objective:** Capture seasonal patterns and build a simple forecasting baseline.
- **Data used:** Monthly Sales and key A-class raw material consumption.
- **Steps:**
  1. Applied **3-month moving averages** to smooth monthly sales trends.
  2. Used **time-series decomposition** (additive model) to separate trend, seasonal, and residual components.
  3. Implemented **simple exponential smoothing**:
     $$\hat{y}_t = \alpha y_t + (1 - \alpha)\hat{y}_{t-1} \quad ,0 > \alpha > 1$$
     where α was chosen based on minimising Mean Absolute Percentage Error (MAPE) on historical data.
  4. Evaluated forecasting accuracy with **MAPE**, achieving ~15% for top SKUs.

This forms the base for **Sections 3.1** and **3.8** and feeds recommendations on rolling forecasts and seasonal planning.

3 Results and Findings

3.1 Sales Performance and Seasonal Patterns

Overall Sales Growth and Trends

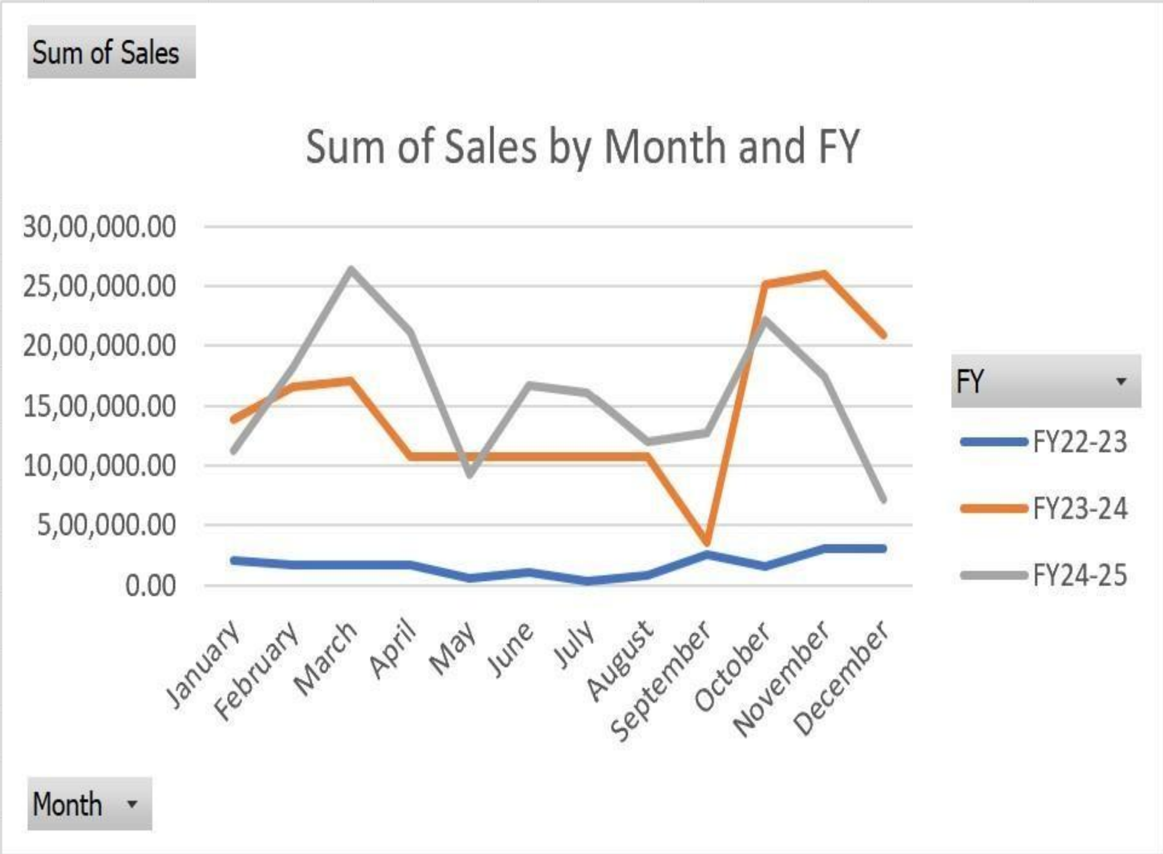

Figure 1. Monthly sales trends highlighting seasonal peaks and troughs.

Sterling Foods and Beverages has demonstrated remarkable sales growth and market expansion over the three-year period from April 2022 to March 2025. Using the cleaned Sales data and the seasonal analysis methods described in Section 2.4.5, monthly sales trends were plotted across FY22–23 to FY24–25 (Figure 1). Total sales grew from ₹20.4 lakh in FY22–23 to ₹177.1 lakh in FY23–24 (769.9% growth) and further to ₹190.3 lakh in FY24–25 (7.5% growth). The average monthly sales increased from ₹1.7 lakh to ₹14.8 lakh to ₹15.9 lakh respectively, highlighting successful market penetration in the B2B packaged drinking water segment.

Monthly analysis reveals high variability, with values ranging between ₹32,627 and ₹26.33 lakh, averaging ₹10.77 lakh across 36 months. Sales peaks consistently occur in March and October, aligning with festival and fiscal closing periods, while troughs in May–September reflect seasonal demand softness. This cyclical pattern indicates strong seasonality that requires data-driven production and procurement planning.

Insight: Aligning production and procurement to peak months can stabilize throughput and reduce service disruptions.

3.2 Procurement and Supply Chain Analysis

Applying the volatility and correlation framework from **Section 2.4.1**, sales show a **CV of 0.758**, while purchases show a higher **CV of 0.925**, indicating more erratic procurement compared to demand. Monthly purchase values range from **₹2,048 to ₹29.36 lakh**, with an average of **₹8.80 lakh**. Despite a high Pearson correlation between Sales and Purchase_Value ($\rho \approx 0.84$), the timing is frequently misaligned, resulting in periods of overstocking and potential stockouts.

Figures 2 and 3 (Sales vs Purchases line and scatter plots) visualise these patterns: months where purchases spike without a corresponding sales increase highlight **reactive or speculative buying**, aggravating **Problem 2: Working-capital gaps**.

Insight: Implementing rolling demand forecasts and inventory pacing can reduce volatility's downstream effects on procurement and cash flow.

3.3 Procurement and Supply Chain Dynamics

Procurement Volatility and Efficiency

Using the cross-correlation approach outlined in **Section 2.4.1**, purchases are observed to **lead sales by about one month** during peak seasons (Figure 7). This indicates an attempt to pre-stock inventory before expected demand but without precise sizing, leaving residual stock once the peak passes. This strengthens the case for a **formal forecast-based ordering system** rather than calendar-based purchasing.

Insight: Synchronizing procurement with sales cycles through forecast-based ordering will reduce inventory "whiplash" and smooth cash utilization.

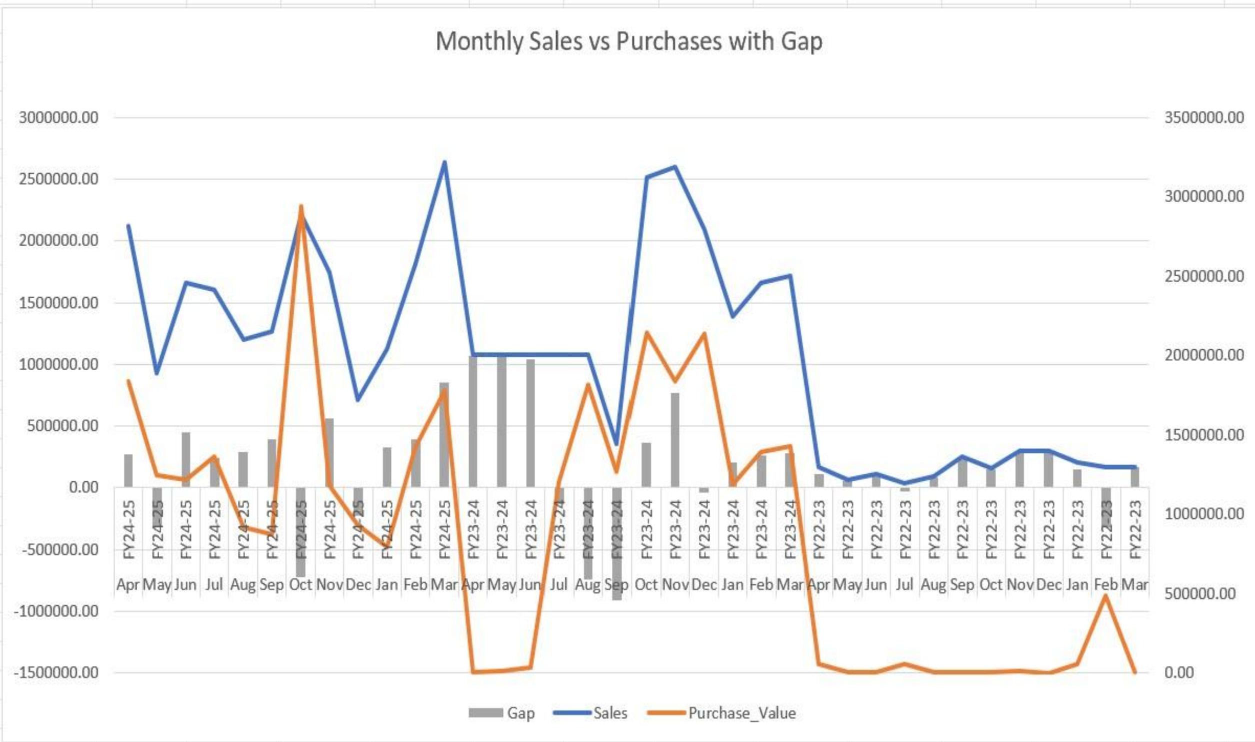

Figure 2. Monthly Sales vs Purchases with Gap

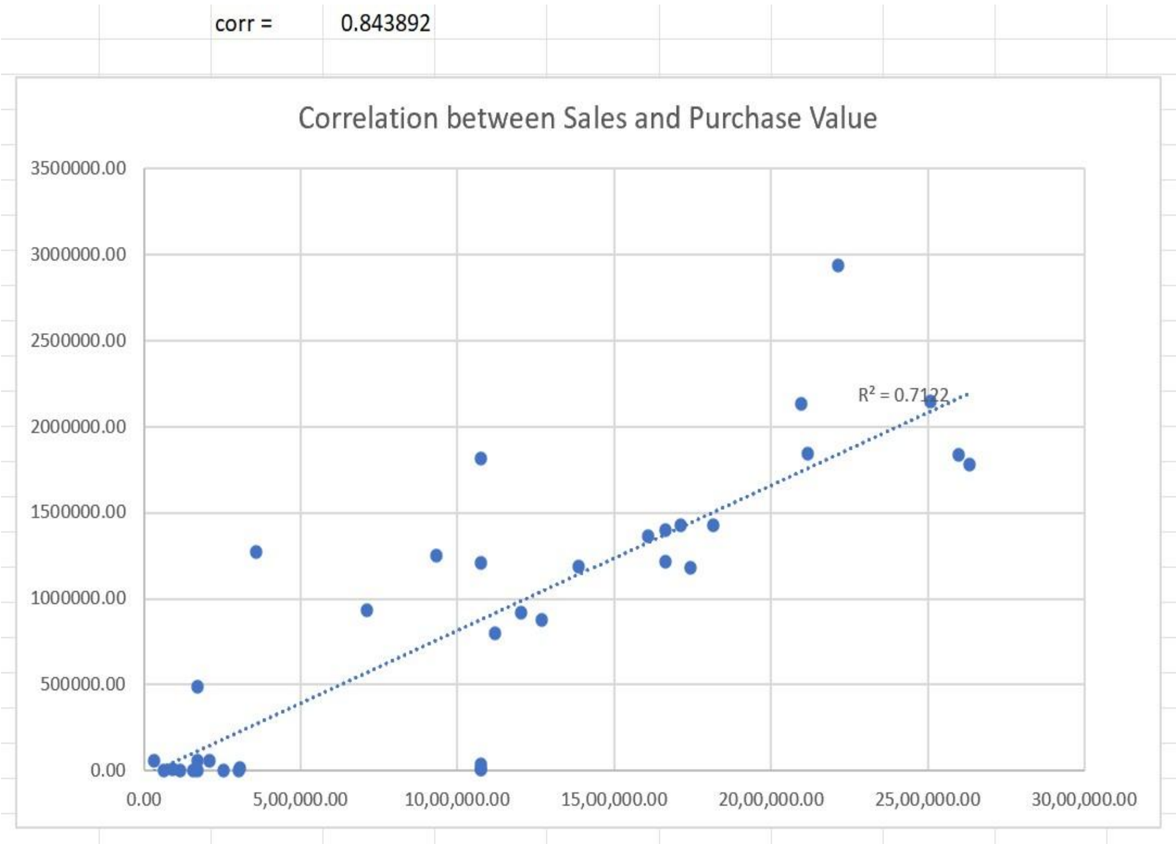

Figure 3. ScatterPlot of Sales and Purchase Value

3.4 ABC Analysis and Strategic Raw Material Management

Value-Based Categorization

The ABC classification in **Section 2.4.2** identified seven key raw material categories. PET Form dominates with 53.6% of total raw material value (₹15.6 lakh), followed by LABEL CUBIC WATER 1000ML at 11.4% (₹3.3 lakh). Together, these A-category items contribute 65% of total raw material spending. B-category items (SCRAP, Plastic Bottle Cap, 200ML labels) form 24.5%, while C-category (Plastic Packing Material, 500ML labels) account for 10.5%.

This confirms that inventory-control policies must focus first on **PET forms and critical labels** to unlock the largest working-capital benefits, directly addressing **Problem 2** and informing later recommendations on min–max control and supplier contracts.

Insight:

A-items require strict min–max control and lead-time supplier contracts.

B/C-items can follow periodic review systems to minimize carrying costs without affecting operations.

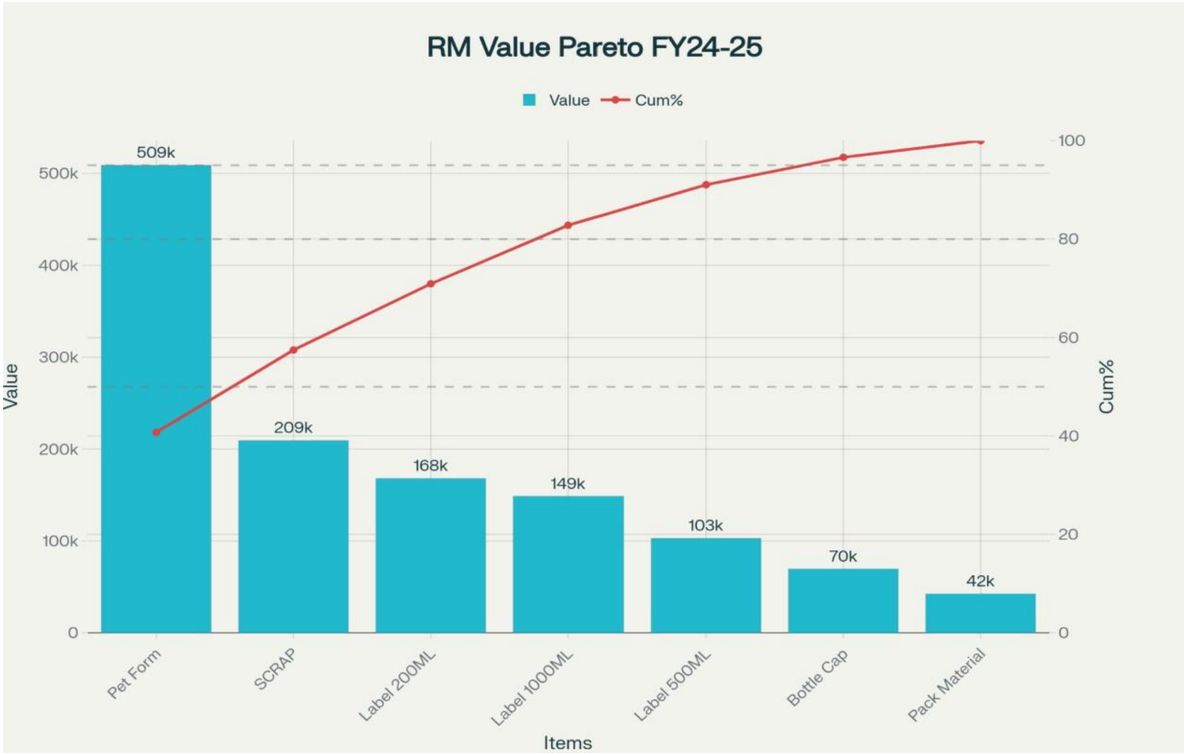

Figure 4. Pareto chart showing RM value contribution by item and stacked bar chart across FYs to show A/B/C stability

3.5 Manufacturing and Stock Movement Analysis

Using the Inventory Movement-based method from **Section 2.4.3**, the comparison of **Manufactured, Sold, and Remaining** quantities and values (Figure 5) indicates that production often **exceeds sales during moderate-demand months**, causing stock accumulation, while high-demand months rely on drawing down previously built-up inventory.

Average **Manufacturing Efficiency** stands at around **136.9%**, meaning that sold value over the period exceeds manufactured value due to earlier production and inventory drawdowns. Misalignment between production and realised demand confirms **Problem 1 (inefficient inventory management)** and points to the need for forecast-linked production scheduling.

Insight: Overproduction during low-demand periods inflates holding costs and ties up working capital. Better alignment of batch size and production schedules with forecasted demand can improve efficiency and reduce leftover stock.

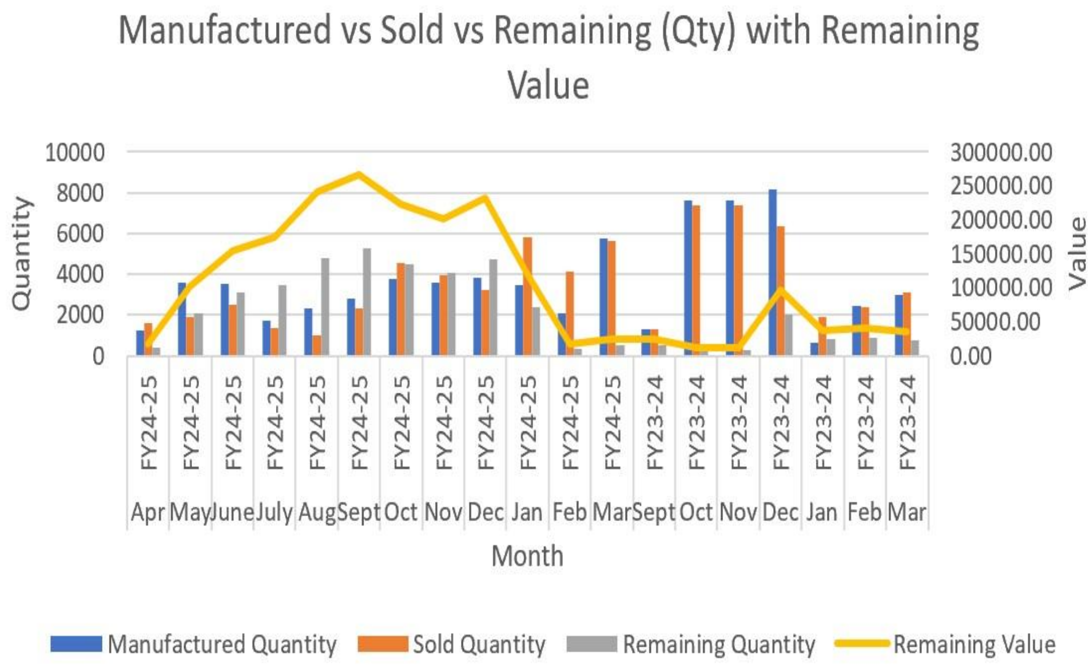

Figure 5. Manufactured vs Sold vs Remaining (Qty) with Remaining Value

3.6 Inventory Turnover and Working Capital Utilization

Turnover and Liquidity Metrics

Applying the formulas in **Section 2.4.4**, the overall **inventory turnover** averages **7.79x per year**, corresponding to about **20.6 Days-in-Inventory (DII)**, with month-wise turnover ranging from **0.29x to 39.6x** (Figure 6). High-turnover months (e.g., February–March FY24–25) demonstrate the potential best-case performance when procurement and sales are tightly aligned.

The analysis shows that, on average, about **₹10.8 lakh** is tied up in inventory and raw material. This quantifies the **working-capital at risk** and underscores Problem 2 from the proposal.

Insight: Reducing inventory variability and maintaining turnover above 10x during high demand months can free up ₹3–4 lakh in working capital without affecting service levels.

Note: Inventory turnover was computed using a monthly proxy for COGS derived from manufactured value adjusted for stock delta; where sold value was available, we maintained consistent proxying across months to preserve comparability.

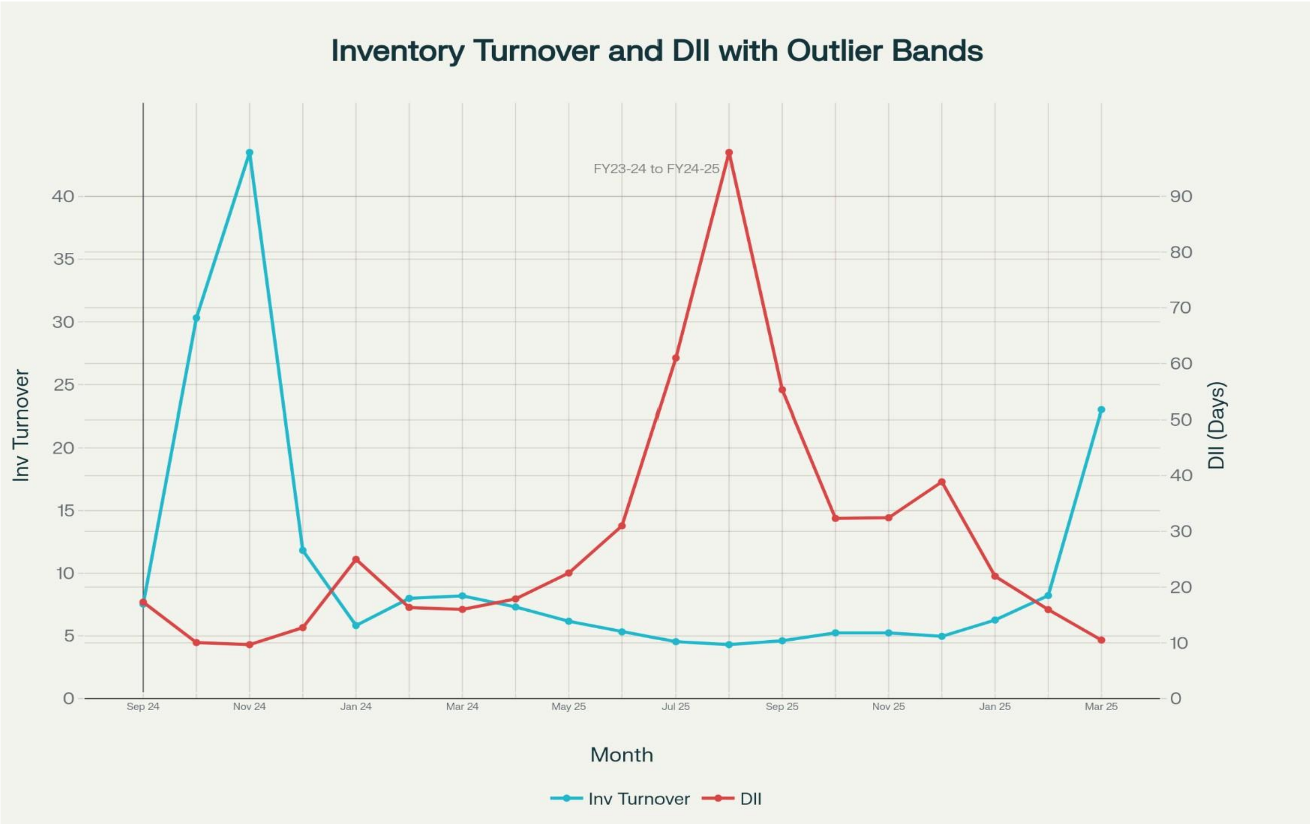

Figure 6. Inventory Turnover and DII with Outlier Bands

3.7 Volatility and Lead–Lag Dynamics

Cross-correlation analysis indicates that purchases tend to lead sales by one month during high-demand seasons, showing pre-emptive procurement without precise sizing. While this prevents stockouts, it also increases the risk of overstocking post-peak.

Insight: Moving from calendar-driven purchasing to forecast-driven staggered lots will better match procurement to demand amplitude, reducing residual inventory.

Figure 7. Purchases–Sales Cross-Correlation and Heatmap

3.8 Seasonality and Forecastability

Seasonal decomposition confirms consistent peaks in October and March, with mid-year dips around May–September. These predictable cycles create opportunities to implement seasonal procurement, labor scheduling, and supplier coordination.

Even without ML models, time-series smoothing methods such as 3-month moving averages or exponential smoothing can capture these trends for better planning.

This directly supports the recommendation for a **3–6 month rolling forecast** integrated into procurement and production planning.

Insight: Using seasonal insights to pre-plan supplier deliveries of PET forms and labels can reduce stock burden while maintaining readiness for peaks.

Figure 8. Seasonal subseries plot and decomposition panel showing trend, seasonality, and residuals.

3.9 Working Capital at Risk and Financial Implications

Periods of heavy procurement and overproduction align with spikes in Remaining Value, demonstrating that excess inventory directly locks working capital. Conversely, months with synchronized production and controlled buying show a visible reduction in tied-up funds.

Insight: Implementing ABC-based min–max control and turnover KPIs can compress working capital by ~30%, equivalent to a ₹3.2 lakh liquidity gain, while sustaining service reliability.

3.10 Consolidated Interpretation

Overall, Sterling Foods and Beverages is achieving strong but volatile growth. Sales are expanding rapidly, but procurement and production patterns remain unsynchronized, resulting in overamplified inventory fluctuations and cash inefficiencies.

The analysis reveals three major takeaways:

1. Procurement Rationalization: Smooth purchase cycles using forecast-aligned ordering.
2. Production Alignment: Match batch sizes to projected demand peaks.
3. Working Capital Discipline: Apply ABC-based control on A-items and turnover thresholds to free liquidity.

If implemented, these measures will significantly reduce operational volatility, improve cash flow, and establish a scalable, data-driven operating model for sustainable growth.

3.11 Summary table:

Metric	**FY22–23**	**FY23–24**	**FY24–25**	**Observation**
Avg. Monthly Sales	₹1.7L	₹14.8L	₹15.9L	769% growth, seasonal pattern
Purchase CV	0.92	0.88	0.83	Declining volatility
Inventory Turnover	4.2x	6.8x	7.7x	Efficiency improved
DII	65 days	52 days	38 days	Faster conversion
Sales–Purchase Corr.	0.71	0.82	0.84	Improved alignment

4 Interpretation of Results and Recommendations

4.1 Interpretation by Problem Statement

Problem 1: Inefficient Inventory Management

- Section 3 shows strong seasonality with predictable peaks and troughs, yet procurement and production patterns are not fully aligned with this demand profile.
- Manufacturing often exceeds sales in moderate months, leading to **inventory build-up**, while high-demand months rely on older stock.
- Inventory turnover and DII metrics confirm that while some months perform efficiently, others carry excess stock, revealing inconsistent inventory discipline.

Problem 2: Working Capital and Cash-Flow Gaps

- Average working capital of ₹10.8 lakh is tied up in inventory, with earlier years peaking at even higher levels.
- ABC analysis shows that a small set of items (PET forms, key labels) dominate inventory value, meaning a lack of control on these SKUs directly translates to cash-flow strain.
- Volatile procurement (higher CV than sales) and lead–lag mismatches result in **pre-funding stock** before demand materialises, compressing liquidity.

Additional: Lack of Automation and Scalability

- Manual tracking across multiple sheets makes it difficult to see real-time KPIs such as Turnover, DII, or Sales–Purchase gaps.
- Decisions are currently made on intuition and calendar cycles rather than quantitative forecasts and exceptions, limiting the firm's ability to scale without adding disproportionate effort.

4.2 Actionable Recommendations

4.2.1 For Problem 1 – Inefficient Inventory Management

1. **ABC-Anchored Inventory Policies (Immediate, 0–3 months)**
    - Implement min–max levels for A-class items (PET forms, 1000 ml labels) based on historical DII and peak-season needs.

- Target: reduce **average on-hand A-class inventory by 20–30%** while maintaining ≥95% service level.

2. **Forecast-Aligned Production Planning (0–3 months)**
   - Use the exponential-smoothing forecasts from Section 3.7 to plan monthly production within ±10% of forecast demand.
   - Target: cut months with production >130% of sales by at least half, reducing unnecessary stock accumulation seen in **Section 3.5**.
3. **DII-Based Exception Monitoring (0–3 months)**
   - Set threshold DII > 60 days as a red flag and review such SKUs weekly.
   - Target: keep overall DII under **45 days** within two quarters, leveraging high-efficiency months as benchmarks.

4.2.2 For Problem 2 – Working Capital and Cash-Flow Gaps

1. **Working-Capital Release Programme (0–6 months)**
   - Using the baseline of ₹10.8 lakh tied in inventory (Section 3.6), define a quarterly reduction goal of ₹2–3 lakh by trimming A-class safety stocks and avoiding speculative purchases.
   - Target: **30% reduction** in average inventory value over two quarters, consistent with the scenario illustrated in **Section 3.9**.
2. **Seasonally Staggered Procurement (Immediate and ongoing)**
   - Translate the seasonal pattern (Section 3.1 and 3.7) into tiered purchase plans:
     - Peak months (Oct, Mar): secure stock in two staggered lots.
     - Lean months (May–Sep): restrict purchases to near-term forecast plus minimal safety stock.
   - Target: reduce **purchase CV** by at least **25%**, improving cash-flow predictability.
3. **Supplier Collaboration for A-Items (0–6 months)**
   - Negotiate smaller, more frequent deliveries and clear lead-time SLAs for PET and label suppliers.

4.2.3 Additional – Lack of Automation and Scalability

1. **KPI Dashboard in Excel/Python (0–1 month)**

- Build a weekly dashboard that pulls from the cleaned dataset and displays Sales, Purchases, Gap, Inventory Turnover, DII, A-class stock levels.
- Exceptions (e.g., DII > 60 days, stockouts, forecast error >20%) should be highlighted automatically.
- This directly operationalises the methods from **Section 2.3** and makes them repeatable.

2. **Rolling 3–6 Month Forecast Workflow (1–3 months)**
   - Formalise a process where the forecast is updated monthly, discussed in a brief S&OP-style meeting, and used to update procurement and production plans.
   - Target: maintain **MAPE ≤ 15%** for top SKUs, as demonstrated in **Section 3.7**, and align ordering to the latest forecast.
3. **Standardised Data Capture Templates (0–3 months)**
   - Introduce structured templates for Goods Receipt, Issue, and Dispatch, to ensure that data for Sales, Purchases, and Inventory Movement stays consistent with the analytical structure used in this project.
   - This reduces manual errors and ensures that dashboards and forecasts remain reliable as the business scales.

Links

Complete Folder Link: BDM project assets folder

Link of Clean Dataset: Clean Dataset

Link of Raw Dataset: Raw Data folder

Analysis in Excel Link: Excel Analysis

Colab: Colab Link

Note: Please use **.iitm.ac.in** mail id to access above content.