Stratify

Vedant Moghe,Shivakshi Gupta , Kartikya Saini

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Final Report: Advanced Inventory Replenishment Model

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1 Executive Summary

This report details the successful implementation of an Advanced Inventory Replenishment Model designed to optimize stock levels, reduce costs, and improve product availability. By leveraging historical sales data and supplier performance metrics, the model provides data-driven recommendations for key inventory parameters, including Economic Order Quantity (EOQ), Reorder Points (ROP), and Safety Stock.

A 21-day simulation was conducted to validate the model's performance. The results demonstrate a significant potential for improvement over traditional inventory management methods. The model achieved a 98.1% fill rate and a 95.2% service level, indicating high product availability and minimal stockouts. The analysis projects substantial cost savings, primarily through a reduction in excess holding costs and lost sales, leading to a more efficient and profitable supply chain. The accompanying Python-based dashboard provides a dynamic tool for ongoing, SKU-level performance monitoring.

2 Model Performance and Key Findings

The model's effectiveness was evaluated using a 21-day simulation based on historical data. The primary goal was to test the optimized inventory parameters against realistic, variable demand.

Simulation Performance Summary

Key Performance Indicator (KPI)	Result	Significance
Fill Rate	98.1%	Over 98% of customer demand was met immediately from stock, minimizing lost sales.
Service Level Achieved	95.2%	The model successfully avoided stockouts on 20 out of 21 simulated days (95.2%), meeting its target.
Forecast Accuracy (MAE)	88.7%	The auto-selection forecasting method proved highly effective at predicting variable demand.
Stockout Days	1 Day	Only one stockout event occurred during the entire 3-week simulation period.

Key Findings

- **Dynamic Forecasting is Crucial:** The model's ability to adapt its forecasting method based on demand variability (e.g., using Croston's method for intermittent demand) is a key driver of its accuracy.
- **Supplier Reliability Matters:** Adjusting lead times based on supplier delay rates resulted in more reliable safety stock calculations, preventing stockouts caused by late deliveries.
- **Data-Driven Parameters Outperform Rules-of-Thumb:** The calculated EOQ and ROP led to a more responsive inventory system compared to static, manually set levels.

3 Interactive Dashboard (Python)

A key output of this project is a comprehensive visualization dashboard generated directly from the Python simulation. This dashboard serves as a powerful tool for supply chain managers to analyze the performance of any given SKU in detail.

Dashboard Components

- **Stock Level vs. Reorder Points:** Visualizes inventory levels over time, clearly showing when orders are placed (at the ROP) and how close stock gets to the safety stock level.
- **Demand Forecast vs. Actual:** Tracks the accuracy of the demand forecast, highlighting periods of unexpected volatility.
- **Cumulative Service Level:** Shows how well the model maintains the target service level over the simulation period.
- **Cost Breakdown:** A pie chart illustrating the split between total holding costs and ordering costs.

- **Stockout Analysis:** A bar chart pinpointing the exact days when stockouts occurred.
- **KPI Summary:** A text-based summary of the most critical performance metrics for a quick, at-a-glance review.

4 Assumptions and Limitations

Key Assumptions

- **Stable Lead Times:** The model assumes that average supplier lead times and delay rates are relatively stable.
- **Constant Costs:** Ordering costs and holding cost rates are assumed to be constant.
- **Historical Data is Representative:** Forecasts rely on the assumption that past sales patterns are a good predictor of future demand.
- **No Supply Constraints:** The supplier is assumed to always fulfill the ordered quantity.

Limitations

- **External Events:** The model does not account for black swan events (e.g., natural disasters, pandemics).
- **Promotions and Marketing:** Marketing campaigns are not modeled; manual adjustments are required.
- **Shelf Life:** The model does not actively prioritize stock rotation (FIFO/FEFO).

5 Cost-Benefit Analysis

Implementing this model is projected to yield a strong return on investment by optimizing the trade-off between inventory costs and service levels.

Category	Description	Projected Annual Impact (Per SKU Example)
Benefit: Reduced Holding Costs	Minimizes excess inventory by optimizing EOQ and safety stock levels.	$1,250 (Based on 100 excess units at $50/unit cost & 25% holding rate)
Benefit: Reduced Lost Sales	Improves product availability through higher fill rates, capturing previously lost revenue.	$2,000 (Based on a 2% fill rate improvement on $100k annual sales)
Benefit: Improved Efficiency	Automates complex calculations, freeing up supply chain planners for strategic tasks.	Qualitative (High)
Cost: Initial Setup	Time and expertise to integrate with ERP and train personnel.	One-Time
Cost: Data Maintenance	Ongoing effort to ensure data remains accurate.	Ongoing (Low)

Summary

The financial benefits from reduced inventory costs and recovered sales revenue are expected to far outweigh the implementation costs, with a projected payback period of under one year.

6 Recommendations and Next Steps

- **Pilot Program:** Deploy the model in a pilot program focusing on a limited set of high-value or high-variability SKUs.
- **Integration with ERP System:** Develop a workflow to automatically feed ERP data into the model and export ROP/EOQ values back.
- **Develop an Excel Dashboard:** Export key outputs (ROP, Safety Stock, EOQ) and KPIs into a shareable Excel template.

Future Enhancements

- Incorporate a machine learning module (e.g., XGBoost) to model the impact of promotions and external factors.
- Add FEFO (First-Expired, First-Out) logic to better manage products with limited shelf life.