Superstore Demand Forecasting & Inventory Policy

An Excel-based inventory simulation and forecasting project.

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Tagline:

A practical supply chain Analytics case study.

Tools used:

Microsoft Excel (Forecast.ETS, PivotTables, Simulation Logic)

Objective:

To forecast daily demand and evaluate reorder policies that minimize stockouts and reduce order frequency in a simulated retail environment.

1. Introduction & Goals

In this project, I aimed to predict how many units a fictional ‘Superstore’ sells each day and then determine an inventory reorder policy, including when and how much to reorder to avoid stockouts or excessive orders. Without cost data, I focused on balancing reorder frequency with stock risk.

Key Steps:

1. Data Cleaning (daily sales extraction)
2. Forecasting (using Excel’s FORECAST.ETS)
3. Inventory Simulation (daily stock tracking)
4. Scenario Comparison (testing reorder points and quantities)
5. Final Recommendation (the best approach for fewer orders & minimal stockouts)

2. Data Cleaning

Data Source: “Superstore” dataset with Order Dates, Sales, Ship Dates, etc.

- Created a PivotTable to sum Sales by Order Date for daily totals.
- Extracted data into a “Cleandata” sheet with Date and Daily sales columns.
- Split data into training (80%) and test (20%) sets: rows 2-991 for training, 992 -1237 for testing.

3. Forecasting

- Used Excel’s **FORECAST.ETS** function is used to predict daily sales on the test set.
- Evaluated accuracy by calculating the Mean Absolute Percentage Error (MAPE)
- Created a line chart comparing actual vs forecast sales in the test period, showing close tracking with some underestimation on peak days.

Forecast Accuracy Visualization

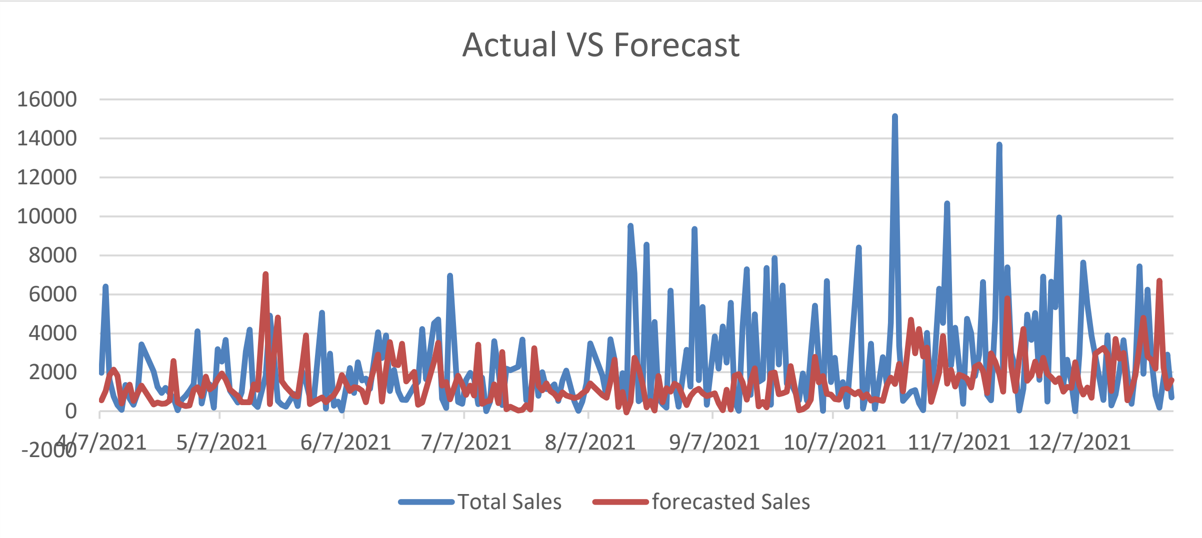
To evaluate the performance of the forecast, I created a line chart comparing actual sales to forecasted values over the test period (rows 992-1237). The chart uses:

X-axis: Date

Y-axis: Sales

Two lines:

- Actual Sales (From Column B)
- Forecasted Sales (From Column C)



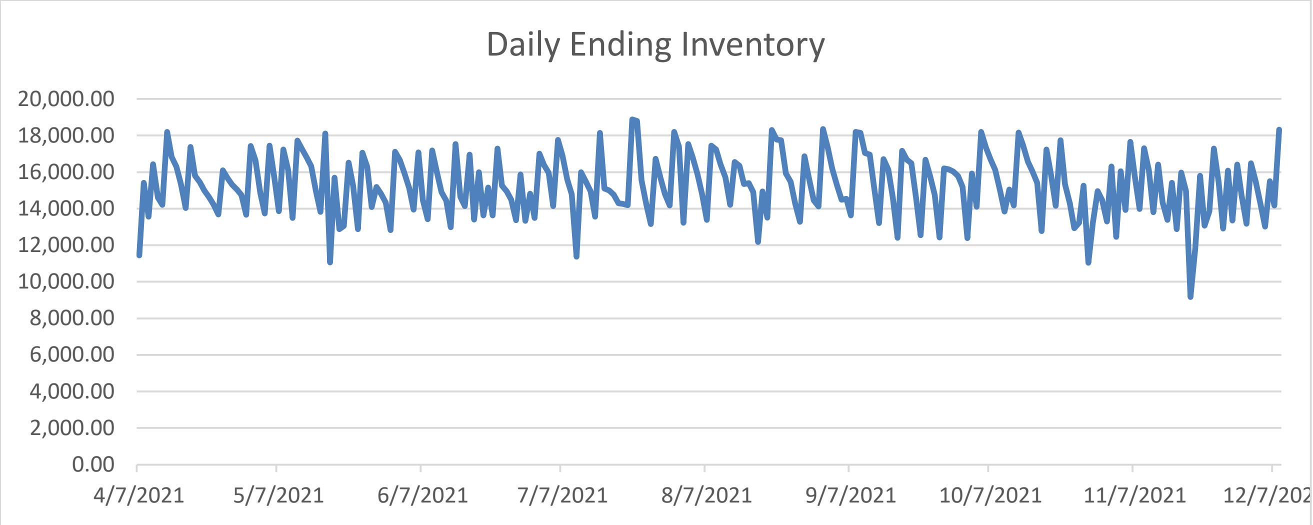
This Visualization helps identify how well the forecast tracks daily sales patterns, particularly during high and low demand periods.

4. Inventory Simulation

Built a daily inventory model tracking:

Column	Description
E	Beginning inventory
F	Forecast Demand
G	Ending Inventory = E-F
H	Order Placed? = IF(Ending inventory < ROP, “Yes”, “No”

- Manually set initial Beginning Inventory (E.g, 12000)
- Updates inventory daily, placing orders when stock fell below the reorder point (ROP)



"Figure 2 shows how daily ending inventory fluctuates, and each time it dips below ROP, we place an order the next day."

5. Scenario Comparison

Tested variations in:

Scenario	ROP	RQ	# of Reorders
Original (Baseline)	14,215	3,424	107
Lower ROP	12,000	3,424	106
Increase RQ	14.215	5,000	73

Observations:

- Lowering ROP from 14,215 to 12,000 barely changed reorder frequency.
- Increasing the reorder quantity drastically reduced the number of orders.

6. Final Recommendation

Given my main goal is to reduce reorders while avoiding frequent stockouts, I concluded:

- Maintain ROP at approximately 14,215 to prevent stockouts.
- Increasing the Reorder Quantity drastically reduced the number of reorders.

Trade-Off:

- Higher reorder quantity means more inventories held on average, potentially increasing holding costs (not accounted for here)

Conclusion & Takeaways

1. Forecasting achieved a reasonable MAPE, demonstrating accuracy.
2. The simulation modelled inventory levels and reorder timing effectively.
3. Scenario testing showed that increasing the reorder quantity reduced orders significantly.
4. The final policy balances reorder timing and quantity for efficiency.

Looking Forward:

With cost data, applying an Economic Order Quantity (EOQ) model would further optimize inventory management.