GS – CASE STUDY: DUVEL

I. INTRODUCTION

Duvel Moortgat group aims to evaluate the effectiveness of two forecasting approaches (statistical forecast and consensus forecast) to optimize inventory management for its products, here *La Chouffe 20L Keg A_8001* in France.

The objective is to compare these forecasting methods in terms of accuracy, impact on inventory, and customer service, while recommending the most suitable inventory strategy.

This study focuses on the following aspects:
1. Quantitative comparison of the forecasts using standard performance metrics.
2. Testing and analyzing different inventory policies for each forecast.
3. Proposing an optimal inventory policy and providing clear recommendations.

II. DATA CLEANING AND PREPARATION

The forecasting data contains anomalies for weeks 36, 37, and 38 of 2023, where both forecasts have values equal to zero. These anomalies must be corrected to ensure the reliability of the analysis.

To address these issues, missing values were replaced with the average of the three weeks of sales preceding the weeks where forecasts were null. This method ensures continuity and prevents bias, as the forecasts generally fluctuate around a stable average. The correction was validated by comparing the impact of removing these values versus using this imputation method.

The study is conducted over a period of 80 weeks, following the correction of these anomalies.

III. FORECAST ANALYSIS

To analyze and compare the forecasts, the following performance indicators were used:

- **Bias (%)**: Measures whether the forecast tends to overestimate or underestimate sales. A bias close to zero is ideal as it indicates a balance between forecasted and actual values.
- **MAE (Mean Absolute Error) (%)**: Represents the average absolute error, evaluating overall accuracy without excessively penalizing large errors.
- **RMSE (Root Mean Squared Error) (%)**: More sensitive to large errors, RMSE is suitable for detecting significant fluctuations in demand.

To select the best forecast, a composite score was introduced: $\boldsymbol{Score} = |\boldsymbol{Biais}| + \boldsymbol{MAE}\%$

The obtained values for the two forecasts are as follows:

	Statistical Forecast	Consensus Forecast
Biais	-1%	6%
MAE	25%	26%
RMSE	31%	34%
Score	26%	32%

The statistical forecast is globally more precise, with lower MAE and RMSE values and it slightly underestimates (-1%), while the consensus forecast significantly overestimates demand (+6%).

The **statistical forecast** is preferred due to its higher accuracy, more balanced bias, and lower overall score.

IV. INVENTORY POLICY SIMULATIONS

The inventory simulations were conducted using the following settings:

- Lead Time (L): 1 week.
- Review Period (R): 1 week.

Additionally, the studied inventory policies follow the (R, S) model, meaning that each week (review period R), the stock level is checked and adjusted to a target stock level (S). This level is determined based on the chosen policy and computed using forecasts and a safety stock (SS).

1. Tested Inventory Policies

Four inventory policies were tested for both forecasting methods:

- Fixed Target Level (Fixed Policy)
- Fixed Safety Stock (Hybrid Policy)
- Dynamic Safety Stock (Dynamic Policy)
- Standard Safety Stock (Classical Policy)

Each of these policies introduces different ways to calculate the target inventory level S.

2. Assumptions

Several assumptions were made to enable inventory simulations:

No information on holding costs or lost sales costs was provided. However, lost sales are converted into backorders, meaning that lost sales costs do not need to be considered. Consequently, the objective is to minimize cumulative average inventory, which serves as a proxy for holding costs.

Since no initial stock level was provided, an assumption was made to start with 1,500 units, approximately corresponding to two months of forecasted demand.

3. Inventory Policies and Optimization Approach

a) Fixed Policy

The Fixed Policy maintains a constant target inventory level S. This fixed level is optimized using the solver to minimize cumulative average inventory. Each week, stock levels are evaluated, and orders are placed to reach S.

b) Hybrid Policy

The Hybrid Policy keeps the safety stock (SS) constant, with its value optimized using the solver. The target inventory level is determined as: $S = \text{Forecast for 2 months} + SS$

c) Dynamic Policy

The Dynamic Policy defines the target inventory level S as: $S = \text{Forecast for 2 months} + \alpha \times \text{Forecast for month 3}$, where the coefficient α, ranging between 0 and 1, is optimized using the solver.

d) Classical Policy

The Classical Policy determines the safety stock using the following formula: $SS = z\sigma\sqrt{R+L}$, where:

- z is the safety factor for a decided service level.
- σ represents the last 5-month RMSE.
- R is the review period.
- L is the lead time.

The target inventory level is then calculated as: $S = \text{Forecast for 2 months} + SS$

For each of these policies, the following key metrics were evaluated:

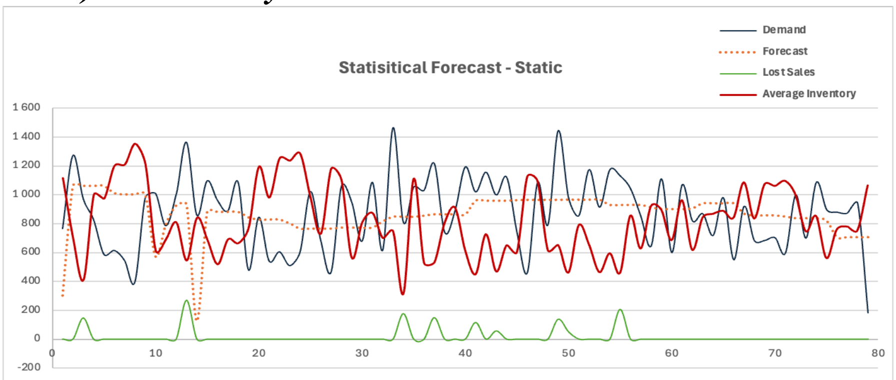
- **Cumulative average inventory:** Main metric to minimize.
- **Average inventory:** Weekly stock level over the study period.
- **Weekly service level:** Percentage of weeks where demand was fully met.
- **Fill rate:** Percentage of total demand satisfied.

To prevent excessive backorders, a constraint was applied in the solver a fill rate of at least 98% was enforced. This ensures realistic inventory levels and prevents solutions where orders are systematically delayed, which would be unrealistic in a real-world scenario. In fact, having too much backorders could lead to a loss of clients, which is not the objective.

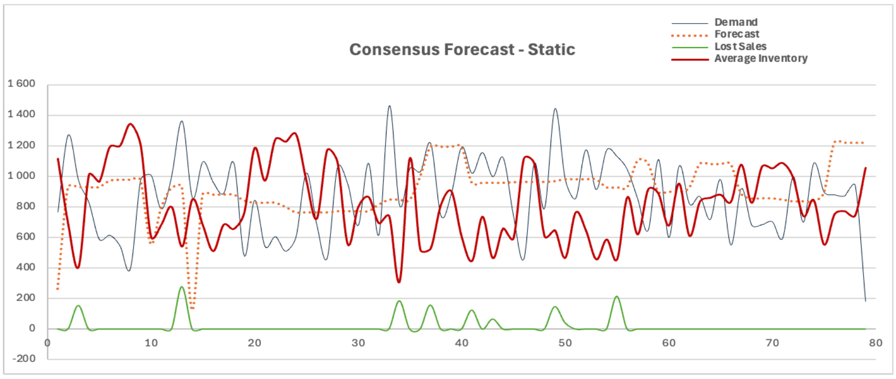
4. Simulation Results

Below are the key graphs and performance indicators for the four inventory policies across the two forecasts.

a) Fixed Policy

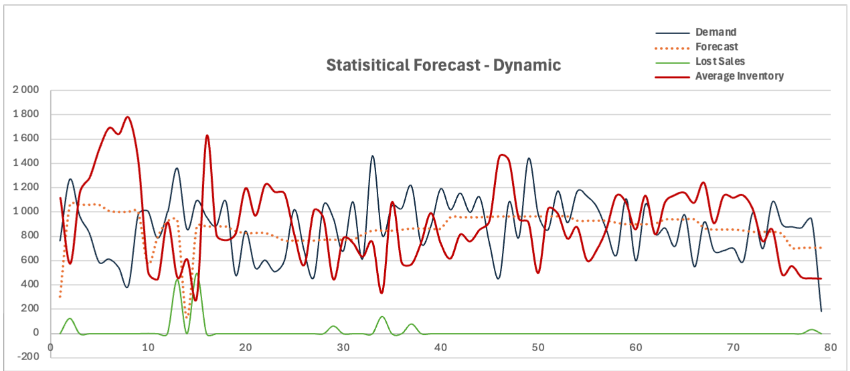


KPIS	SS
Average invent cumulated	65082
Average invent	824
Fill Rate	98,11%
Monthly Service Level	89%

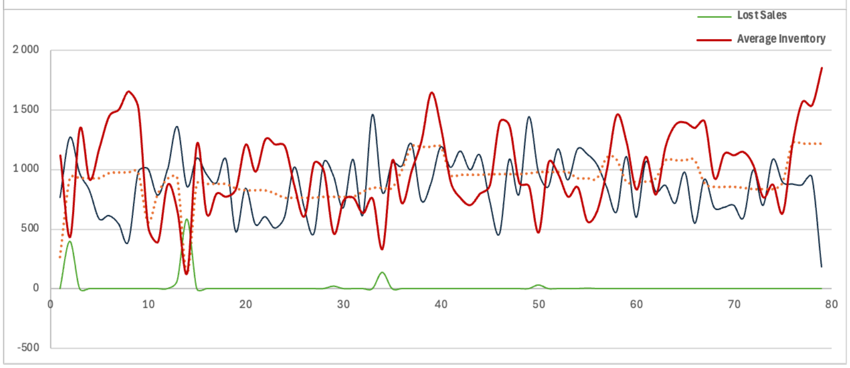


KPIS	CS
Average invent cumulated	64552
Average invent	817
Fill Rate	98,02%
Monthly Service Level	89%

b) Hybrid Policy

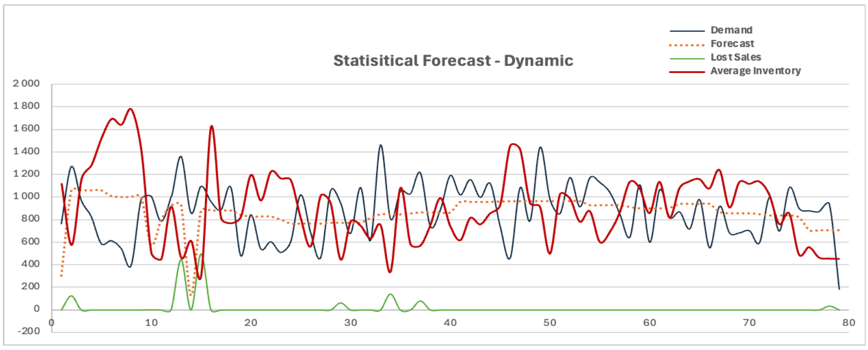


KPIS	SD
Average invent cumulated	71953
Average invent	911
Fill Rate	98,00%
Monthly Service Level	90%

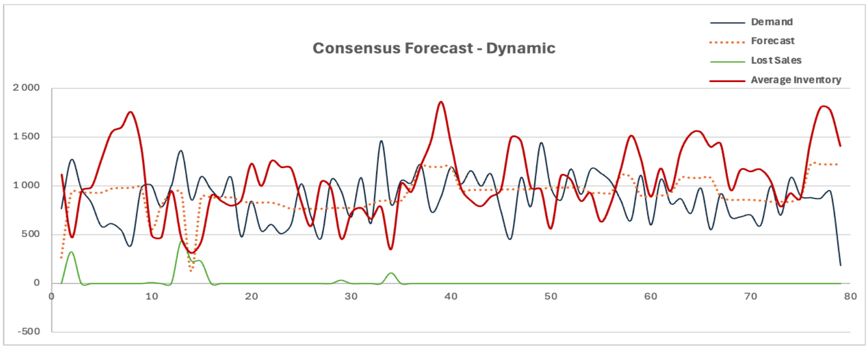


KPIS	CH
Average invent cumulated	78786
Average invent	997
Fill Rate	98,19%
Monthly Service Level	91%

c) *Dynamic Policy*

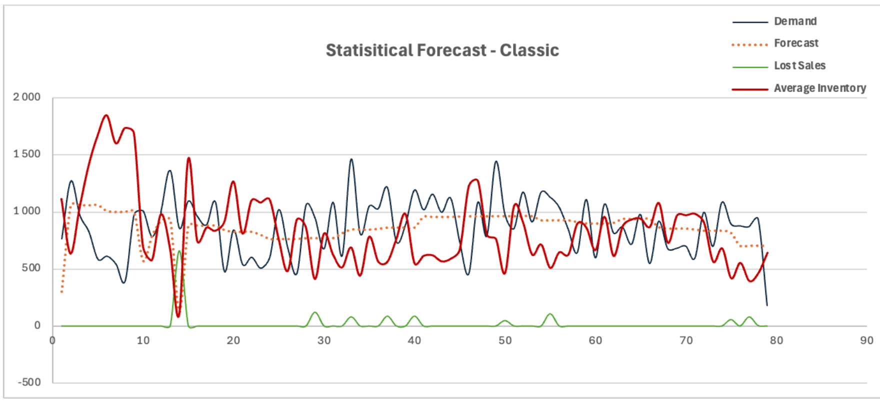


KPIS	SD
Average invent cumulated	71953
Average invent	911
Fill Rate	98,00%
Monthly Service Level	90%

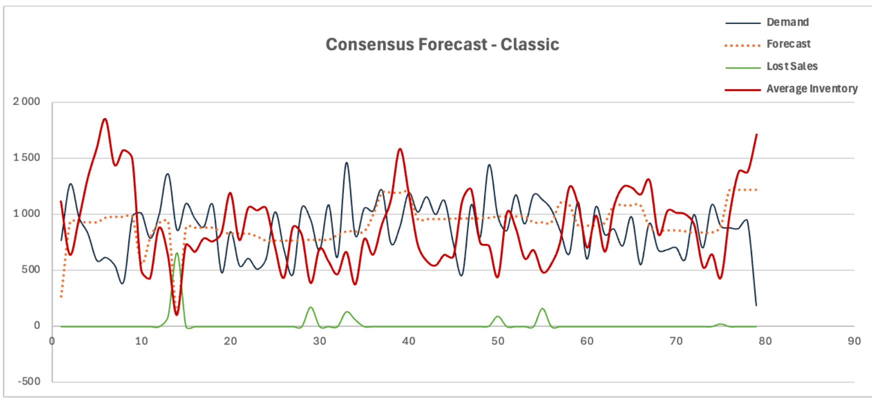


KPIS	CD
Average invent cumulated	82660
Average invent	1046
Fill Rate	98,00%
Monthly Service Level	91%

d) *Classical Policy*



KPIS	SC
Average invent cumulated	66537
Average invent	842
Fill Rate	98,07%
Monthly Service Level	86%



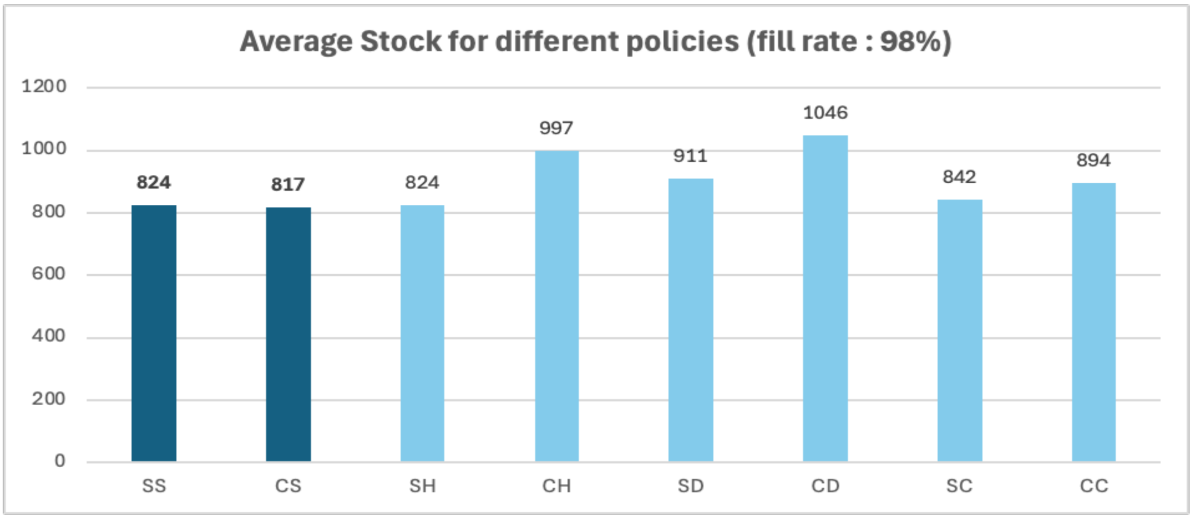
KPIS	CC
Average invent cumulated	70664
Average invent	894
Fill Rate	97,98%
Monthly Service Level	89%

All the indicators for each policy are summarized in the table below:

KPIS	SS	CS	SH	CH	SD	CD	SC	CC
Average invent cumulated	65082	64552	69003	78786	71953	82660	66537	70664
Average invent	824	817	824	997	911	1046	842	894
Fill Rate	98,11%	98,02%	98,00%	98,19%	98,00%	98,00%	98,07%	97,98%
Monthly Service Level	89%	89%	89%	91%	90%	91%	86%	89%

V. CONCLUSION

This analysis demonstrates that for a consistent 98% fill rate, the **Fixed Target Level** (**Fixed Policy)** yields the lowest average inventory, making it the most efficient policy.



However, results may vary depending on the chosen fill rate target, as a higher fill rate reduces lost sales but requires more stock. Here the choice was to have a high fill rate to avoid having too much lost sales, but it could be modify and give other results regarding other constraints.

Future work could involve testing alternative lead times and review periods while integrating actual holding costs for more precise cost-based optimization.