CentraleSupélec

université PARIS-SACLAY

Gestion des stocks

CentreSupélec

Gestion des stocks - Etude de cas Duvel

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Table des matières

1 Introduction **3**

2 Visualisation and analysis of each forecast **3**

3 Inventory management **5**
3.1 Fixed safety stock 5
3.2 Dynamic safety stock 6
3.3 Use of the formula to determine safety stock 7
3.4 Fixed safety stock while taking into account the backlogs 8
3.5 Dynamic safety stock while taking into account the backlogs 10

4 Conclusion **11**

1 Introduction

Duvel is a flemish brewery founded in 1871 in Antwerp. They commercialize belgian beers such as Duvel, Maredsous, Vedett or Chouffe. The goal of this project is to optimize the inventory management for one SKU in a particular country. In order to do that, we will first study their two forecasts and see the impact of each strategy of inventory management on the lost sales and inventory level.

2 Visualisation and analysis of each forecast

First of all, we visualize the sales and the two forecasts. We obtain the following graph :

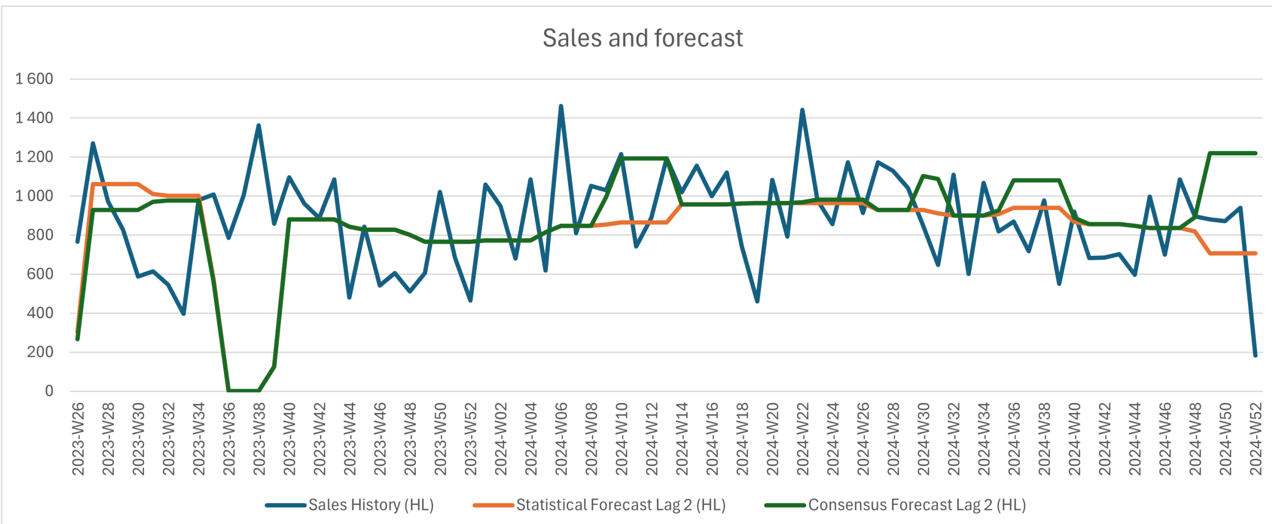


FIGURE 1 – Sales

We see that there was a problem for the forecast for the weeks 36 to 38 in 2023, which was also explained by Duvel.

As we do not want to have an impact of the models because of this problem, we try to manage this error. We can :

— Use the mean of the previous weeks
— Use the median of the previous weeks
— Use the last value of both forecast to do as if there was no fluctuation

After seeing the impact of these 3 methods on the caracteristics of the dataset and analysis the indicators, I chose to use the median to fill the values of the week 36 to 38 2023.

We obtain the following graph :

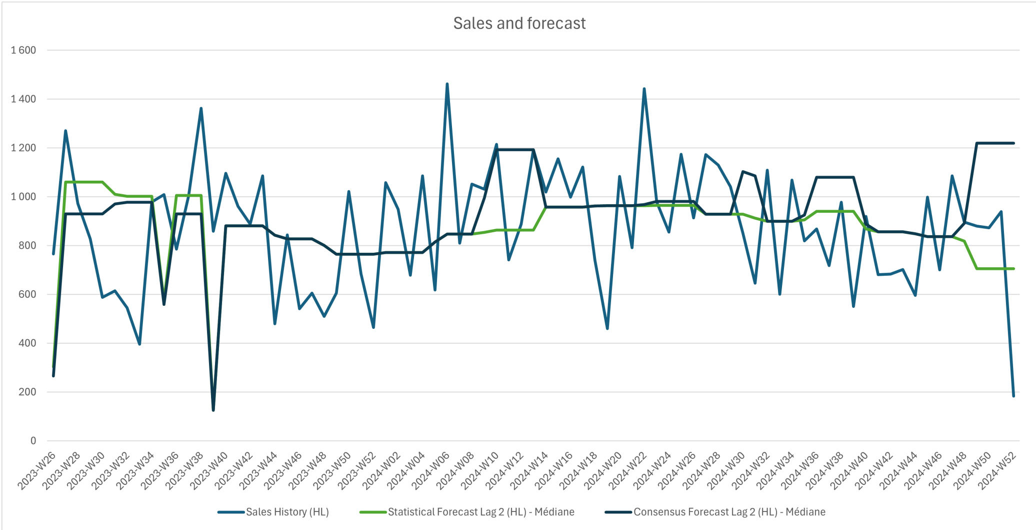


FIGURE 2 – Sales

After cleaning and replacing the data, we now try to compute different indicators to see which forecast is the best.

We use the following indicators :

— $Bias\% = \frac{\frac{1}{n}\sum e_t}{\frac{1}{n}\sum d_t}$

— $MAE\% = \frac{\frac{1}{n}\sum |e_t|}{\frac{1}{n}\sum d_t}$,

— $RMSE\% = \frac{\sqrt{\frac{1}{n}\sum e_t^2}}{\frac{1}{n}\sum d_t}$

— $Score = |Biais\%| + MAE\%$

— $Score + RMSE = |Biais\%| + MAE\% + RMSE\%$

We compute the following KPI for both forecasts.

Forecast	Bias%	MAE%	RMSE%	Score	Score + RMSE
Statistical Forecast Lag 2 (HL)	-0,4%	25,2%	30,7%	25,6%	56,3%
Consensus Forecast Lag 2 (HL)	4,9%	27,1%	34,3%	32,0%	66,2%

FIGURE 3 – KPI for each forecast for the period from W26 2023 to W52 2024

We see that for all indicators, the best forecast is the Statistical Forecast Lag 2 (HL).

3 Inventory management

In order to measure the efficacity of the inventory policy, we define different indicators :

— $Fillrate = 1 - \frac{Missedsales}{Demand}$, in %

— $OTIF = 1 - \frac{Noferrors}{Nofweeks}$, in %

We have seen that the definition of the fill rate shows better the state of the inventory. I will therefore keep this indicator to measure the service level and analyze the following inventory policy.

We know that the lead time and the review period are one week long, so the risk horizon is two weeks long. To compute the base for our inventory level to obtain the cycle stock, we look at the sum of the 2 following months' forecasts. I will now describe different models to compute the safety stocks :

— Fixed safety stock

— Dynamic safety stock

— Use of the formula $S_s = z\sigma\sqrt{R+L}$, with R = Review period and L = Lead Time

3.1 Fixed safety stock

In this method, we look the impact of the level of safety stock on the average inventory level and on the service rate computed thanks to the fill rate.

We compute it as the following screenshot shows :

SI | fx =SOMME(C6:C7)+E6

	A	B	C	D	E	F	G	H	I	J	K
5	Data	Sales History (HI	Statistical Forecast Lag 2 (HI	Up-to-level	Safety Stocks	Inventory Star	Sales	Lost Sales	Inventory En	Average Invento	Order t+1
6	2023-W26	766	302,953083	C7)+E6	800	766	766	-	-	383	1 397
7	2023-W27	1270,800018	1060,335732	2 921	800	1 397	1270,800018	0	126,488796	762	1 523
8	2023-W28	972,4000015	1060,335732	2 921	800	1649,871445	972,4000015	0	677,471443	1 164	1 271
9	2023-W29	827,8000031	1060,335732	2 921	800	1948,271461	827,8000031	0	1120,47146	1 534	972
10	2023-W30	588	1060,335732	2 870	800	2092,87146	588	0	1504,87146	1 799	778
11	2023-W31	614,8000031	1010,121073	2 812	800	2282,456804	614,8000031	0	1667,6568	1 975	529
12	2023-W32	545,0000076	1001,751862	2 804	800	2197,072931	545,0000076	0	1652,07292	1 925	606
13	2023-W33	396,4000015	1001,751862	2 804	800	2258,503716	396,4000015	0	1862,10371	2 060	545

FIGURE 4 – Screenshot of the model

As a hypothesis, I put the inventory start level equal to the sales history, as we do not have any information on it.

I compute the "Up-to-level" as the sum of the 2 next months' forecast and the fixed safety stock. The column G "Sales" corresponds to the minimum between the sales history and the inventory start. That allows me to compute the lost sales and the inventory end. I only have Order t+1 then the lead time is one week.

I then change the safety stock for both forecasts (Statistical forecast Lag 2 and Consensus forecast Lag 2) to see the average inventory and the fill rate.

I obtain the following fontier efficiency :

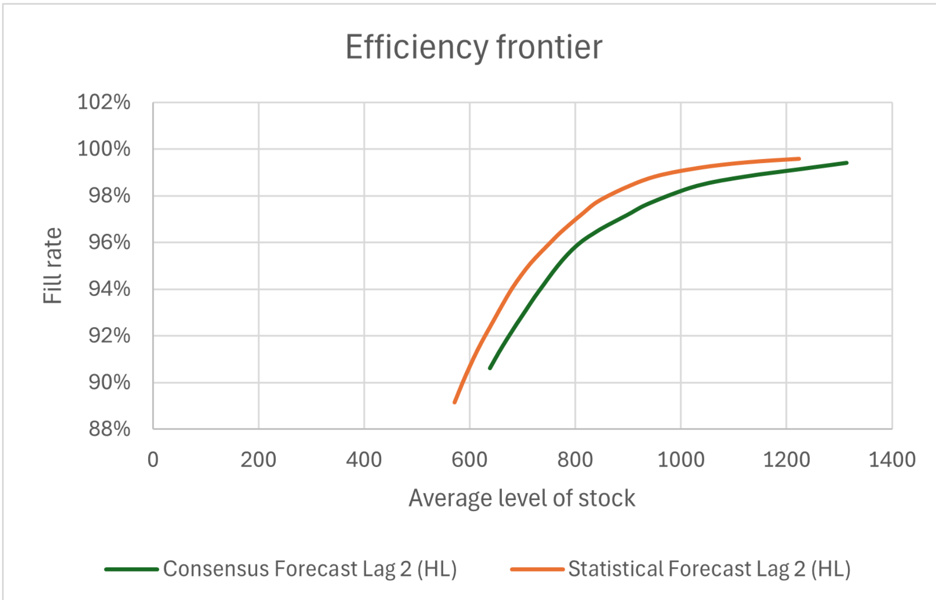


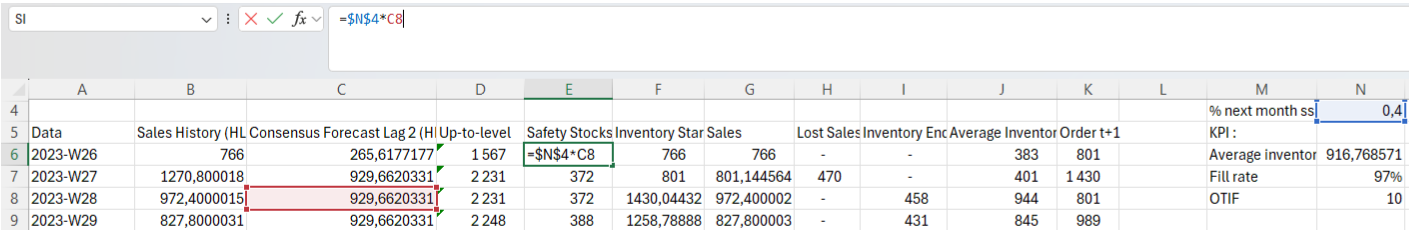
FIGURE 5 – Frontier efficiency of the inventory policy

We see that the best policy is done thanks to the Statistical Forecast Lag 2 as for a given level of stock (so a given level of costs), the fill rate is better.

3.2 Dynamic safety stock

I then implemented a dynamic safety stock policy to see the impact on the fill rate. We have the same columns as before, only the method to compute the safety stock is different.

To do so, I choose a coefficient between 0 and 1 and I multiply it to the forecast of t+2 (forecast t and t+1 are already taken into account), as we can see below :



SI =$N$4*C8

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
4													% next month ss	0,4
5	Data	Sales History (HL	Consensus Forecast Lag 2 (HI	Up-to-level	Safety Stocks	Inventory Star	Sales	Lost Sales	Inventory Enc	Average Inventor	Order t+1		KPI :	
6	2023-W26	766	265,6177177	1 567	=$N$4*C8	766	766	-	-	383	801		Average inventor	916,768571
7	2023-W27	1270,800018	929,6620331	2 231	372	801	801,144564	470	-	401	1 430		Fill rate	97%
8	2023-W28	972,4000015	929,6620331	2 231	372	1430,04432	972,400002	-	458	944	801		OTIF	10
9	2023-W29	827,8000031	929,6620331	2 248	388	1258,78888	827,800003	-	431	845	989			

FIGURE 6 – Screenshot of the model

I then change the safety stock coefficient for both forecasts (Statistical forecast Lag 2 and Consensus forecast Lag 2) to see the average inventory and the fill rate.

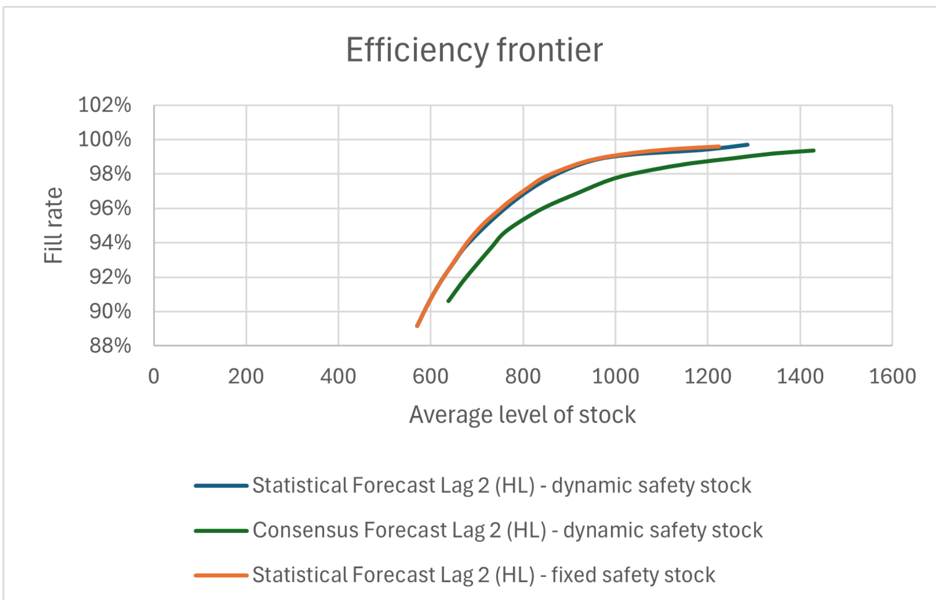


FIGURE 7 – Frontier efficiency of the inventory policy

We see that the best couple forecast x inventory policy is fixed safety stock with the forecast "Statistical Forecast Lag 2", which is slightly better than the couple dynamic safety stock with the forecast "Statistical Forecast Lag 2".

3.3 Use of the formula to determine safety stock

To compute the safety stock, I now use the following formula : $S_s = z\sigma\sqrt{R+L}$, with R = Review period and L = Lead Time.

SI =RACINE(2)*E59*LOI.NORMALE.INVERSE($P$3;0;1)

	A	B	C	D	E	F	G	H	I	J	K	L	M
5	Data	Sales History (HL	Consensus Forecast Lag 2 (H	Error	Rolling 12 month RMSE	Up-to-level	Safety Stocks	Inventory Star	Sales	Lost Sales	Inventory End	Average Inventor	Order t+1
57	2024-W25	1174	981,0129547	-192,9870453		2 362	400	1506,6259	1174	-	333	920	855
58	2024-W26	914	981,0129547	67,01295471		2 310	400	1188,02591	914	-	274	731	1 122
59	2024-W27	1172,799988	928,6738739	-244,1261139	299,0914668	3 430	$P$3;0;1)	1395,68683	1172,79999	-	223	809	2 035
60	2024-W28	1130	928,6738739	-201,3261261	293,7453109	3 402	1 545	2257,61441	1130	-	1 128	1 693	1 145

FIGURE 8 – Screenshot of the model

The coefficient P3 corresponds to the coefficient to obtain z with the inverse normal distribution.

I then change the P3 coefficient for both forecasts (Statistical forecast Lag 2 and Consensus forecast Lag 2) to see the average inventory and the fill rate.

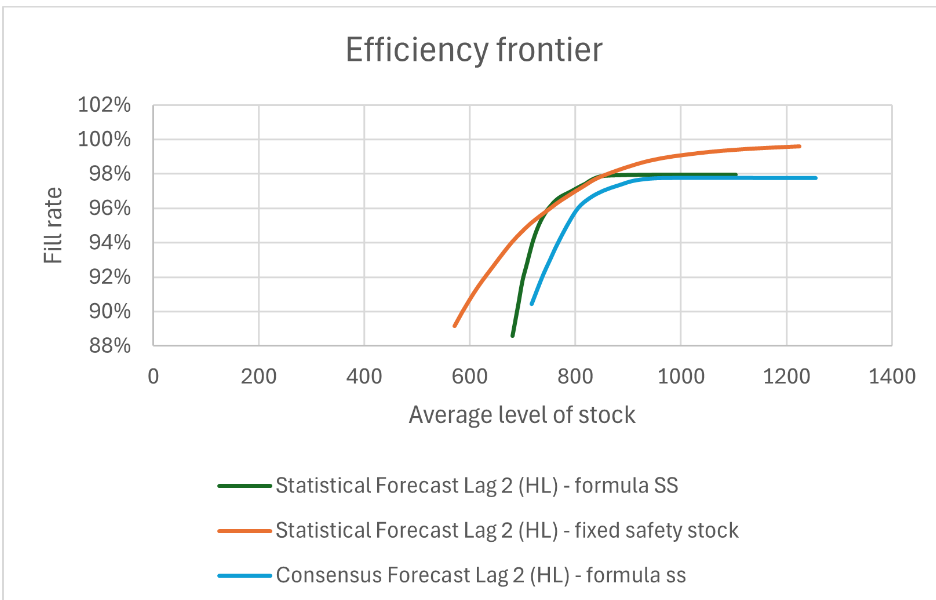


FIGURE 9 – Frontier efficiency of the inventory policy

We see that the couple "fixed safety stock with the forecast "Statistical Forecast Lag 2"" is globally the best, even if the model with the formula and the Statistical forecast is slightly better for an average level of stock of 800.

3.4 Fixed safety stock while taking into account the backlogs

For all models above, I did not take into account the backlog i.e. when the lost sales spill over into the following week.

This is what I tried to do in this part and the following. We now have the following model :

SI =B7+I6

	A	B	C	D	E	F	G	H	I	J	K	L
5	Data	Sales History (HL	Sales + backlog	Statistical Forecast Lag 2 (HL)	Up-to-level	Safety Stocks	Inventory Start	Sales	Lost Sales	Inventory End	Average Inventory	Order t+1
6	2023-W26	766	766	302,953083	1 438	75	766	766	-	-	383	672
7	2023-W27	1270,800018	=B7+I6	1060,335732	2 196	75	672	672	599	-	336	1 523
8	2023-W28	972,4000015	1 571	1060,335732	2 196	75	1523,38265	1 523	48	-	762	672
9	2023-W29	827,8000031	875	1060,335732	2 196	75	672,288815	672	203	-	336	1 523
10	2023-W30	588	791	1060,335732	2 145	75	1523,38265	791	-	732	1 128	622
11	2023-W31	614,8000031	615	1010,121073	2 087	75	1354,41706	615	-	740	1 047	732
12	2023-W32	545,0000076	545	1001,751862	2 079	75	1472,07293	545	-	927	1 200	606
13	2023-W33	396,4000015	396	1001,751862	2 079	75	1533,50372	396	-	1 137	1 335	545
14	2023-W34	978,6000366	979	1001,751862	1 649	75	1682,10372	979	-	704	1 193	-

FIGURE 10 – Screenshot of the model

It is the same model as previous but instead of taking into account the sales history, I looked at the columns "Sales + backlog".

We obtain the following efficiency frontier (by changing the value of the fixed safety stock) :

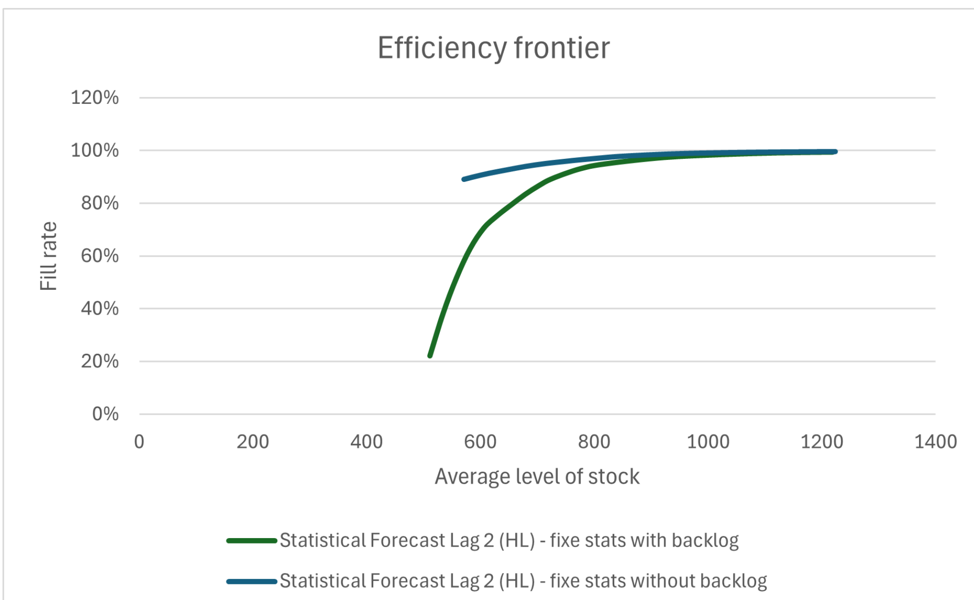


FIGURE 11 – Frontier efficiency of the inventory policy

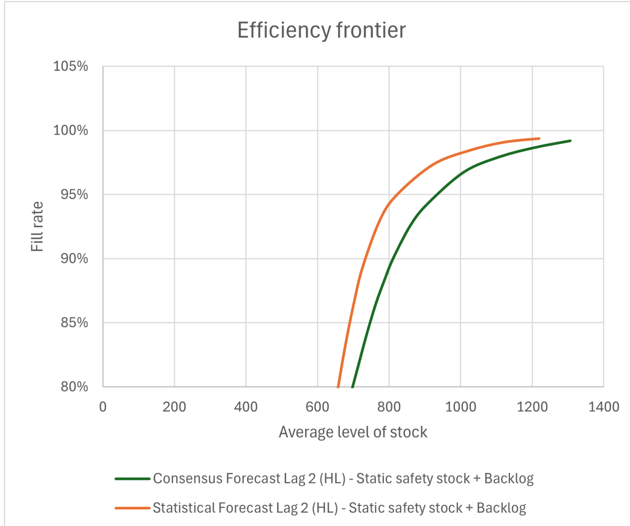


FIGURE 12 – Frontier efficiency of the inventory policy

We see that even if the values are a little over-estimated in the case without backlogs, the best couple forecast x inventory policy is the same.

3.5 Dynamic safety stock while taking into account the backlogs

It is the same model as previous but instead of taking into account the sales history, I looked at the columns "Sales + backlog".

We obtain the following efficiency frontier (by changing the value of the fixed safety stock) :

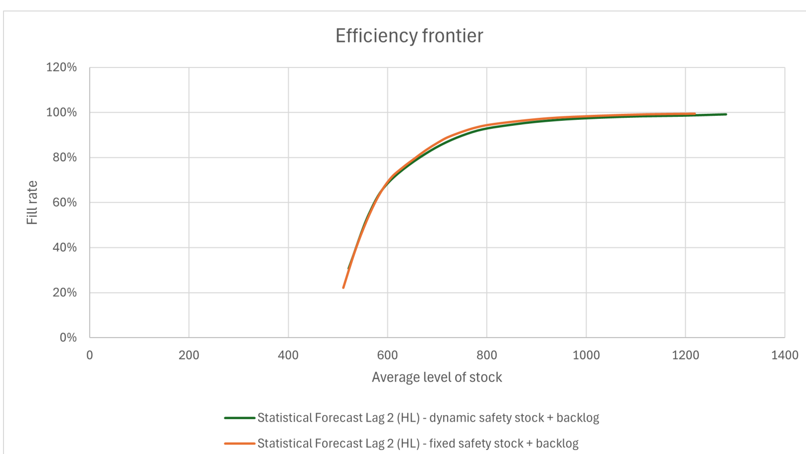


FIGURE 13 – Frontier efficiency of the inventory policy

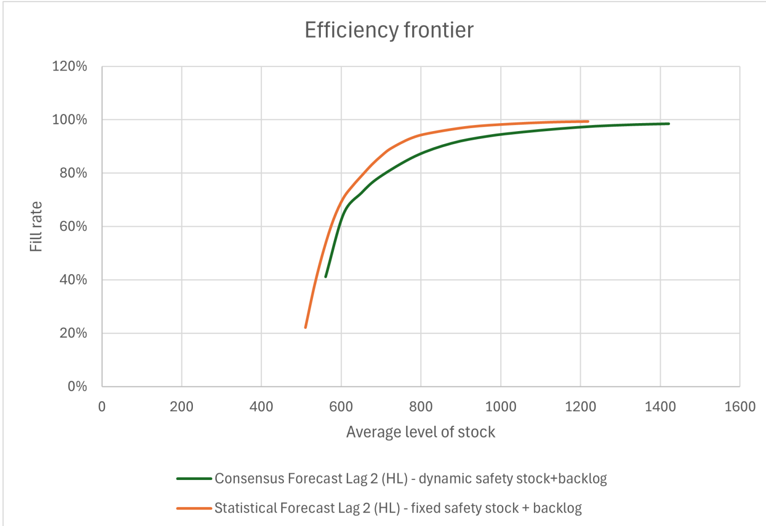


FIGURE 14 – Frontier efficiency of the inventory policy

We see that even if the values are a little over-estimated in the case without backlogs, the best couple forecast x inventory policy is the same.

4 Conclusion

As a recap of all models, we have the following frontier efficiency :

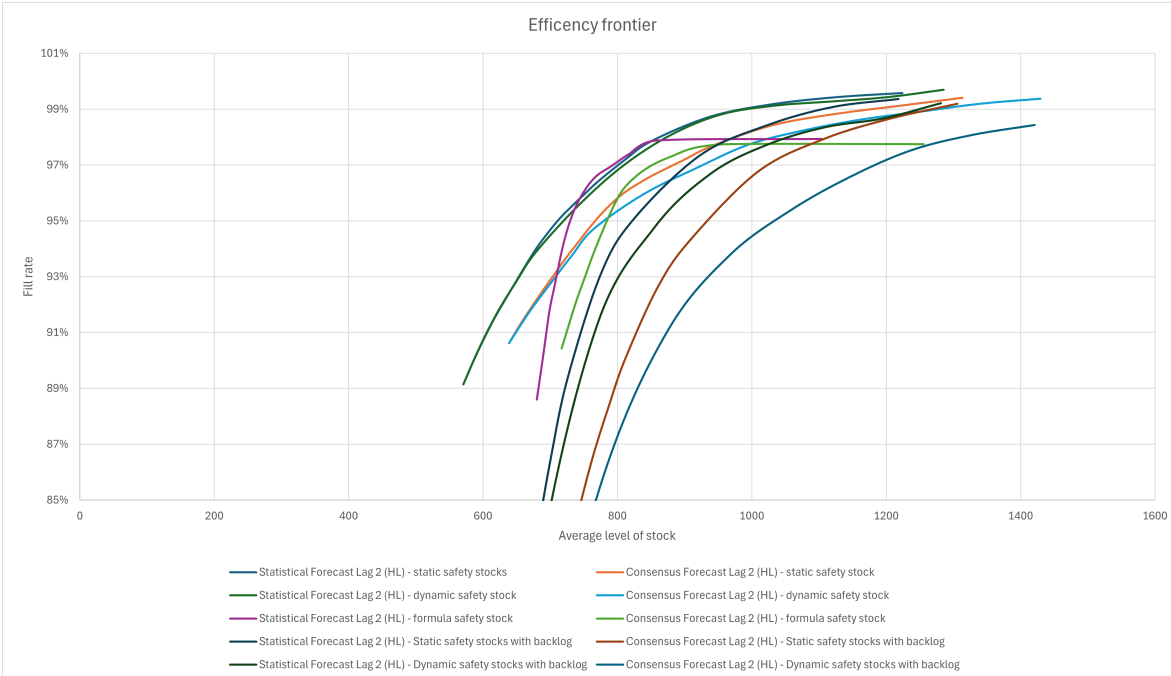


FIGURE 15 – Frontier efficiency of the inventory policies

We have seen that independent of the calculation of the backlogs, the generally best couple is the model with the fixed safety stock with the Statistical forecast Log 2. It is consistent with the fact that the best forecast is the statistical one if we look at the bias, the MAE, the RMSE, the score and the score+RMSE.

I would advise to use the statistical forecast with the inventory policy "Fixed safety stock" for this product in that region as it is one of the simplest method with the best results. To optimize the level of stock, Duvel should either choose the service level that they want to achieve or optimize the costs thanks to a solver. As we do not have any information on the costs (missed sales, invetory costs, transaction costs...), I would advise to reach 95% of service level, which corresponds to an average inventory level of 820 if we have backlogs or 715 else. This results in a safety stock equal to 400 with backlogs and 225 without.