

Switching Rules for Optimal Ordering in a CPG Company

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SENS

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Research Problem

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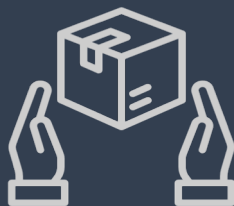
Model Development

Results & Conclusion

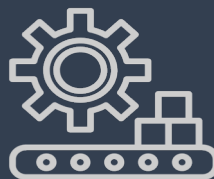
Product Overview

SENSE is in the FMCG industry with thousands of products

Consumer Product



Sourced and
Manufactured in one
country



Distributed to retail
channels across the
world



Project sample size:
3 SKUs with differing
demand patterns

High demand

Medium demand

Low demand

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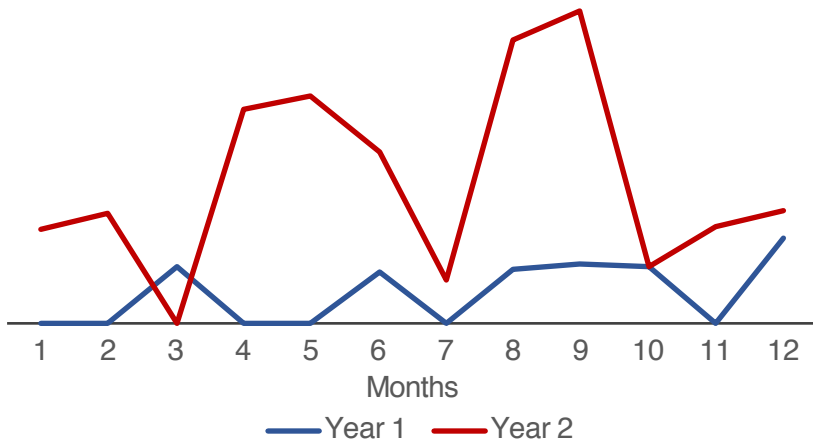
Results & Conclusion

Project objective

To optimize the raw material ordering policy for SENSE by determining the best minimum order quantity (MOQ) to use.

High volatility and unexpected spikes in demand

Demand pattern YoY
(monthly final demand, in units)



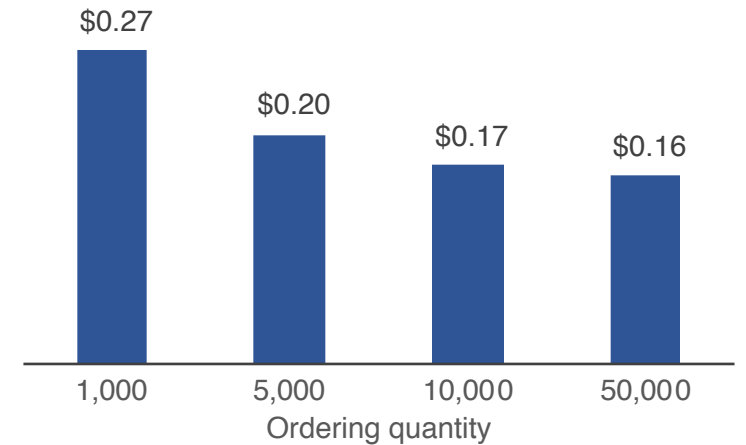
Varying MOQ
~ 1 month of demand

Cannot leverage the discount

High cost and stock-outs

Discounts offered for greater quantities

Quantity discounts
(unit price, in \$)



How much raw material to order?

Balance ordering and holding costs



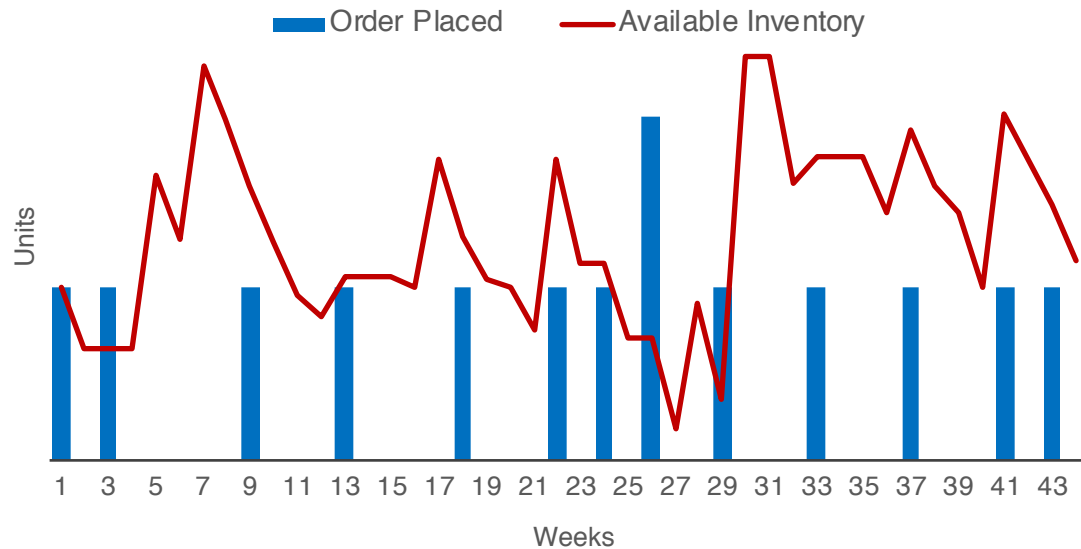
Solution Approach

Maintain a balance between under-stocking and over-stocking.

Goal: Choose an ordering policy which fully avoids stock-outs and is the lowest cost

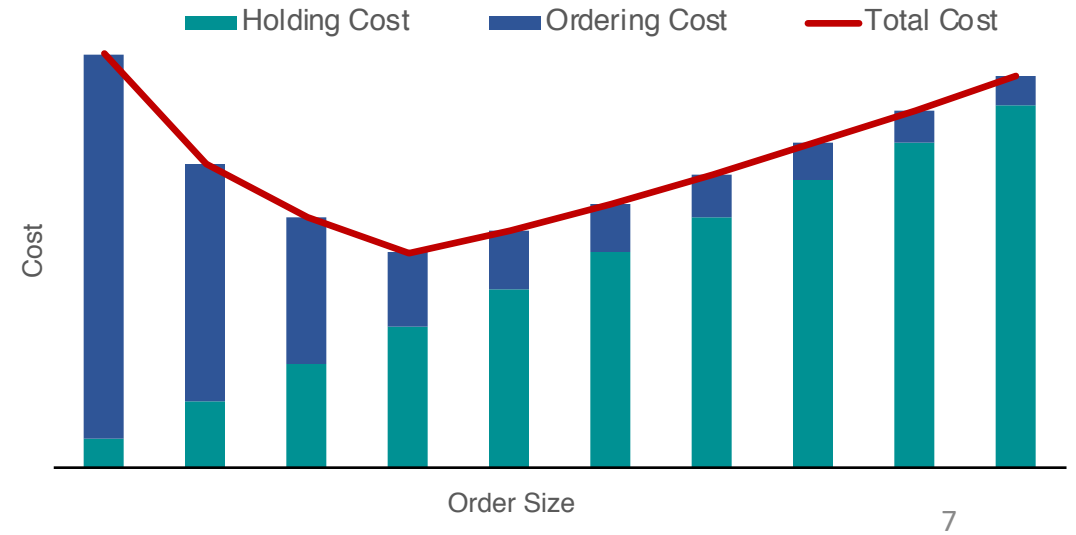
Target Service level = 99.3%
In a 1-year period, no stock-out event

Available Inventory
(weekly final inventory, in units)



Total Cost =
Holding Cost + Ordering Cost

Cost vs. ordering quantity
(cost with changing order size, in \$)



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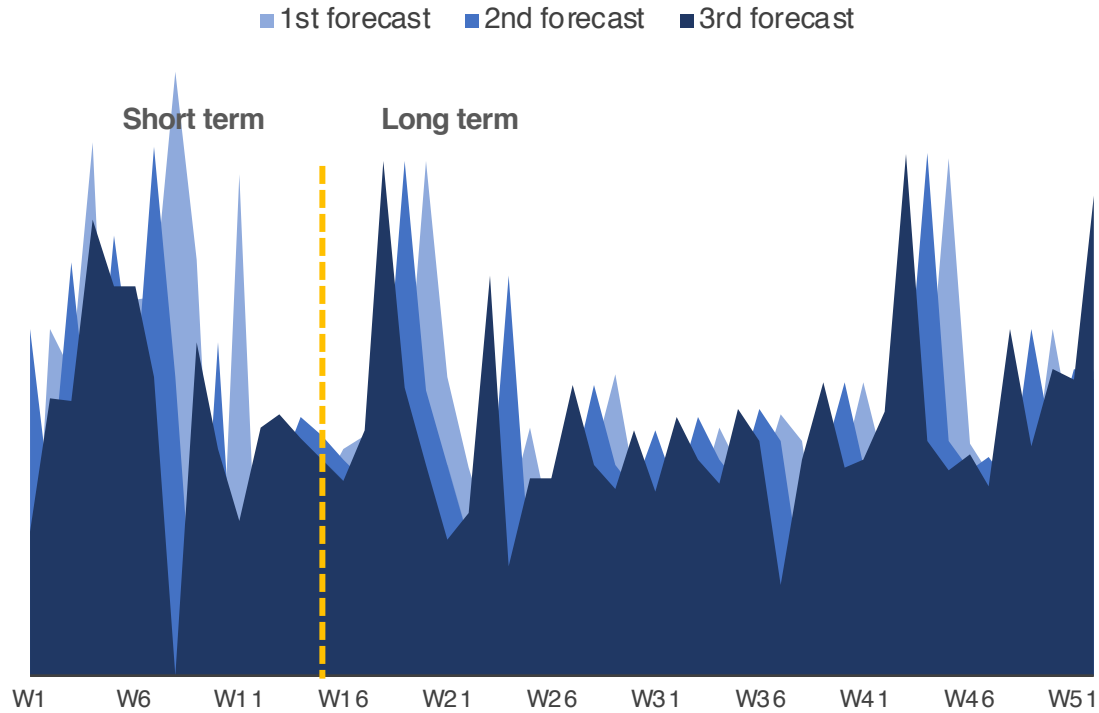
Results & Conclusion

Input datasets

Two sets covering demand and inventory

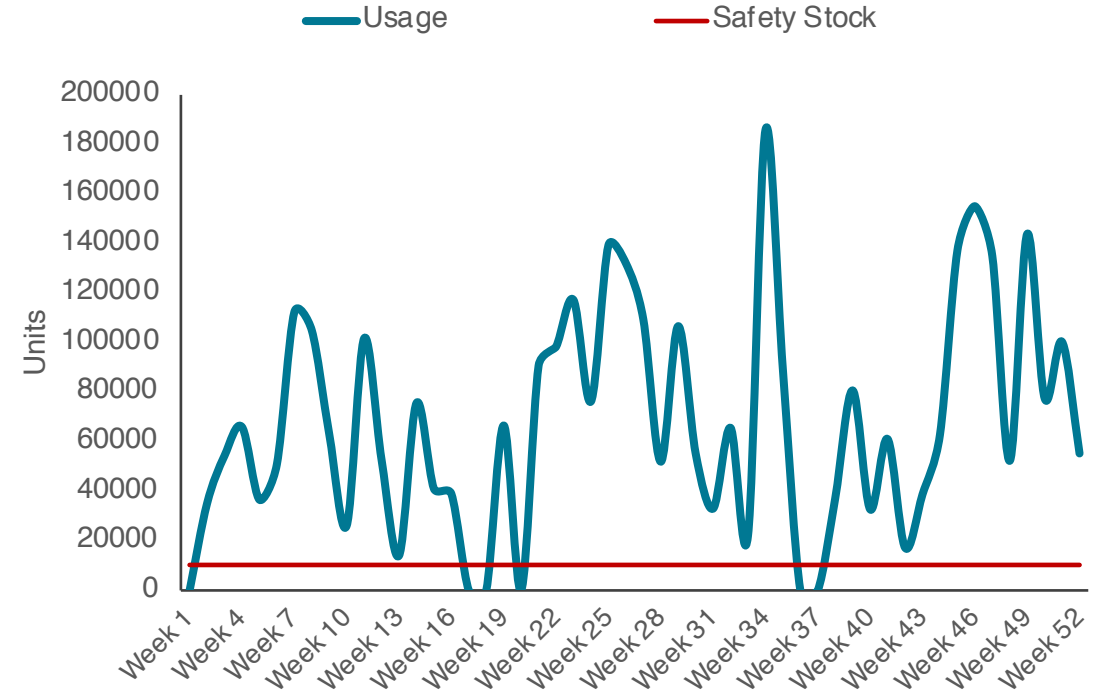
Rolling Forecast Evolution

(weekly final forecast position, in units)



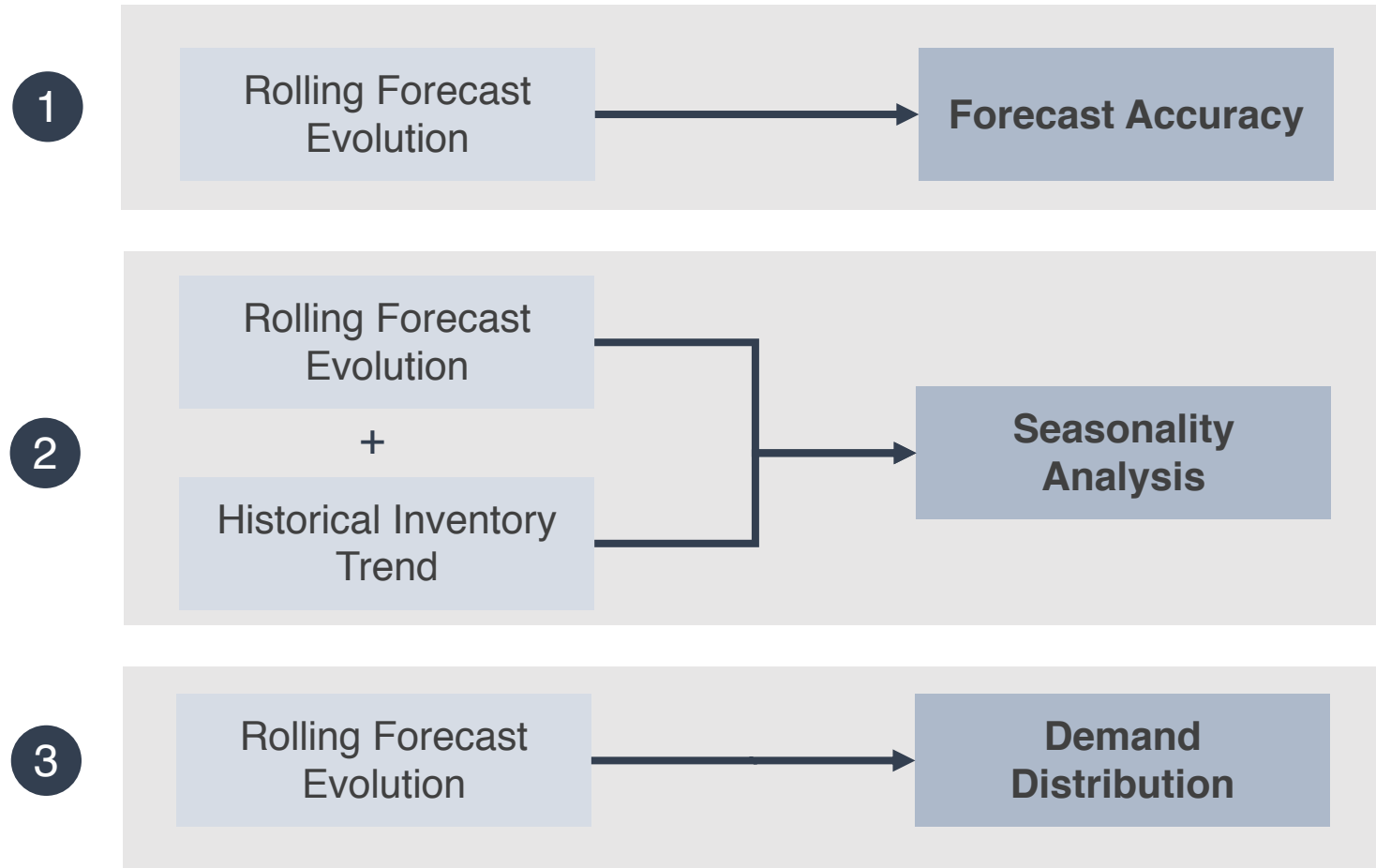
Historical Inventory Trend

(weekly final inventory position, in units)



Data analysis

Forecast accuracy, seasonality, and demand distribution



Data analysis

Forecast accuracy, seasonality, and demand distribution

Forecast Accuracy

- Forecast vs. actual usage to measure forecast quality
- Forecast error =
actual usage - forecast
- Mean Absolute Percent Error (MAPE) to measure accuracy

Identify Seasonality

- Compared demand patterns year-over-year
- Calculated seasonality factors for each year
- De-seasonalized data so identify similarities

Demand Distribution

- Spread of observations around the mean
- Descriptive statistical analysis
- Observations close to mean
→ **Normal distribution**
- Variation equal to mean
→ **Poisson distribution**

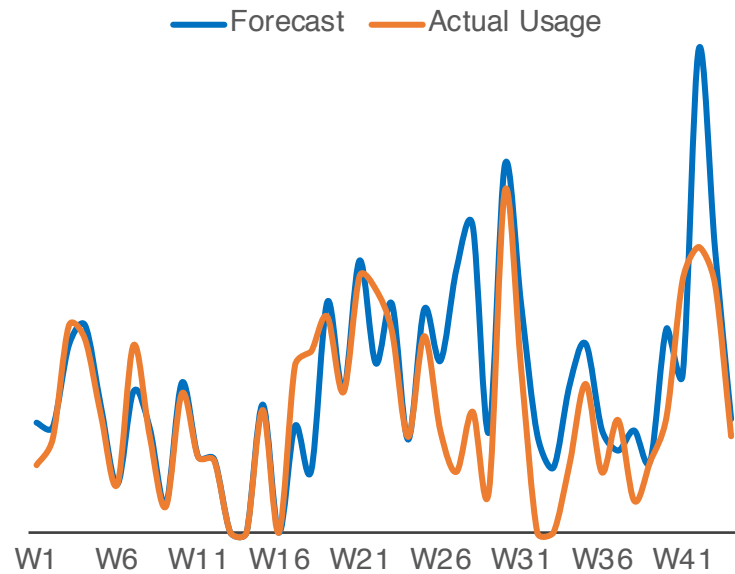
Forecast accuracy

Forecast vs. actual usage for the 3 SKUs under consideration

High demand SKU

MAPE = 44%

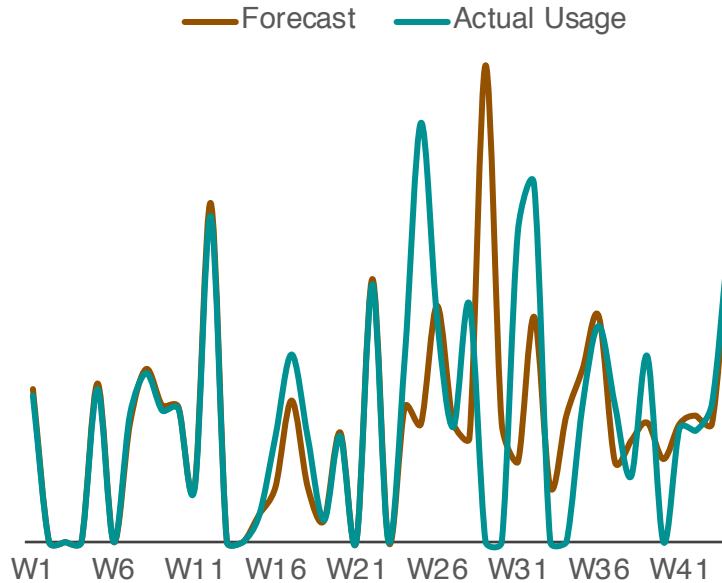
(weekly final demand, in units)



Medium demand SKU

MAPE = 26%

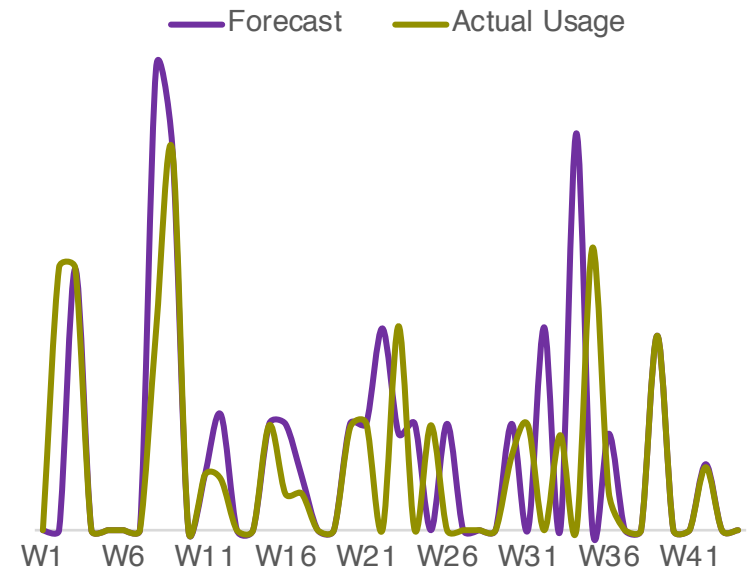
(weekly final demand, in units)



Low demand SKU

MAPE = 40%

(weekly final demand, in units)

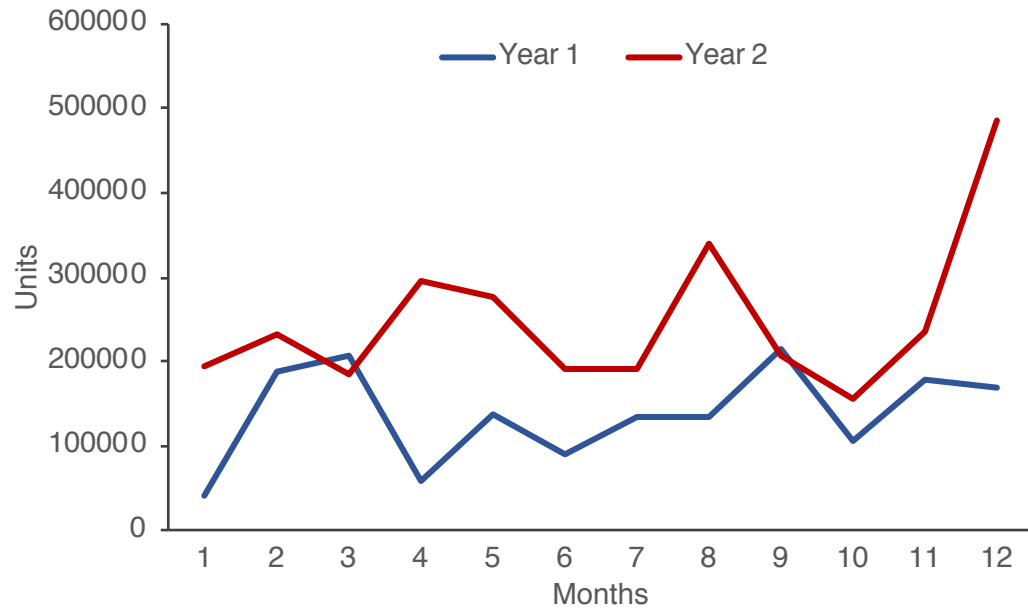


Seasonality analysis

No seasonality identified. Unexpected demand spikes occur, subject to promotions by retailers

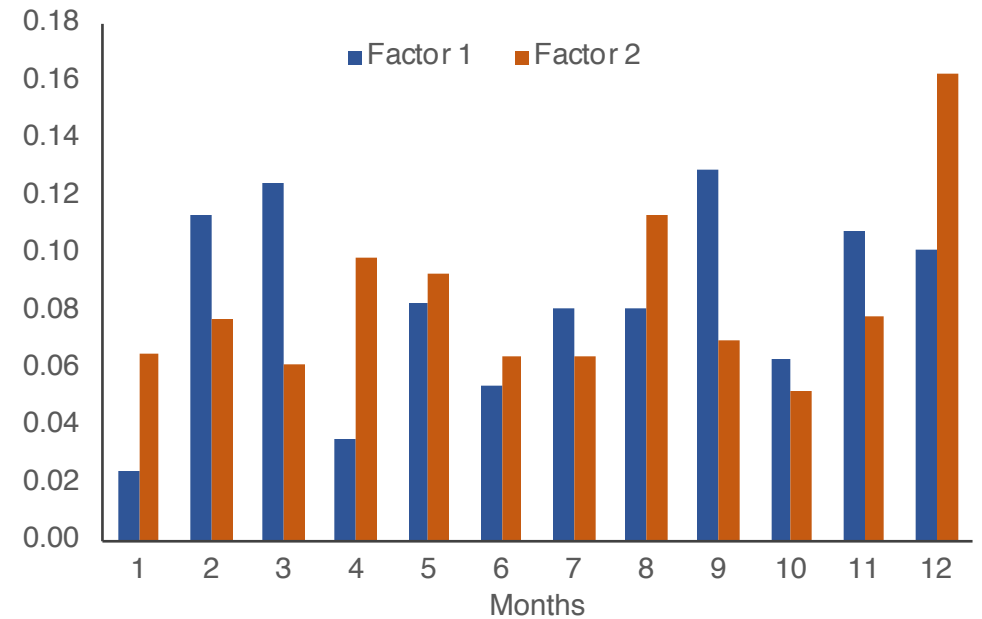
Demand pattern YoY

(monthly final demand, in units)



Seasonality factors for 2 years

(monthly seasonality factor)



Demand distribution

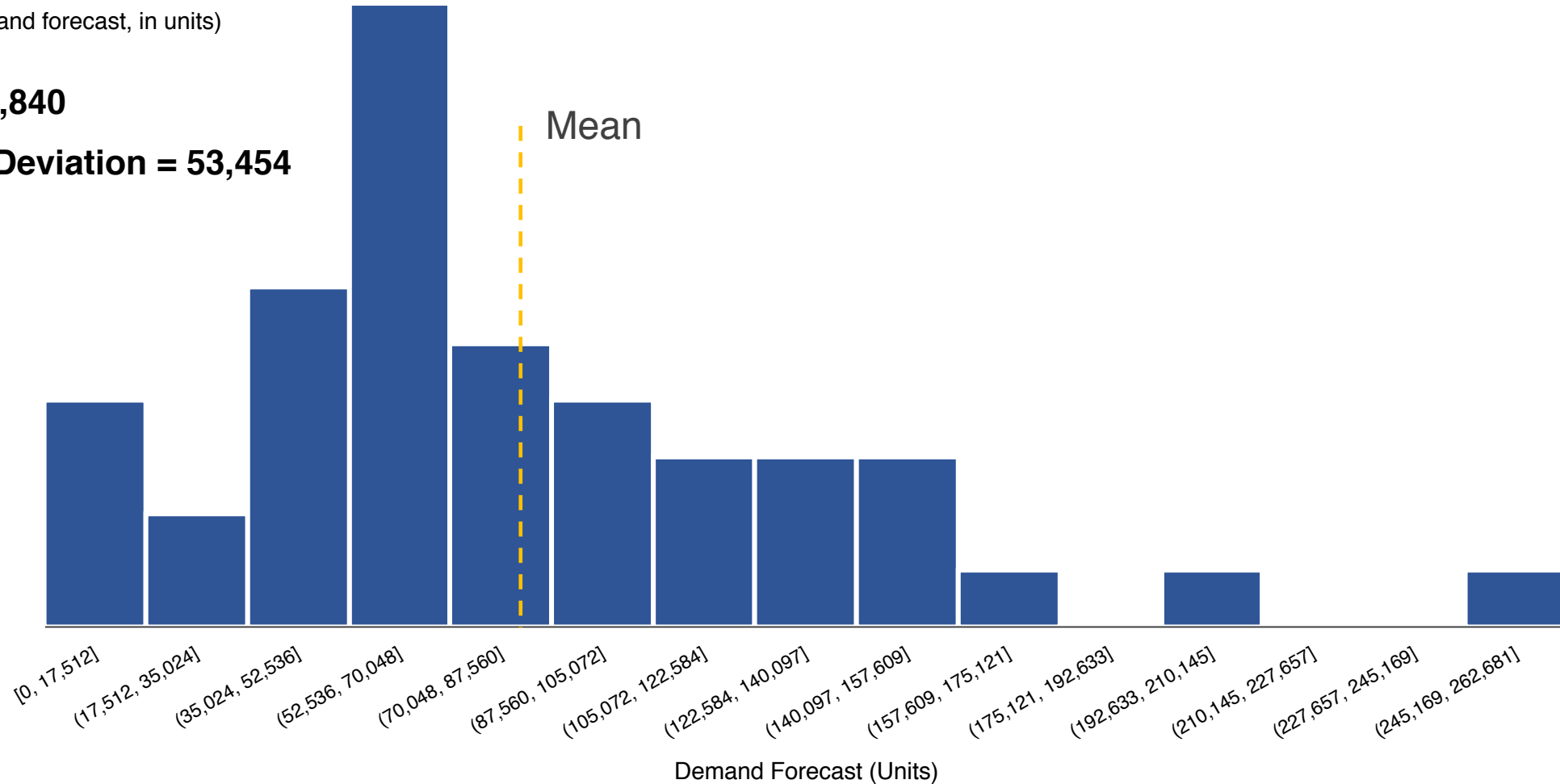
for high demand SKU

Demand distribution

(15 bins of demand forecast, in units)

Mean = 80,840

Standard Deviation = 53,454



Demand distribution

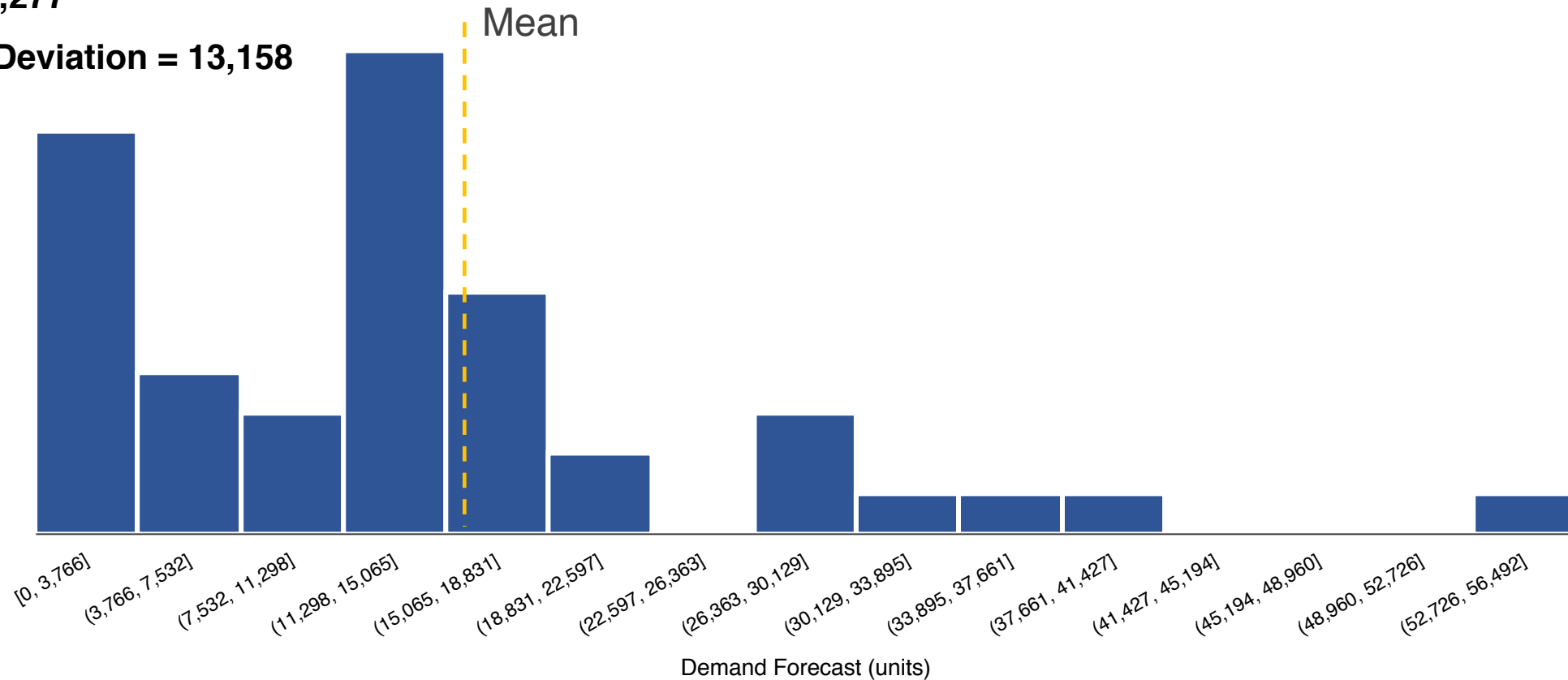
for medium demand SKU

Demand distribution

(15 bins of demand forecast, in units)

Mean = 15,277

Standard Deviation = 13,158



Demand distribution

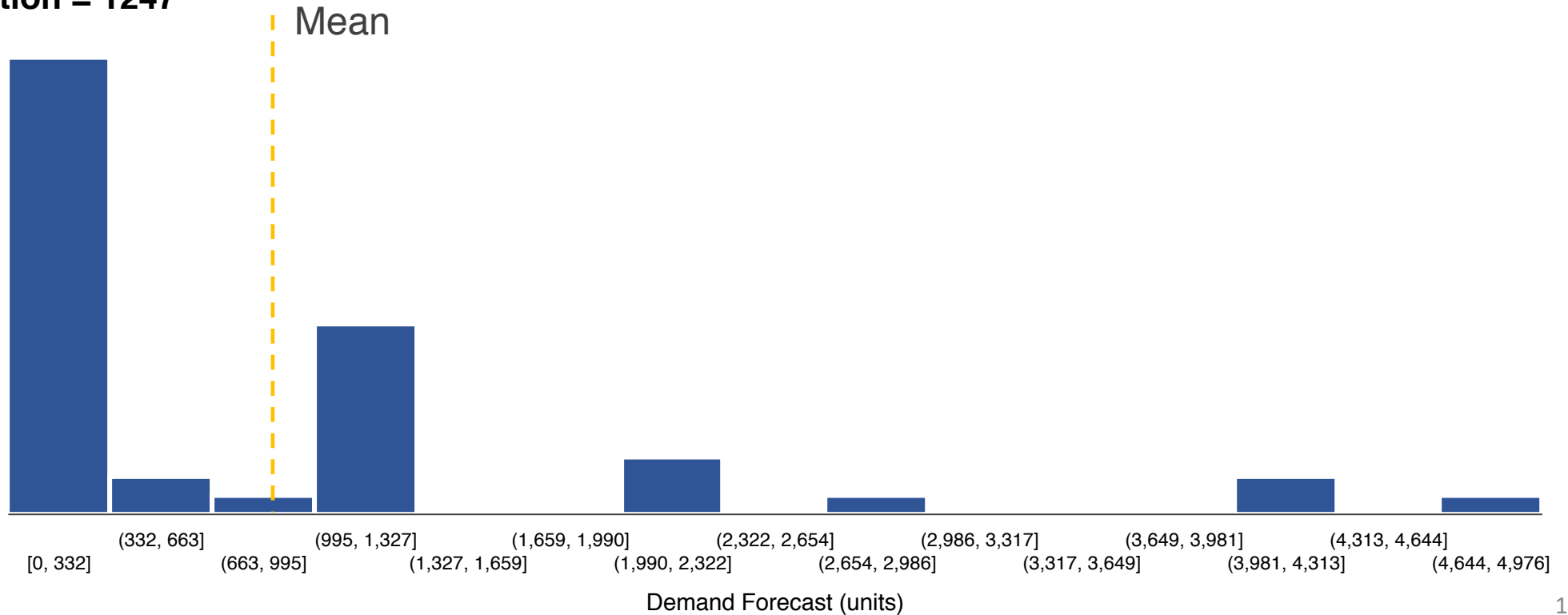
for low demand SKU

Demand distribution

(15 bins of demand forecast, in units)

Mean = 816

Standard Deviation = 1247



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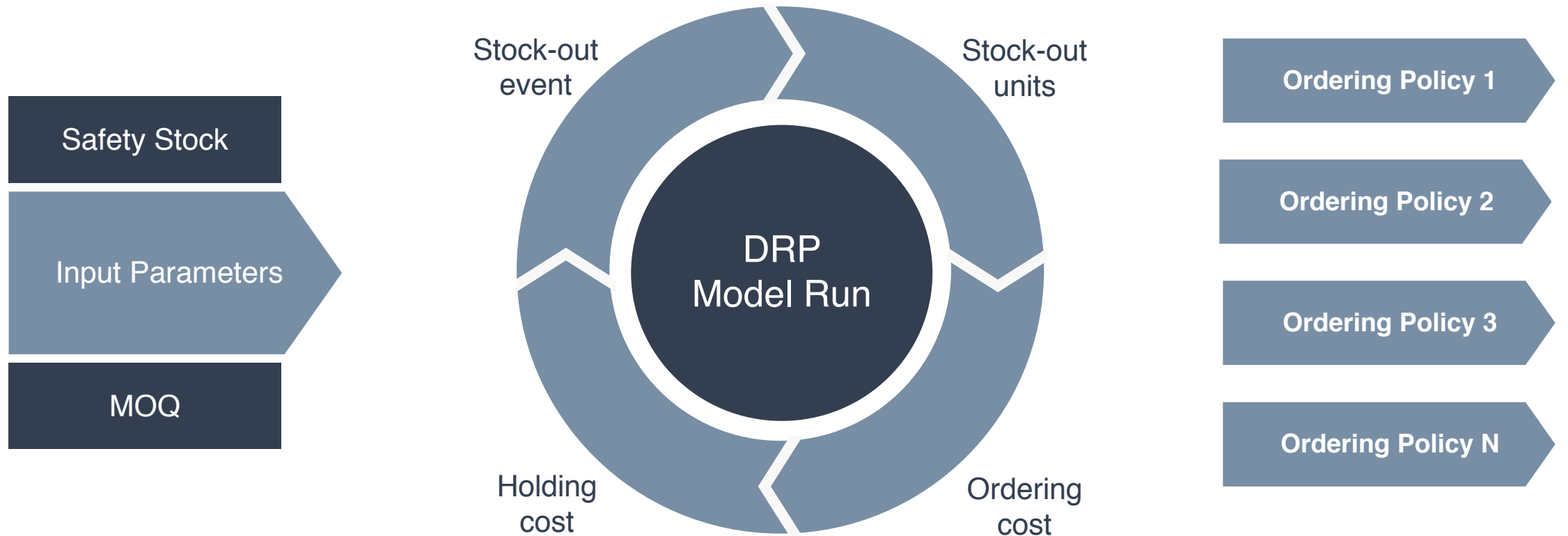
Model Development

Results & Conclusion

Model Simulation

Iterations with different values of input parameters to reach the solution

Using a Distribution Requirement Planning (DRP) system:
Covering 4 Weeks of demand



Base Model

Ordering Policy: How much and when to order

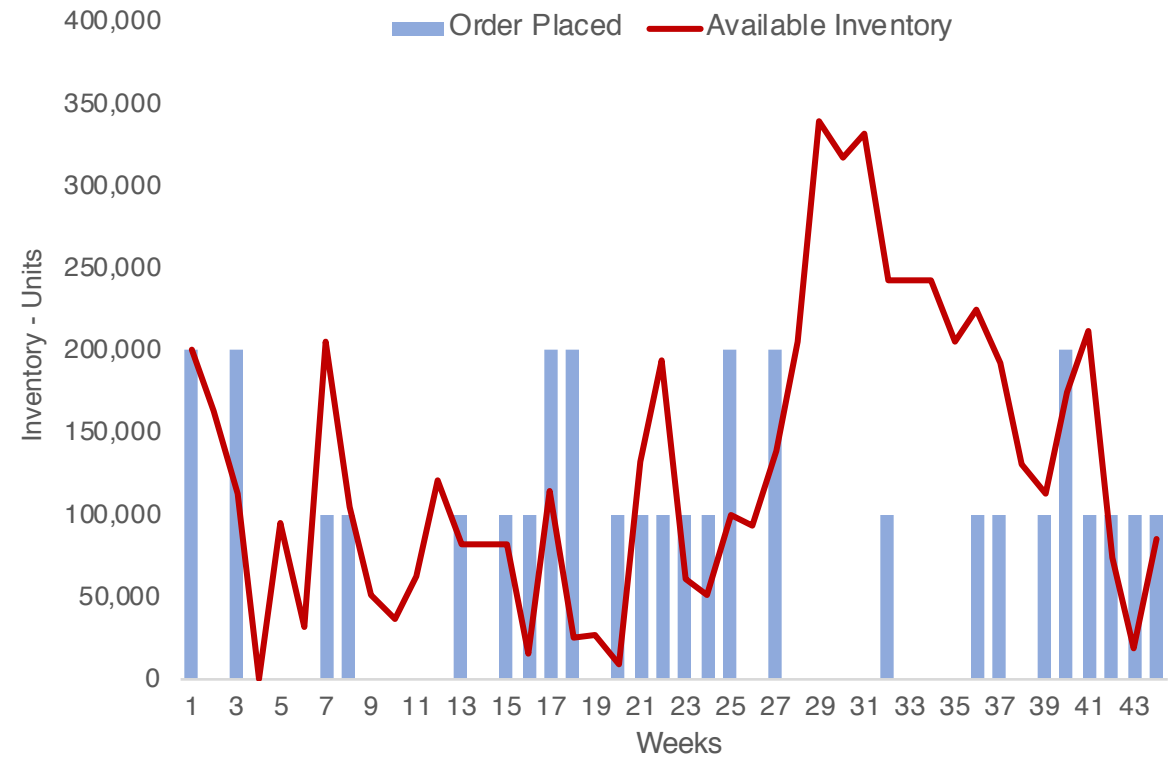
Simulation Results

(by changing Safety Stock and MOQ)

Safety Stock	MOQ	Stock-Out Events	Ordering Cost	Holding Cost	Total Cost
262,702	10,000	0	\$ 479,111	\$ 5,916	\$ 485,028
262,702	50,000	0	\$ 476,942	\$ 6,110	\$ 483,051
131,351	50,000	0	\$ 476,942	\$ 4,691	\$ 481,632
52,540	50,000	1	\$ 476,942	\$ 3,757	\$ 480,699
52,540	100,000	0	\$ 476,942	\$ 4,051	\$ 480,993
26,270	50,000	2	\$ 476,942	\$ 3,578	\$ 480,520
26,270	100,000	0	\$ 476,942	\$ 3,821	\$ 480,763
26,270	150,000	2	\$ 476,942	\$ 4,192	\$ 481,134
26,270	200,000	0	\$ 476,942	\$ 4,256	\$ 481,198

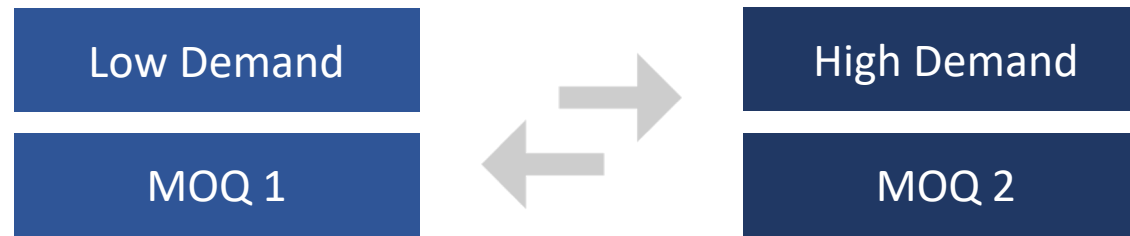
Inventory Position for best scenario

(weekly final inventory position, in units)



Switching Rule

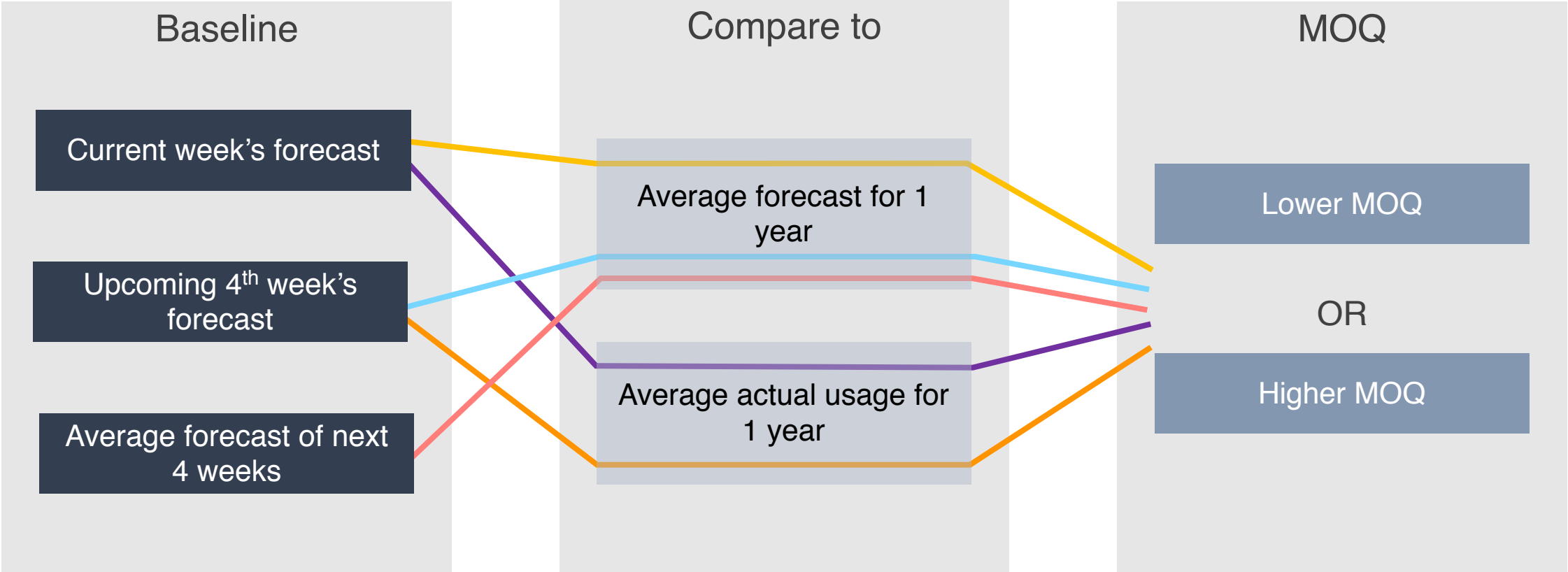
Switch MOQ to higher or lower values depending on the demand forecast



- Since demand is highly volatile, there are periods of very high demand and very low demand
- Having one MOQ throughout the year can lead to over-stocking during the low demand periods
- Holding cost can be further reduced if we switch to lower MOQs for the low demand season
- Smaller MOQs also mean higher ordering cost. Need to balance the ordering cost and holding cost

Simulation with switching rules

Experimented with 5 switching rules



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Switching rule result

The switching rule determines the MOQ values, and when to switch to a lower or higher MOQ.

Current demand forecast vs. actual usage

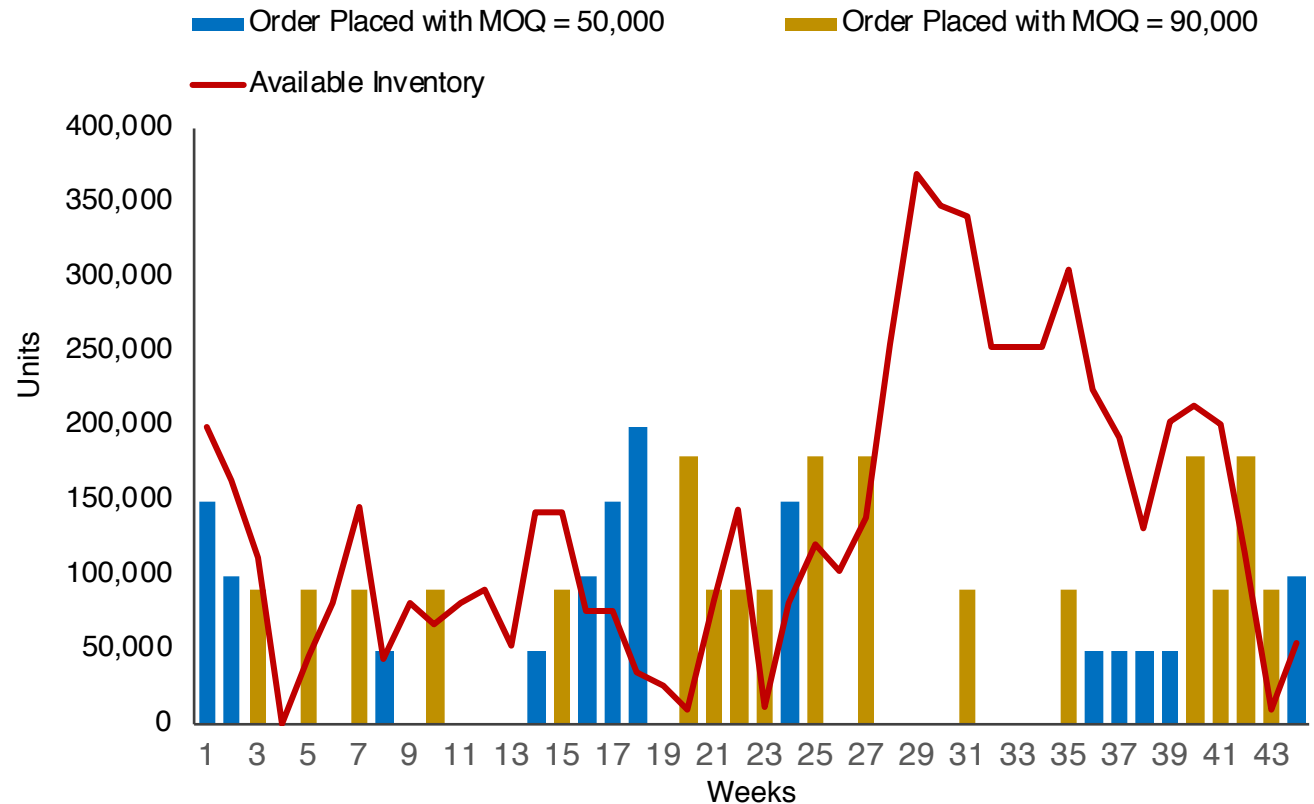
MOQ1 = 50,000

MOQ2 = 90,000

Forecast	Average	MOQ
59,669	66,038	50,000
57,205	66,038	50,000
101,744	66,038	90,000
112,617	66,038	90,000
67,813	66,038	90,000

Ordering policy with switching

(weekly final inventory, in units)



Model results

Ordering policy with 5 switching rule choices

Comparison between different policies for the high demand SKU

The company can choose the best policy from the options

Switching Rule	Safety Stock	MOQ 1	MOQ 2	Stock-Out Events	Ordering Cost	Holding Cost	Total Cost
No Switching	52,540	100,000	100,000	0	\$476,942	\$4,051	\$480,993
Switching Rule 1	52,540	80,000	155,000	0	\$476,942	\$4,223	\$481,165
Switching Rule 2	52,540	100,000	190,000	0	\$476,942	\$4,437	\$481,379
Switching Rule 3	52,540	50,000	90,000	0	\$476,942	\$3,862	\$480,804
Switching Rule 4	52,540	90,000	150,000	0	\$476,942	\$4,322	\$481,264
Switching Rule 5	52,540	53,000	85,000	0	\$476,942	\$3,876	\$480,818

With a holding charge of 7%

Switching Rule 1:

Current week's forecast vs. Average 1 year forecast

Switching Rule 2:

Current week's forecast vs. Average 1 year usage

Switching Rule 3:

Upcoming 4th week's forecast vs. Average 1 year forecast

Switching Rule 4:

Upcoming 4th week's forecast vs. Average 1 year usage

Switching Rule 5:

Average next 4 week's forecast vs. Average 1 year usage

Conclusion

The model can be used to determine the best material ordering policy. It suggests the safety stock and MOQ value to use

There is no switching rule that fits all products and demand patterns. By changing the input datasets, the company can use the best solution

The ordering cost holds a lot of weight in determining the total cost. Due to this, the cost of the switching rule is close to the base policy

This model standardizes the MOQ to use while re-ordering, and can be applied across other products in the company

Thanks!