University of Exeter

Business School

Supply Chain Analytics

Forecasting Methodologies

Student Id: 740072479

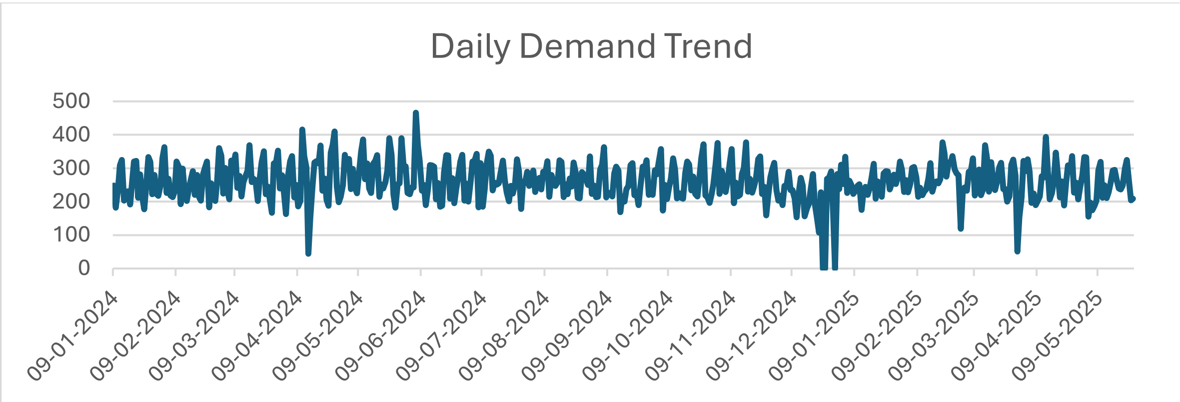
Course Code: BEMM783

Converting daily demand into weekly demand involved the following steps:

1. Created a “weekday” column to check the check the day of the week for the respective demand date, to create a reference point for the start and end of the week which could be used to aggregate daily demand into weekly demand.
2. Used weekday = 3 as the starting point as I had the data for 7 days (a week) prior to it, which could be aggregated and then the same pattern be continued for the rest of the dates.
3. Then I removed the “weekday” column and just used the “Date” column to remove the dependency on the “weekday” column which I don’t require in my final output.
4. Then I created new column “weekly demand” and used the formula IF(WEEKDAY(A9) =3, SUM (B2:B8),0) to check for the day of the week using the date column, sum data for the previous 7 records if the weekday was 3, otherwise put value as 0. Dragged the formula across the column to get values for all the dates. Got the sum of the previous week’s demand wherever the day of the week was 3 and got 0 for other records.
5. Filtered rows where the data was the data was not 0 and copy and pasted just the date column and “weekly demand” column into a separate excel file and renamed the “weekly demand column” to “Demand” as per the requirements of the Forecast Explorer app.

<u>Daily Demand Trend</u>

Figure 1.



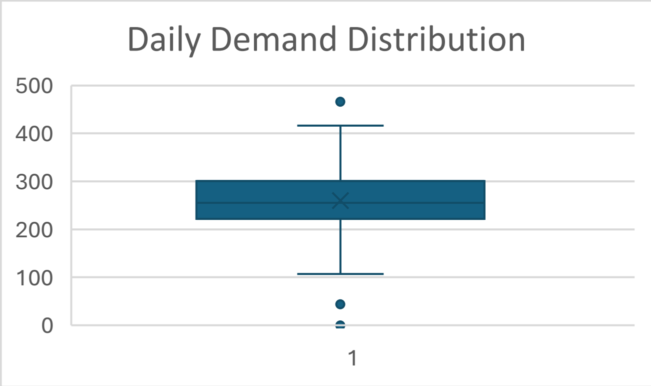
<u>Daily Demand Descriptive Statistics</u>

Table 1.

Minimum	0
1st Quart.	222
Median	255
Mean	259.64
3rd Quart.	300.25
Maximum	466
St. Dev.	57.61

Daily Demand Distribution

Figure 2.

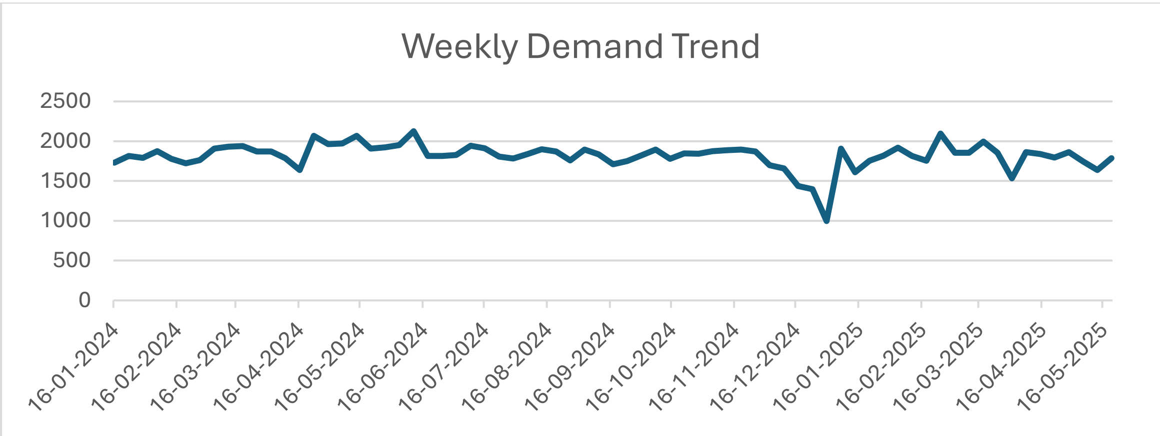


Observations

- The daily demand is fairly constant in the range of 200 to 300 units as could be observed from the line plot and bar plot. There are a few downward spikes in the daily demand which could also be seen as outliers in the box plot.
- There has been an almost similar downward spike in April 2024 and April 2025, which indicates seasonality in data.

Weekly Demand Trend

Figure 3.



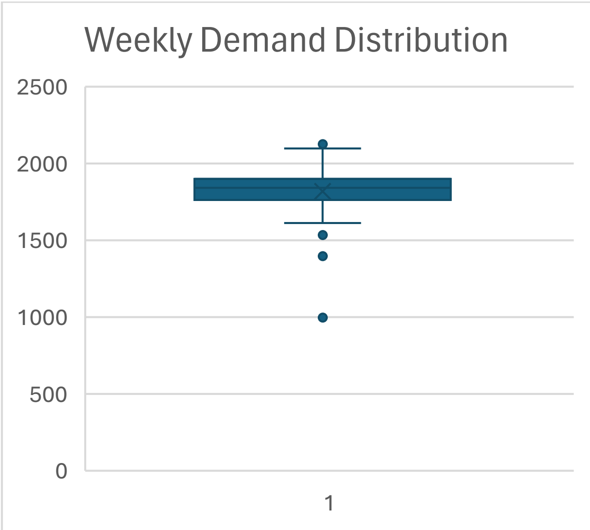
Weekly Demand Descriptive Statistics

Table 2.

Minimum	997
1st Quart.	1769.5
Median	1841
Mean	1817.9
3rd Quart.	1898
Maximum	2126
St. Dev.	161.77

Weekly Demand Distribution

Figure 4.



Observations

- Aggregating daily data into weekly data smoothens out the spikes but the major downward spike of January 2025 is still clearly visible, indicative of anomalies in market during that time.

The overall demand pattern is fairly linear, with some downward data spikes and a significant drop in January 2025.

Forecasting Method Recommendations

Case where inventory cost is the most important consideration

Given the fairly linear trend of the data and the objective of minimizing inventory cost, I have decided to opt for the Exponential Smoothing method.

Reasons:

1. Exponential Smoothing method best captures the linear trend of the data as it just has a level component and just one parameter to tune, alpha.
2. The most important consideration while minimizing the inventory cost is minimizing the variance of sum of the forecast errors which is directly dependent upon the forecast errors. Since exponential smoothing forecast does not depend upon the lead time, so the forecasts would be same irrespective of the lead time and at lower values of alpha, the forecast for the next time step would be very close to the previous forecast. As the weekly demand trend is fairly linear, having forecasts for the next time step closer to the previous forecast would keep the forecasts closer to the actual demand as the forecast for the first time step is same as the demand for the first period.

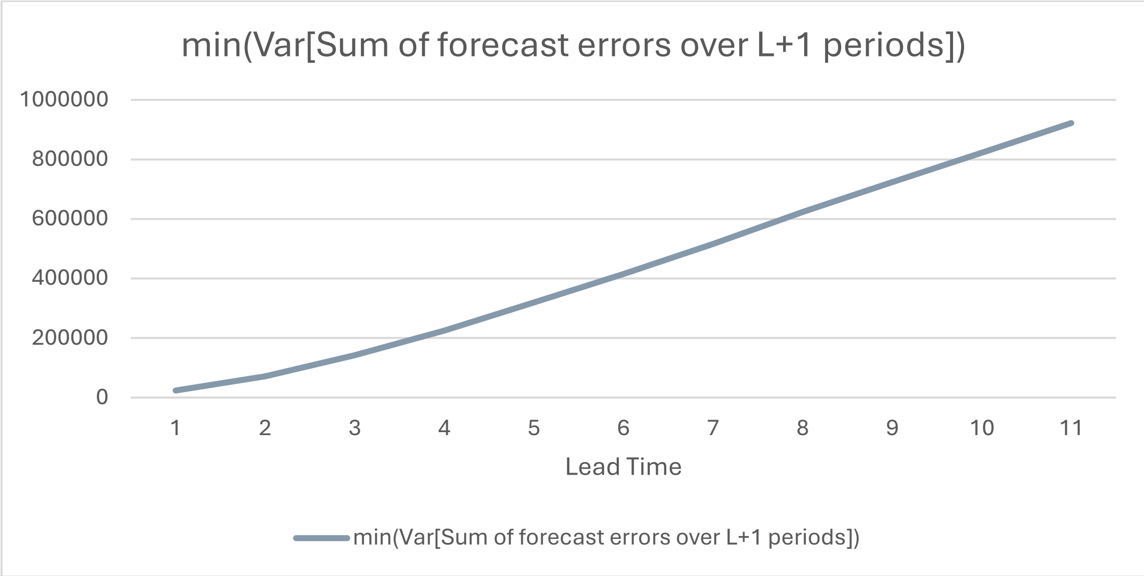
   Exponential Smoothing Forecast = $\alpha * d_t + (1-\alpha) * \hat{d}_{t-1,\, t-1+n}$

   This would help keep the forecast error minimal and hence the variance of the forecast error would be minimal.

3. Minimizing the forecast error would directly impact the sum of the forecast error and which would in turn minimize the variance of the sum of the forecast error.
4. Keeping the value of alpha lower, would not only help reduce forecast error but also keep the bias in check. As described in point number 2 at lower values of alpha forecast for the next time step would be closer to the forecast for the next time step and which would in turn be closer to the actual demand and hence keep the bias minimum as bias = E[forecast] – E[demand], where E signifies expectation(average).

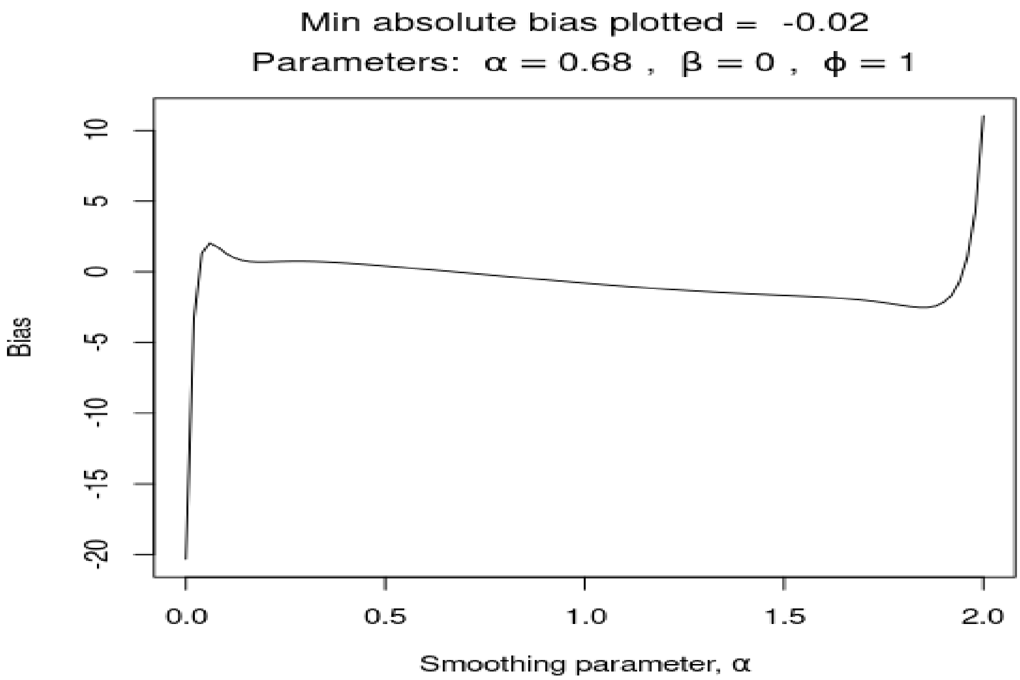
As I decided to take lower alpha values to achieve lower variance and bias, I decided to check the suitable lead time at alpha = 0.1 and plotted the following graph as per the values obtained from the Forecast Explorer App (Disney, S.M., 2024).

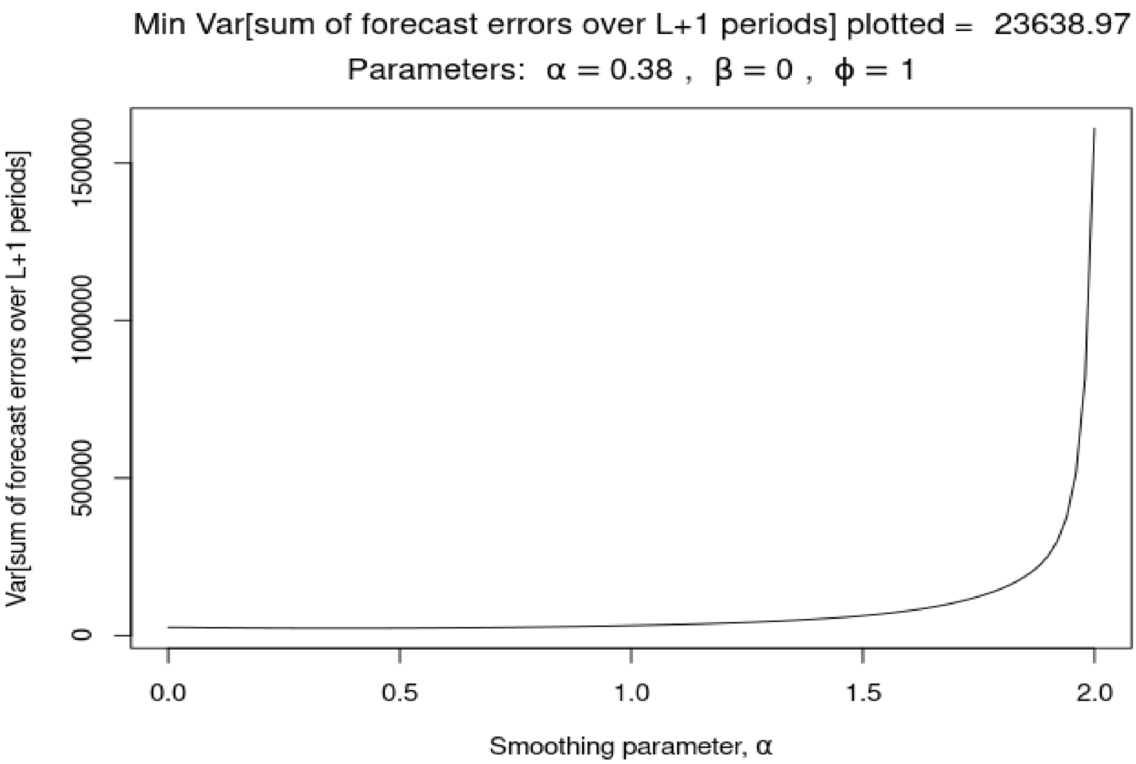
Figure 5.



From the plot, it can be clearly inferred that the minimum value of variance of sum of forecast errors over L+1 periods is getting minimized at the lead time of 0.

Figure 6.

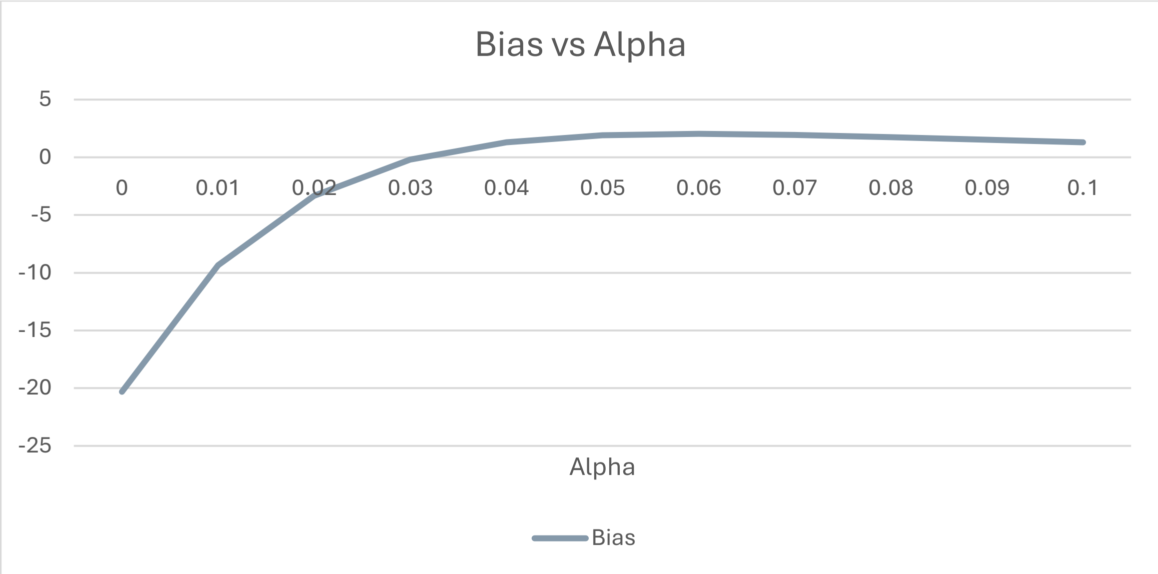




From the above two plots as per the explorer app for the Exponential Smoothing forecasting method, it can be clearly seen that variance of sum of forecasting methods over L+ 1periods increases as alpha goes away from zero and also bias is also very close to 0 when alpha is close to 0.

So, I plot only the bias values for alpha between 0 and 0.1 to get an optimum value of alpha since the variance only increases as we go away from 0.

Figure 7.



From the plot, we can clearly see that bias is close to 0 near alpha = 0.03 and crosses to the positive side between 0.03 and 0.04, so the alpha would be closest to 0 in this case only while keeping the variance minimum.

So, I decided to check the bias values between 0.03 and 0.04 and got the following and at alpha = 0.031 I got the following results:

Table 3.

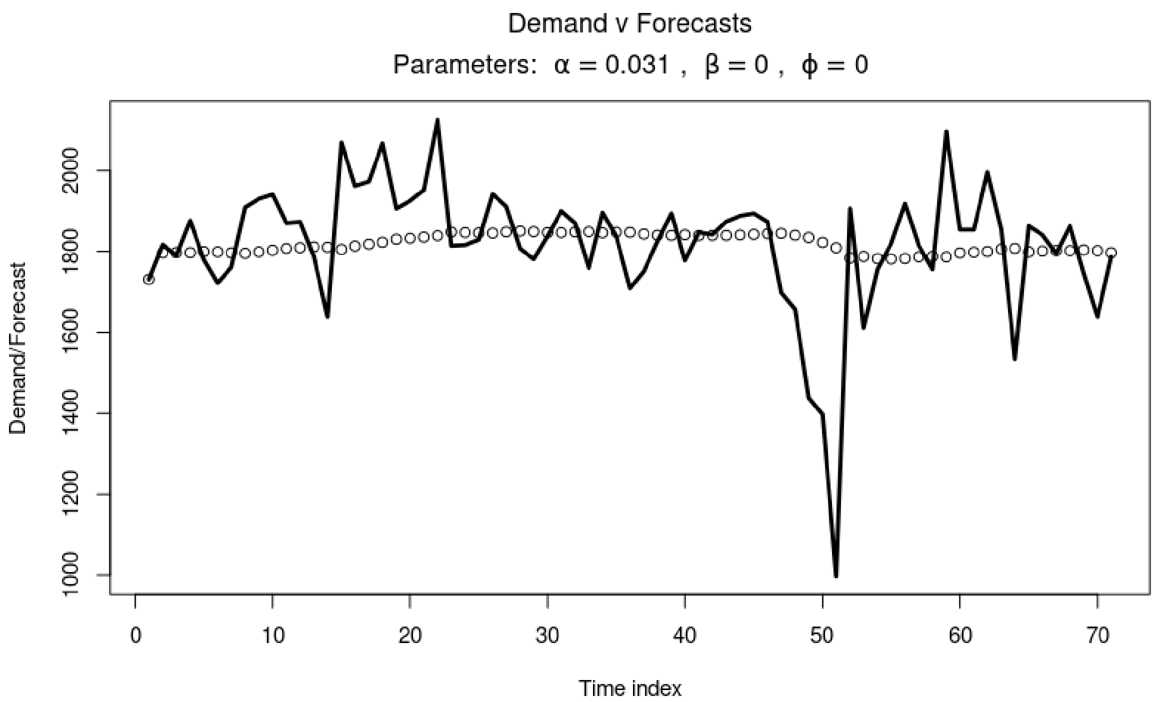
Parameters	**Values**
alpha	0.031
lead time	0

Table 4.

Measures	**Values**
Bias	0.017
var [sum of forecast errors over L+1 periods ahead]	26353
var [L+1 periods ahead forecast]	26353

Plot for the Forecast

Figure 8.

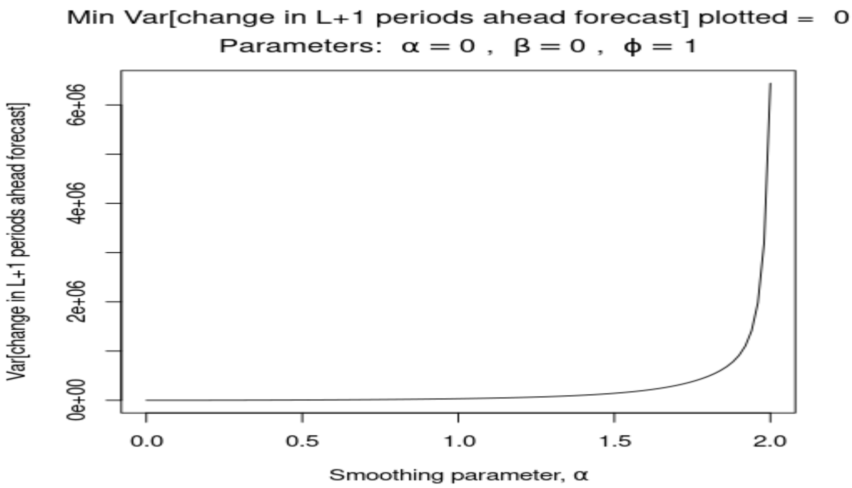


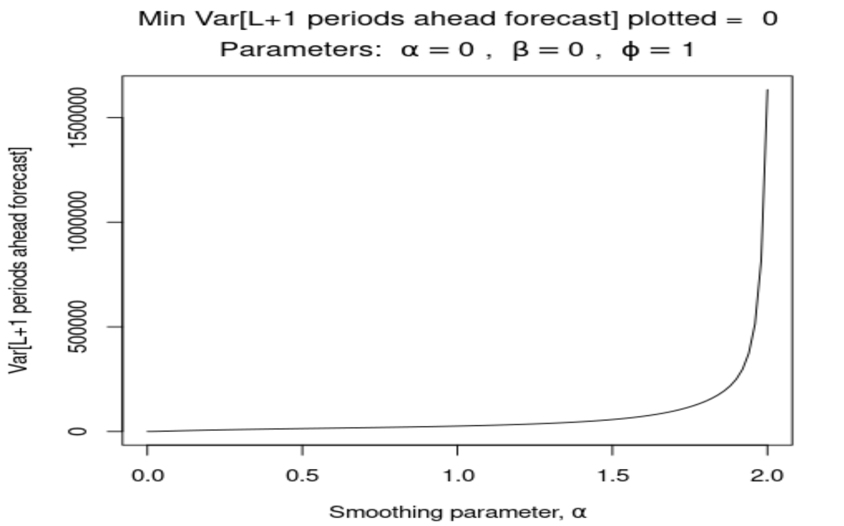
Case where capacity cost is the most important consideration

Variance of L + 1 periods ahead forecast is the most important measure while keeping bias close to 0 for minimizing the capacity cost.

Forecasting using Exponential Smoothing method with low alpha and low lead time surely reduces variance of sum of forecast error as the demand is fairly linear and keeping those parameters the forecast imitates the demand, but it might not be the best suited way for minimizing variance of forecast as imitating the demand would bring the variance of forecast closer to the variance of demand. Also increasing alpha in Exponential Smoothing method would increase variance of forecast which could be ascertained from the plot below.

Figure 9.





Since the weekly demand data does not have exponential growth or decay, Damped Trend method might not be the best suited in this case.

So, I decided to opt for the Holt’s method to best capture the little variations in the data, to minimize the variance of forecast and variance of change in forecast while keeping the bias close to 0.

As it has been observed above that as alpha moves away from 0, the variance keeps increasing. So, I decided to opt for lower values of alpha to get the optimum values of the measures.

I assumed a lead time = 3 as provided in the Forecast Explorer App (Disney, S.M., 2024).

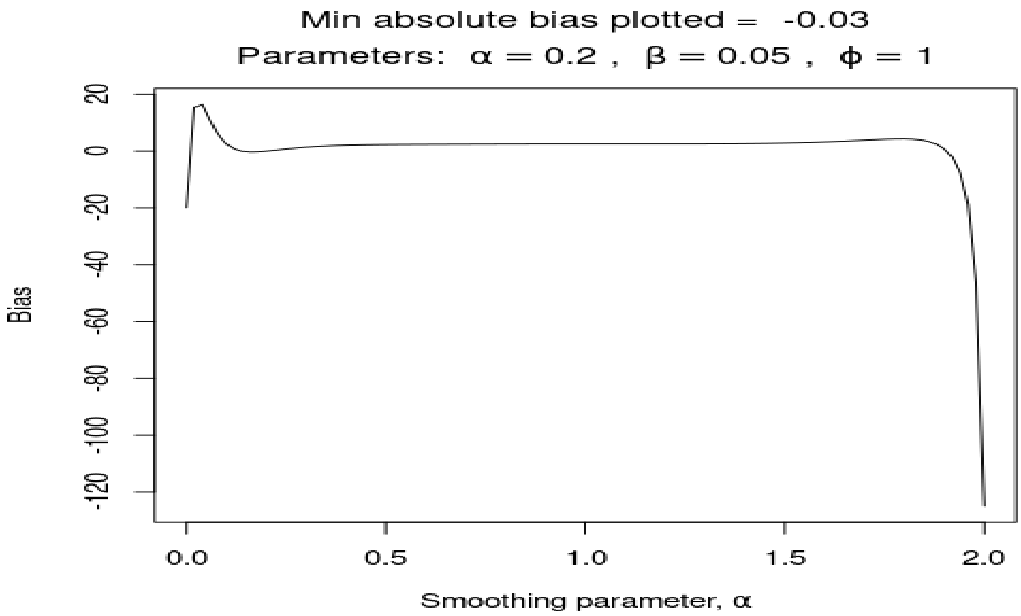
So, I decided to use α = 0.2 and ß = 0.05, recommended for lower lead times (Disney, S.M., 2023b), as my starting point.

Since, as alpha increases the variance increases so I tried to use even lower values of alpha to get minimum variance and optimal bias. I got the following results:

Table 5.

alpha	**bias**	**Var [L+1 periods ahead forecast]**	**Var [change in L+1 periods ahead forecast]**
0.2	-0.025	11458	1440
0.1	2.558	7264	384
0	-19.961	0	0

Figure 10.



Clearly as per above table and plot bias comes close to 0 when alpha is between 0.1 and 0.2.

At alpha = 0.01 bias is 5.375, so the bias would be closer to 0 between 0 and 0.01

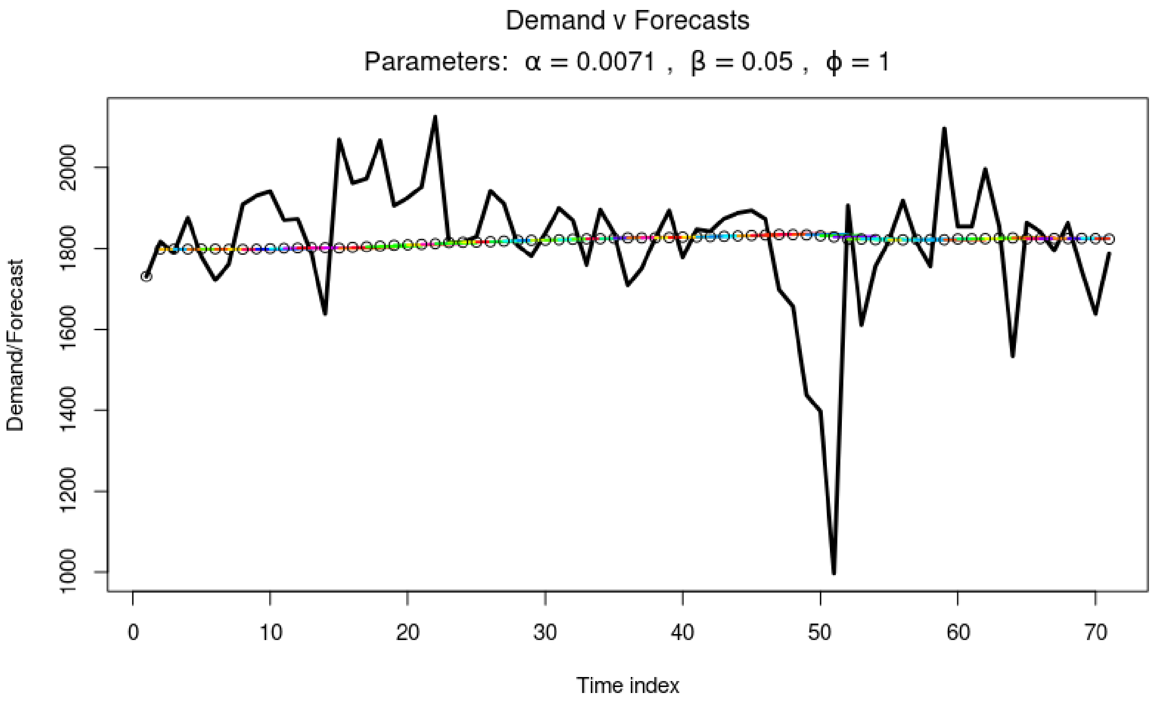
The table below shows the results of optimum variance and bias for minimizing the capacity cost at alpha = 0.0071, lead time = 3 and beta = 0.05

Table 6.

alpha	0.0071
bias	0.063
Var [L+1 periods ahead forecast]	138
Var [change in L+1 periods ahead forecast]	2

Plot for the Forecast

Figure 11.



Case where both inventory cost and capacity cost are the most important consideration

The most important measure for minimizing inventory cost is the variance of sum of forecast errors over L+1 period, while for capacity cost the most important measure is variance of L+1 periods ahead forecast.

As observed in the case of inventory cost, the minimum variance of sum of forecast errors over the L+1 periods is way high as compared to the minimum variance of L+1 periods ahead forecast for minimizing capacity cost.

Thus, for this case I would be selecting the Exponential Forecasting method which was used for minimizing measures related to inventory cost and using the same parameters as used in that case.

Using Exponential smoothing method in this case helps in optimizing both the metrics related to inventory cost and the metrics related to the capacity cost. Although, the capacity cost related variances are more as compared to the case where the capacity cost was the most important consideration, it provides an opportunity to create a fine balance between the variations related to inventory cost and variations related to capacity costs.

At alpha = 0.031 and lead time = 0, the variance of sum of forecast errors over L+1 periods is minimized and the variance of L+1 periods ahead forecast is optimized while bias is close to 0 too.

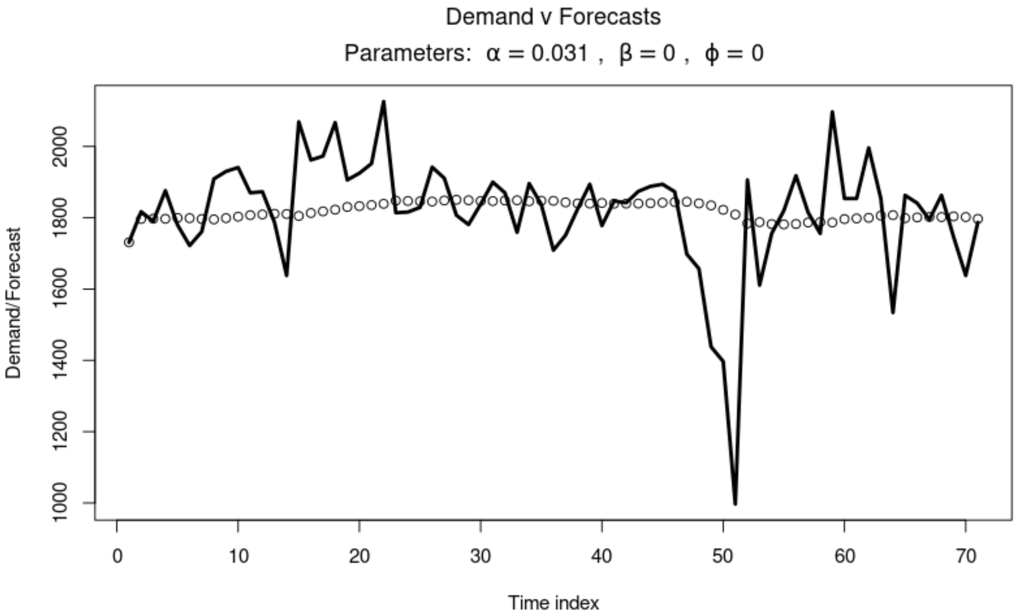
Minimum measure values for this for this case:

Table 7.

Bias	0.017
Var [L+1 periods ahead forecast]	524
Var [sum of forecast errors over L+1 period]	26353

Plot for the Forecast

Figure 12.



Short Report for Senior Management

The weekly demand trend exhibits a fairly linear demand pattern with a major downward spike in January 2025 and some seasonal fluctuations in April 2024 and April 2025.

For the case where optimizing the inventory cost is the most important consideration, using Exponential Smoothing method with a lead time of 0 weeks helps best in minimizing the variations in the forecast errors, the most important metric for minimizing inventory cost, while keeping the forecast unbiased.

Even if there is a change in the lead times, Exponential Smoothing helps in keeping the forecast stable as it is not affected by the lead time. This would in turn keep the inventory in check, prevent excess inventory and lost sales and thus minimize inventory cost.

In the scenario where optimizing the capacity cost is the most important consideration, Holt's method with a lead time of 3 weeks is the most efficient in minimizing the variations in forecast and the variations in the change in forecast, the most significant metrics for optimizing the capacity cost.

Using Holt's forecasting method, in this case provides an opportunity to optimize capacity utilization, by minimizing the variations in the forecast, while also accounting for any changes in lead time in the forecasts, while minimizing the capacity cost and other related overhead costs at the same time.

In the case of minimizing both the inventory and capacity cost, the Exponential Smoothing method with a lead time of 0 is the best as it captures the variations in the metrics related to the inventory cost as those variations are way larger than the variations in the metrics related to the capacity cost and the metrics related to the capacity cost are also getting optimized using this method.

Bibliography

Disney, S.M. (2023a), "Lecture notes on forecasting", available for download from https://ele.exeter.ac.uk/pluginfile.php/3904988/mod_label/intro/2023%20Forecasting v2
.pptx

Disney, S.M. (2023b), "Setting the cadence of your pacemaker: A lean workbook to reduce
Mura", available from https://www.bullwhip.co.uk/cadence/.

Disney, S.M. (2024), "An R-shiny Forecast Explorer", available from https://bullwhip2.shinyapps.io/ForecastExplorer/