TAGLIATELA COLLEGE OF ENGINEERING

EGRM-6611

Project 1

Forecasting Game

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Executive Summary

As a supplier and distributor of parts to the manufacture of BOEING 787 Project we establish our relationship based on integrity and trust. Our main goal in our company was to establish the most accurate forecast for us to be able to satisfy our customers, as well as maintain the good profit levels. Since the demand of previous days was given, we wanted to make sure we had enough material to supply the manufacturers, so we used forecasting methods to ensure we have enough material to supply in a timely manner.

The way our organization was able to approach the order, was by analyzing previous data and looking for previous trends with the previous orders. We analyzed the previous data using different models and compared the errors of each model to find the best for forecasting future needs. Afterwards, we forecast the future orders and manufactured a percentage of the order which approximate to demand that was required. As we analyzed the order we took different approaches to calculate and manufacture the quantity that it was required by taking in consideration both parties which helped prevent losses as well as to have enough merchandise to supply our client and satisfy them. As the days went on, we kept updating the models with the latest i.e. actual demands and then modified the forecasting models accordingly.

We were able to smoothly forecast demand for 3 continuous days by recursively updating the model and forecasting for the next days. This way, we were able to minimize the margin of error and thereby produce the optimum order numbers while keeping in mind the profit/loss of the company. We will explain the detailed process further in the report.

Understanding the data

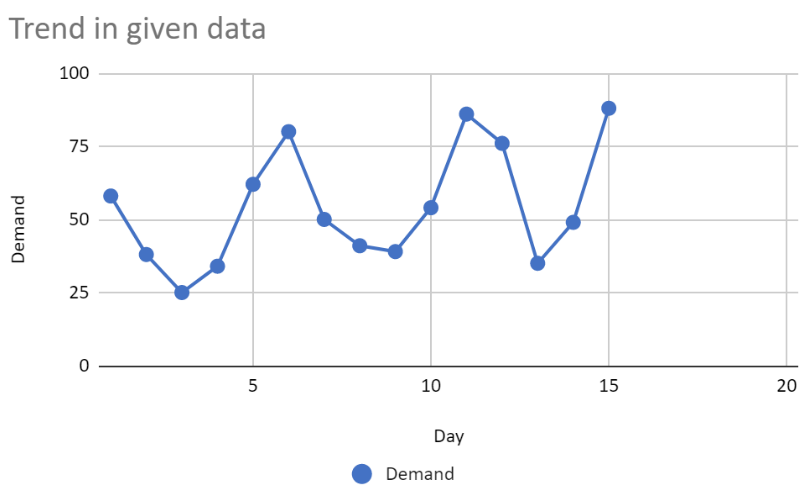
To be able to predict future demand, we analyzed the data of previous days and established the trends and seasonalities, if any. The given data and the 'supposed' trend / seasonality is shown below. Using this analysis, we were able to decide whether the demand has any pattern.

Season	1					2					3				
DAY	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
DEMAND	58	38	25	34	62	80	50	41	39	54	86	76	35	49	88

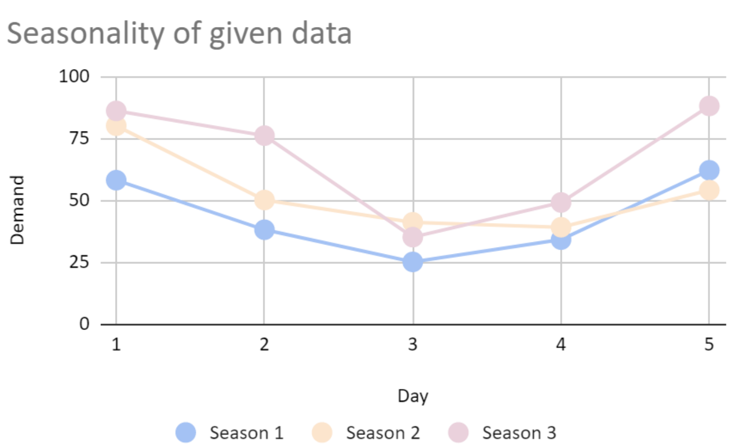
Table 1- Given data

To better understand the given data, it has been split into seasons. Since there are 15 days, we split it into 3 seasons with 5 days in each season. This division was decided by looking at the trend in the data.

Since the trend seems to drop after the first day and increase after the 3rd day every 5 days, we decided to break each season into a 5 day period.



Graph 1 - Trend in given data



Graph 2 - Seasonality in given data

Once the seasons were decided, we plotted the demand individually for each season to confirm the trend as in the overall data. From this, it is evident that after the first day, there is a drop, which again goes up from the 4th day onwards. This trend repeats itself after every 5 days, i.e. the length of each season.

Day 1

Since we have no place to start, day 1 began from scratch. We created different forecasting models for the given data and then calculated the errors for each model. The models that we considered for comparison were as below:

1) Moving average, (n = 3)
2) Weighted moving average, (n = 3) and weights as:
   w1 = 0.727272
   w2 = 0
   w3 = 0.272728
   All the weights were selected using excel solver to minimize the error.
   Making sure that the sum of all weights is equal to 1.
3) Exponential smoothing, $\alpha = 0.117209$
   Again, α was selected using excel solver to minimize the error
4) Double exponential smoothing
   $\alpha = 0.076$, $\beta = 0.897598$
   S = 58 (demand of Day 1)
   G = -2.42321
   The values of α, β, and G are selected to minimize the error
5) Trend + Seasonality using linear regression
6) Seasonality forecasting using seasonal factors

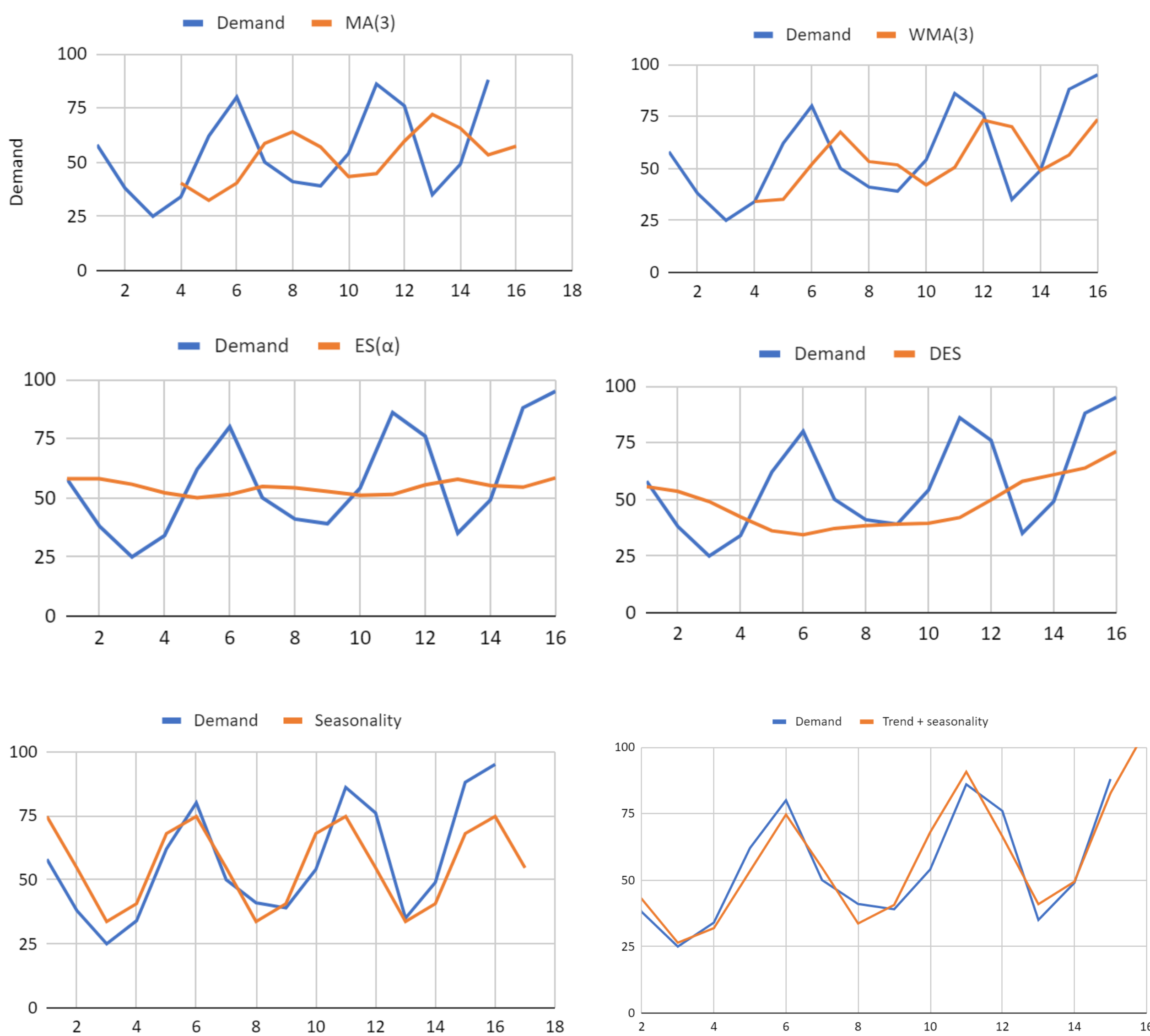
The errors from all the models were compared to determine the best model. Although we calculated MAD, MSE, as well as MAPE, we decided to use MAPE as the deciding factor.

	MAD	MSE	MAPE
MA(3)	23.50	696.61	42.01%
WMA(3)	17.87	480.79	31.60%
ES(α = 0.117209)	17.44	421.97	36.59%
DES(α = 0.076, β = 0.897598)	18.74	527.78	35.08%
Trend + seasonality	5.11	39.07	9.71%
Seasonality	10	137.91	19.03%

Table 2 - Errors of models on day 1

Since the trend + seasonality has the lowest error, we chose that model to predict the demand of Day 1. The forecast using this model was 106.82. Hence, we rounded it off to 107 as our final demand for day 1. We did realize that the actual demand would be 107 ± 10%(107) because error.

We also wanted to compare the actual trend with the forecast for all the models using visual aid. Thus, the demand v/s forecast trend for all models is as shown below.



Graph 3 - model forecast v/s actual demands

Just by analysing the graphs of comparing actual demand with forecast, it is quite evident that the trend + seasonality model is the best suited one. It most closely follows the trend of the actual data. Note that in all of the graphs, the blue line indicates the actual demand whereas the orange line represents the forecasted value by the model that is specified in the legend which helped predict the future orders.

Day 2 and Day 3

As expected, the actual demand from day 1 was 95, which is ~10% less than the forecast value, 107. At this point in time, since we had already created models for forecasting data, we simply added a new value to the demand (the actual demand of day 1) and calculated all the error rates again. Although it was expected that the trend + seasonality model would have the least error, we calculated it just to be sure of the same.

	MAD	MSE	MAPE
MA(3)	24.59	752.16	41.82%
WMA(3)	18.15	479.21	30.90%
ES(α = 0.117209)	18.64	479.43	36.72%
DES(α = 0.076, β = 0.897598)	19.06	530.43	34.46%
Trend + seasonality	5.53	45.36	9.88%
Seasonality	10.65	155.13	19.18%

Table 3 - Errors of models on day 2

As expected, the trend + seasonality model had the least error. The forecast of this model for day 2 was 78. However, considering the difference that was seen in the previous forecast (107) and the actual demand (95), we decided to try something new. We went ahead and took the average forecast from all the models, which was nearly 75. Since we had 12 leftovers from the previous day, our order value was 63 to compensate for the leftovers.

Similarly, we updated the actual demand of day 2 into the trend + seasonality model and forecasted the demand for day 2. We updated the model in such a way that we considered the remaining total from the actual total to be able to predict day 3. To be precise:

Forecasted total	= 388.67
Demands for Day 1 + Day 2 = 95 + 73	= 168
Remaining total = 388.67 - 168	= 220.67
Forecast Day 3 = NSF_3 * RemainingTot	= 52.19

This way, the forecast of day 3 boiled down to approximately 52. Since there were 2 leftovers from the previous day, the actual order value would have been 50 units. However, since this was the last day and to avoid the charges of producing extra products, we placed a safe bet by reducing the order by 10% (i.e. the MAPE of the model). Therefore, at the end of day 3, we were able to send in an order value of 45 units.

Predicting the Future

After considering the actual demand of days 16, 17 and 18: we are to create a forecasting model to predict the demand for the next 3 days. Again, we have updated all the three models to fetch the final results. The MAPE of each model for data with 18 days forecast is as follows.

	MAD	MSE	MAPE
MA(3)	23.16	689.42	39.15%
WMA(3)	17.36	436.46	29.27%
ES(α = 0.117209)	17.25	432.29	33.59%
DES(α = 0.076, β = 0.897598)	18.68	506.71	33.33%
Trend + seasonality	6.43	54.01	11.83%
Seasonality	12.06	201.17	20.98%

Table 4 - Errors of models after day 3

Since we do not have enough data to finish the entire season, the error rates for the models depending on seasons has gone up as compared to day 1. This is not the case in the models that do not depend upon the seasonality of the data. It is interesting to see how missing data can cause problems in the forecasting model and hence, it is necessary to model the data in the right way depending on the values that are actually present. However, although the error rate for the seasonality models has gone up, the trend + seasonality model still has the lowest overall error values. Thus, we use that model to predict the demand for the next 4 days. The predicted values are given in the table below.

Day	Forecast Demand	Season	Lower (-12%)	Upper (+12%)
19	59.38	4	52.25	66.50
20	99.29	4	87.37	111.20
21	123.65	5	108.81	138.48

Table 5 - Demand forecast for the future

It is important to note that we need to allow an error deviation of about ±12% for each of the values. Thus, the actual values would most likely fall into ranges as given in the table above.

Conclusion

Our company was able to sustain the promise of delivery and satisfy the customers. It wasn't an easy task due to the lack of insights at the beginning, but in the end we studied the previous data and put into practice different approaches. The original data was given for the demands from the previous 15 days. We modeled different approaches for forecasting, and noticed the seasonalities and the trends in the data. Eventually, we learned that the most efficient method to predict the future demand for this data was the seasonality + trend formula. It had the lowest error score for the forecast and hence we expected the answers to be near the desired amount from the customers.

On day 1, we realized that the actual demand was within the negative range of MAPE hence, for day 2, we decided to take the average forecasted demand from all the models. This was a creative approach and we wanted to see how it would behave in a real world situation. We were quite surprised by how close the day 2 forecast was with the actual demand. On day 2, we only had 2 products as surplus which is a huge difference from the 12 leftovers on day 1.

For day 3, to keep the company from going into loss due to any over manufactured products, we decided to order products with 10% less than forecasted so as to remove any discrepancies. The 10% was decided based on the MAPE of the forecasting model. We were excited to learn that on the last day we culminated the shipping with zero inventory on hold for the company. However, it was 15 items short; which was expected as a possible outcome because of the reduction that was made to prevent our company from overprocessing inventory. Our company decided to play safe towards the end to avoid extreme losses. Overall, we were 15 items short in the entire 3 day journey, which would indicate that we fulfilled around 93.5% of all the orders. We believe that this was a great success rate. Additionally, the feedback from the customers was that they were satisfied which was our main intention from the very beginning.