The Supply Chain Game 1

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1) General strategy for approaching the game

The very first step we take in this project is to plot the demand. Graph one in the Appendix shows the plot of the past demand. We also plot the ACF curve to check any seasonality and autocorrelation in the demand, and the graph in appendix 8 illustrates that there is a high seasonality and the high ACF in lag 182 tells that the time window from peak to low is approximately around 182 days.

In this project, we assumed that the general seasonal cycle of demand would remain the same. Furthermore, we assumed that the high and low demand seasons are not autocorrelated. To investigate the distribution of demand, we used ARENA to find the best fitting probability distribution for the demand. We assumed that demand had a seasonality of 183 days, which we encountered a peak half a year after the lows. We also decided that demand can be divided into high and low demand seasons each year. We also assume that the demand is independent of time during the high and low demand seasons, which is stationary.

Originally, we used the beta distribution to model the overall demand cycles, but then we split the high and low seasons by using the mean demand of the last two years as a criterion. By doing so, we found that the low seasons were between the days 730 to 823, 1007 to 1193, and 1378 to 1460, while the high seasons were between the days 824 to 1006, and 1194 to 1377 (Appendix 1).

After separately analyzing the high and low seasons, we found that both high and low seasons followed a Weibull distribution. However, the RMSE difference was small enough that we chose to use the normal distribution instead (Appendix 2). So ultimately, for high demand, we found that the seasons followed the normal distribution with mean 57.4 and standard deviation 20.6. Conversely, for low demand, we found that it followed a normal distribution with mean 20.3 and standard deviation of 14.

We then used the Q,R model to find the optimal reorder point and order quantity (refer to Appendix 4 and Appendix 5 for calculations) . When the high season begins, we will set the order quantity and reorder point as 457 and 820 respectively, whereas in the low season, we will set as 441 and 308. We fixed the lead time to be 12 days, which we used to calculate the average lead time demand and variance. We periodically changed this at the predicted high and low season beginning days. Also, we decided to increase the production capacity from 20 to 40 units per day from the first day because the mean demand of the last 2 years is equal to 39.19 or around 40 units per day.

2) Aspects of the strategy that went well

With the strategy that separates the demand into two types: the low and high season demand, we are able to obtain more precise and accurate values of Q and r, thereby enhancing the efficiency of our overall production process.

We determined that increasing our production capacity to 40 units per day would be adequate to meet the demand for both seasons, as it aligns with the average demand over the past two years. Furthermore, investing an additional $500,000 to $1,000,000 would pose significant financial risk, particularly considering the relatively short two-year timeframe of our project.

3) Aspects of the strategy that went poorly

The major issue that we found with our strategy was that we often dropped to zero stock during our lead time, which indicated that we had poor estimations of our lead time demand (appendix 9). This was particularly the case in high demand seasons. However, within the low demand periods, our ability to meet demand was almost exactly correct. This meant that on the day that we used all our inventory, we received a shipment of goods, and did not miss any demand (appendix 10,11). As a group, we attribute this to our lack of safety stock, lack of constant review of the demand fluctuations, and the desire to meet demand exactly on time rather than holding safety stock.

Furthermore, we did not take the opportunity to stock up on goods during the low season periods. This issue resulted from our strategy of meeting demand exactly, meaning that even though we had excess capacity in low demand season, we decided against stocking up on goods. This could also be attributed to us not thoroughly thinking through how we could exploit the relatively small holding cost. The third reason is that we didn't realize the fact that the production can't catch up with the demand in the high demand season. As a result, without enough stocks, we could not satisfy most of the demand in high demand seasons and missed a chance to boost the profit during the high season.

In an effort to meet demand exactly on time, we also used mailing instead of trucks. In hindsight, we realized that this raised our costs significantly, particularly with the large orders that we made throughout high seasons. If we instead choose to use the truck, we can reduce the shipping cost by almost 50%. Moreover, we mistakenly interpreted the idea behind the 7-days lead time of the truck. It turns out that the 7 days lead time actually doesn't matter since our production is continuous and the 7-days lead time is already considered in the production. Therefore, the initial decision to choose the mailing is indeed mistaken. Ultimately, it seemed that our desire to meet the exact demand rather than holding safety stock throughout the game period led us to miss large portions of demand, and a poor final result.

4) Reflection

Upon review of our performance, we found three main avenues of improvement.

To begin with, improving forecasting for future demand is to use data forecasting methods such as regression, moving average, or exponential smoothing average instead of relying solely on old demand data to determine the distribution of demand and using the (Q,R) model. Additionally, we could've tried to predict demand using ARIMA or other algorithms to further improve our estimations of reorder point on reorder quantity.

Secondly, we believe that it is crucial to continuously fit the demand random variable after obtaining new demand data to ensure the most accurate predictions. For us, we simply defaulted to the same high and low demand season values that we determined initially. Instead, we could've constantly re-fit the data on ARENA to determine new reorder quantity and reorder point values. Upon review of data, we found that certain seasons differed in length and demand volatility, which led us to bottoming out on inventory.

Another error we made was found in hindsight when we recalculated our (Q,R) model. We have since recalculated the results (refer to Appendix 6 and Appendix 7 for calculations). In terms of high season, we underpredicted the order quantity by 95 units, and overpredicted the reorder point by 6 units. In terms of low season, we overpredicted reorder quantity by 108 units, and underpredicted the reorder point by 7 units.

Lastly, our team would implement a strategy to better satisfy demand during the high season by increasing stock and production prior to the onset of the low season; also, change the shipping method to truck when we want to ship these orders. This strategy is crucial to achieve higher profits, as the transition from low to high season marks a pivotal point in the game. Although we may experience longer production times and struggle to meet demand during the low season, the benefits of this strategy are incomparable to the gains reaped during the high season.

5) Discussion

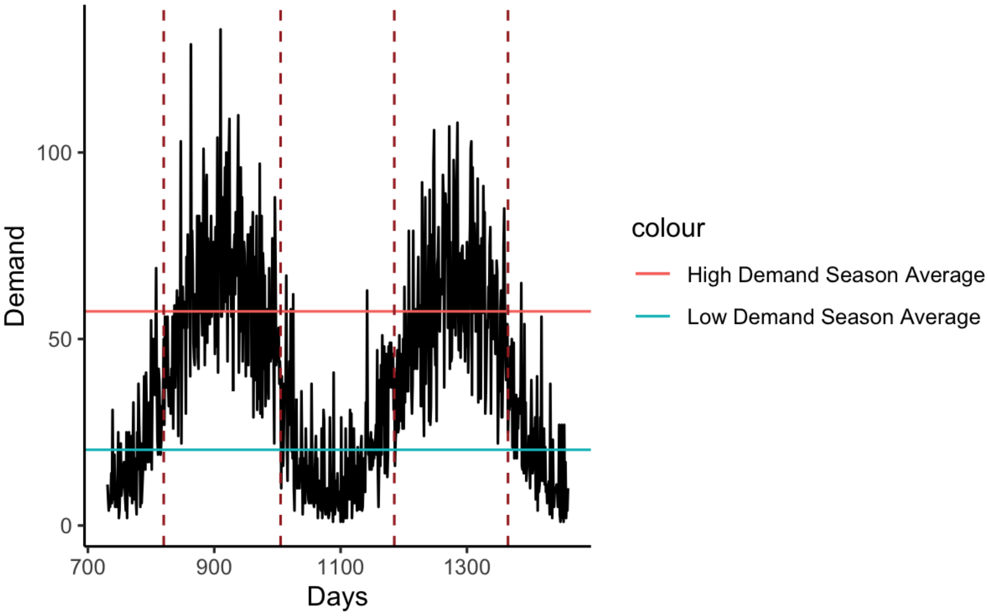
Beyond explaining our efforts and explaining what we could have improved on, we also wanted to explore the possible reasons within the game setting that could've made catching up to "donothing" more difficult. Naturally, we understand that our suggestions are difficult to model in a game setting, but we simply intend to provide some of the discussion points that we had while working through this project.

Firstly, there was no penalty cost for lost demands, this meant that the even if "donothing" constantly had no stock, there would be no risk for them. Without the loss of customer goodwill, meaning that even if they had a horrible reputation of always running out of stock, their returning customer rate would essentially be inelastic to their reputation.

Secondly, interest rate is compounded daily, and a small difference in cash balances can have a significant impact over time. Since donothing didn't invest in increasing the production capacity or reducing their overall costs, allowing them to make use of this advantage. We would have enjoyed extending this experiment beyond the two year time frame to see if we could have had a better return on the 1,000,000 dollar investment we made into increasing capacity at the start of the game.

Appendix

Appendix 1: visualization of demand cycles based on our methodology



Appendix 2: Random Variable Best Fit RMSE

	Low season RMSE	High season RMSE
Weibull	**0.00199**	**0.00328**
Gamma	0.00203	0.00502
Beta	0.00228	0.00338
Lognormal	0.00338	0.0145
Erlang	0.003	0.00561
Exponential	0.00408	0.0412
Triangular	0.00606	0.00986
Normal	**0.00539**	**0.00481**
Uniform	0.011	0.0348

Appendix 3: Base Figures

Parameter	K	h	π	$\mu(D_l)$	$s\ (D_l)$	$\mu(D_h)$	$s\ (D_h)$
Value	1500	0.6301	150	20.3	14	57.4	20.6
Formula	Given	$\frac{0.1*1000}{365} + \frac{1000}{365}$	1450-1000-300				

$\mu(L_l)$	$s\ (L_l)$	$\mu(L_h)$	$s\ (L_h)$
243.6	2352	688.8	247.2

Note: ‘l’ subscript indicates low season, ‘h’ subscript indicates high season

Appendix 4: (Q,R) Model for High Season Demand

1^{st} *iteration*	$Q_0 = EOQ = 436$	$R_0 = 821$	$\bar{b}(R_0) = 0.91$
2^{nd} *iteration*	$Q_1 = 456$	$R_1 = 820$	$\bar{b}(R_1) = 0.946$
3^{rd} *iteration* (Convergence)	$Q_2 = 457$	$R_2 = 820$	$\bar{b}(R_2) = 0.946$

Appendix 5: (Q,R) Model for Low Season Demand

1^{st} *iteration*	$Q_0 = EOQ = 436$	$R_0 = 309$	$\bar{b}(R_0) = 0.204$
2^{nd} *iteration*	$Q_1 = 441$	$R_1 = 308$	$\bar{b}(R_1) = 0.209$
3^{rd} *iteration* (Convergence)	$Q_2 = 441$	$R_2 = 308$	$\bar{b}(R_2) = 0.209$

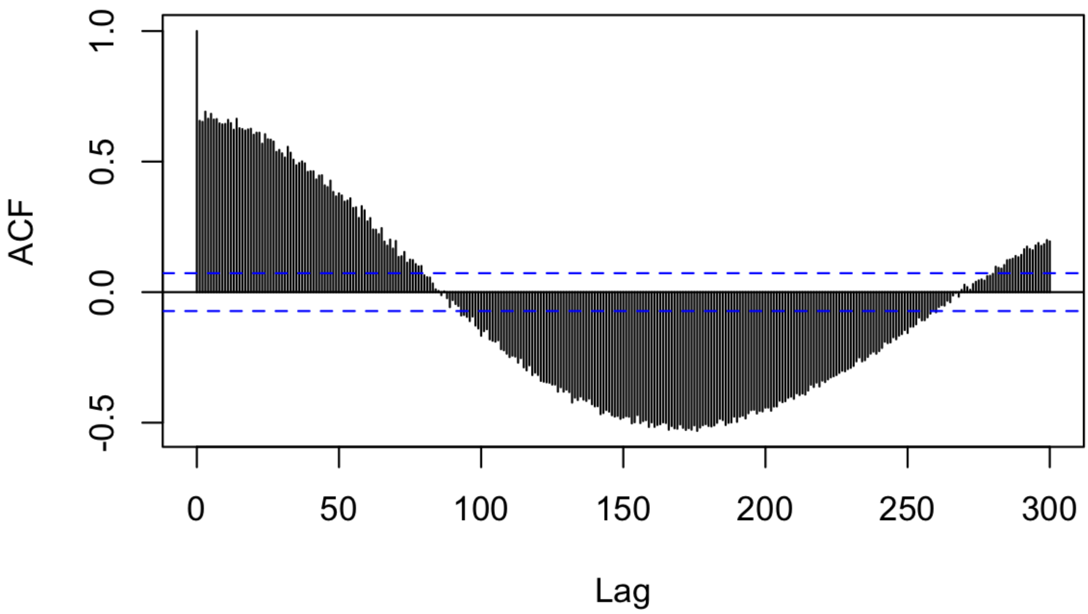
Appendix 6: Corrected (Q,R) Model for High Season Demand

1^{st} *iteration*	$Q_0 = EOQ = 523$	$R_0 = 815$	$\bar{b}(R_0) = 1.11$
2^{nd} *iteration*	$Q_1 = 551$	$R_1 = 814$	$\bar{b}(R_1) = 1.16$
3^{rd} *iteration* (Convergence)	$Q_2 = 552$	$R_2 = 814$	$\bar{b}(R_2) = 1.16$

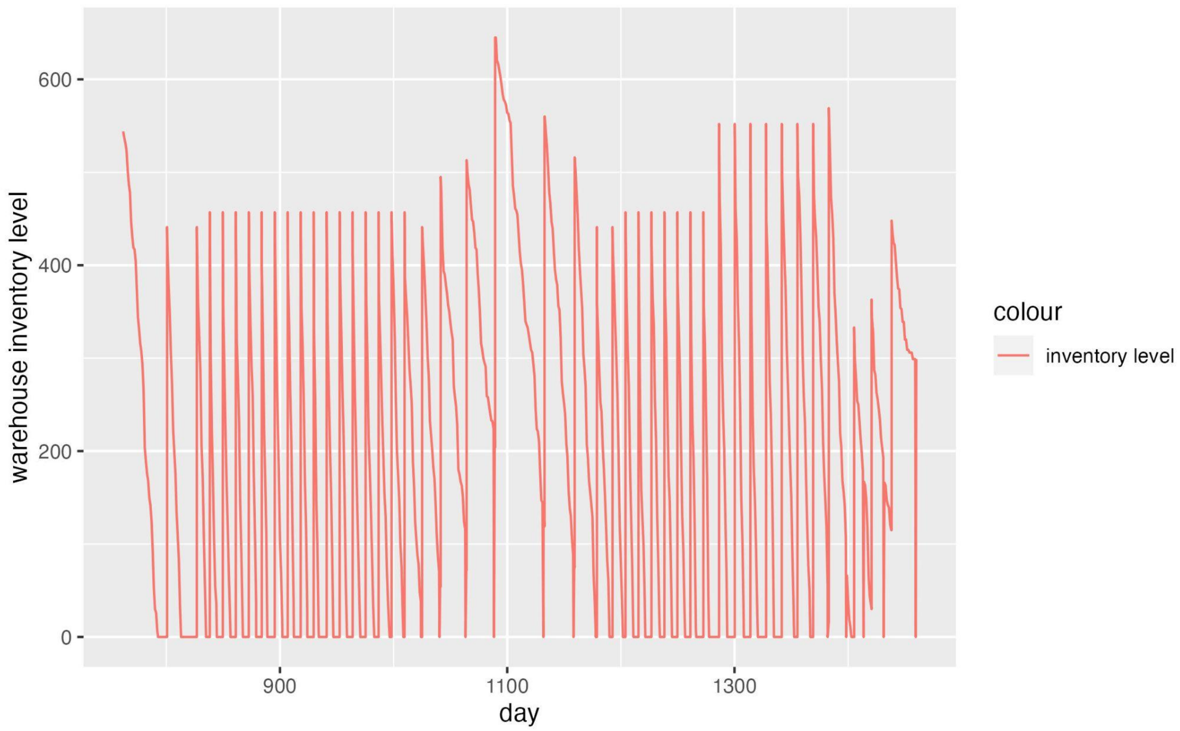
Appendix 7: Corrected (Q,R) Model for Low Season Demand

1^{st} *iteration*	$Q_0 = EOQ = 311$	$R_0 = 317$	$\bar{b}(R_0) = 1.36$
2^{nd} *iteration*	$Q_1 = 331$	$R_1 = 316$	$\bar{b}(R_1) = 1.467$
3^{rd} *iteration*	$Q_2 = 333$	$R_2 = 315$	$\bar{b}(R_2) = 1.5$
4^{th} *iteration* (Convergence)	$Q_3 = 333$	$R_3 = 315$	$\bar{b}(R_3) = 1.5$

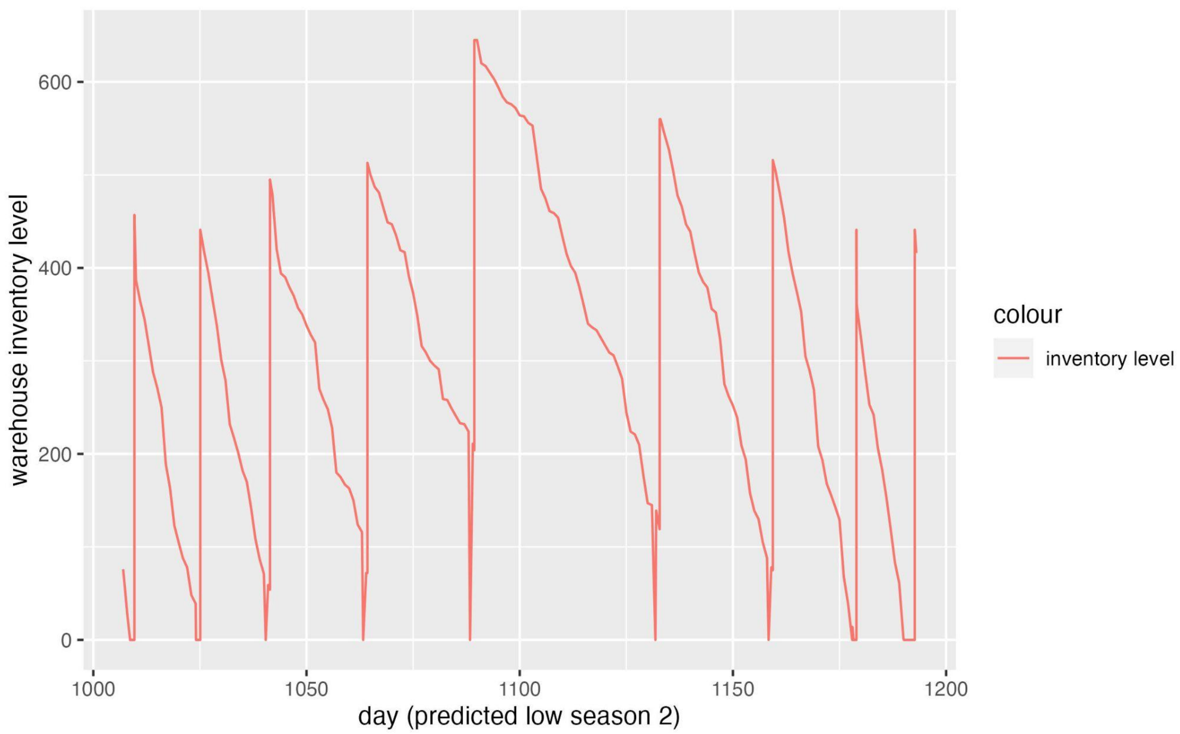
Appendix 8



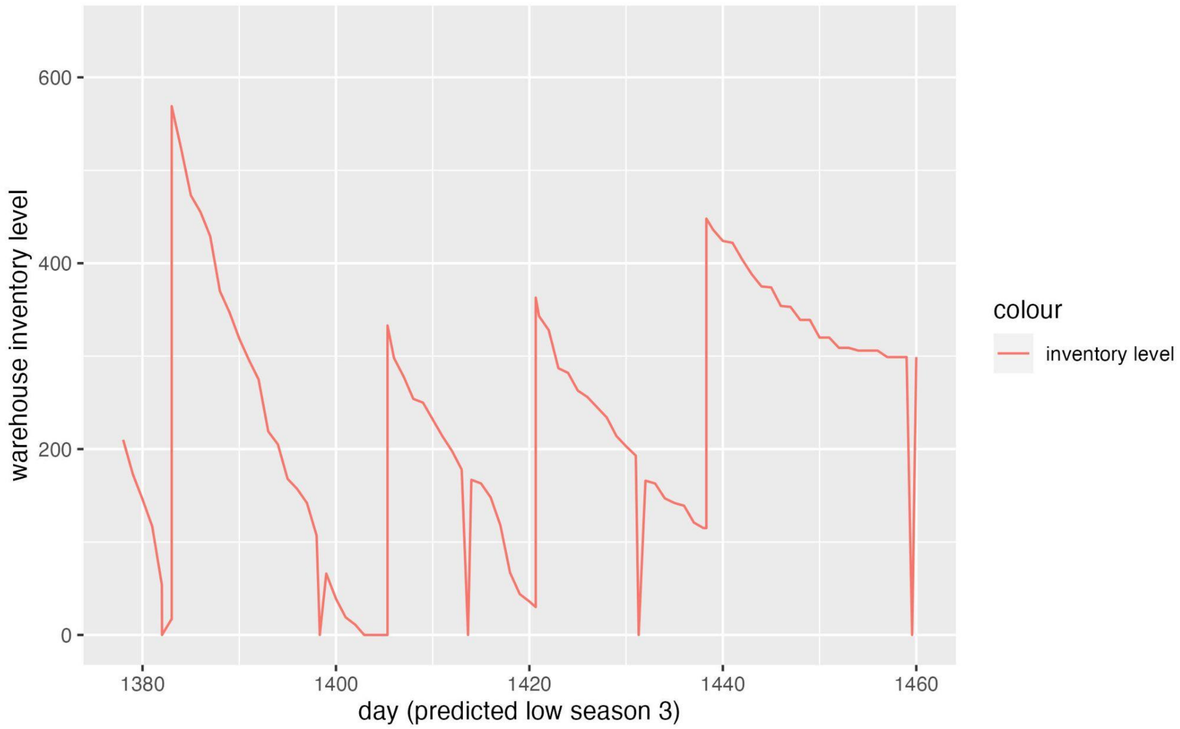
Appendix 9



Appendix 10



Appendix 11



600
400
200
0
warehouse inventory level
1380
1400
1420
1440
1460
day (predicted low season 3)
colour
inventory level

Appendix 12