THE PENNSYLVANIA STATE UNIVERSITY
SCHREYER HONORS COLLEGE

DEPARTMENT OF SUPPLY CHAIN & INFORMATION SYSTEMS

DEMAND FORECASTING FOR PHARMACEUTICALS

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ABSTRACT

This thesis analyzes the demand an animal pharmaceutical company sees and compares forecasting methods to find the most accurate one. Companies collect large amounts of data and a forecast model can utilize the collected data to predict future demand. There are various forecasting techniques that are better suited for different industries. In this research, error terms identify which forecast technique a company should be using by pinpointing which method produces the forecast closest to the historical data.

In order to create this analysis, eighteen months of data were provided by Company Z and three forecast models were set up in Excel. The Excel model relies heavily on data input and subject matter experts from the company to ensure that the correct data is utilized in creating the forecasts. To conclude, this thesis provides information on which forecast method was most accurate for Company Z and how they will continue to monitor and update the forecast to see what their demand will be for the next three to six months.

The findings for the animal pharmaceutical company in this thesis identified that exponential smoothing is the best forecasting method to utilize. The major findings confirm that for a company that sees a relatively low amount of seasonality and year after year sees the same trends, exponential smoothing creates the most accurate demand forecast.

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ACKNOWLEDGEMENTS

Looking back at my four years at Penn State, I can honestly say that everything I have been involved in has surprised me in an amazing way. I am not sure where I would be right now had I chosen to attend a different university, picked a different college to peruse a degree in or even studied a different major. Every decision has been guided by my amazing support system and I am so thankful that everyone was so supportive and willing to share experiences, advice and most importantly listen to my constant indecision.

I would like to say a huge thank you to Dr. Novack, Dr. Bansal and Dr. Spychalski for helping me complete this thesis. I would also like to thank the company who let me utilize their data and Penn State's Center for Supply Chain Research for helping me to use a company's world data to create this forecasting model. My time at Penn State has been greatly impacted by all of my friends and family who have offered me non-stop support and helped me create many incredible memories. Everyone I have on my support team is nothing short of amazing and I couldn't have done this without them.

Chapter 1

Introduction

With the growing portfolio of demand data from markets, it is important for companies to properly utilize the data they have been collecting. This data can be used for a myriad of improvement techniques, such as better forecasting, production planning, transportation management, demand planning, among other things (Langley et al., 2020). The accuracy of the forecast can be increased when there is better visibility into what the data can provide and the factors that are built into the different forecasts. With better forecasting, companies across the globe are able to make better decisions about planning and are able to more accurately hold and plan inventory (Langley et al., 2020). With better insight into what will be needed in the future, companies can make more accurate decisions on what amount of inventory they should be holding and better allocate their costs to research, development, and design that will help push the company forward.

The demand forecast is a projection that is constantly changing, based on consumer needs as well as production capacity. When creating the forecast, there are three main decisions to make: what level the forecast should be made on (warehouse, pallet, stock keeping unit [SKU], etc.), what time interval to build the forecast on (daily, weekly or monthly), and are there seasonal trends that can be accounted for in the forecast. Knowing these factors will help a company plan for the upcoming demand and have the correct amount of labor staffed. This thesis aims to find which factors are most important when creating a forecasting plan and then details what steps are taken to actually create the forecast.

This thesis will determine a forecasting method utilizing a company's historical data. Because the company analyzed operates in a specific market, the thesis will focus on the animal pharmaceutical industry and best practices for said industry. The forecast will be a result of company data and answers provided by a company contact. The company data, analyzed by way of Excel, will use the historical data to predict future demand based on the exponential smoothing method of forecasting. With this forecast, the company will independently use the data to create production and labor schedules. Due to anonymity, the company that this research was originally applied to will be referenced as "Company Z" for the entirety of this thesis. The remainder of this thesis is structured as follows. Chapter 2 will consist of a literature review of forecasting methods in practice today as well as give deeper insight into the company background. Chapter 3 will discuss the methodology that was used to create the forecast. Chapter 4 will be analysis of the forecast created and Chapter 5 will be a summary of the research that has been completed.

Chapter 2

Background

Large companies collect information and data on day-to-day activities; however, it is rarely utilized to the company's advantage. This is referred to by Gartner, Inc. as dark data ("Dark Data Assets," 2019). Because the quantity of this data stored is so vast, it often takes dedicated resources to sift through and find usable pieces to make better decisions and predictions. According to an article in *Supply Chain Digital*, companies that utilize a forecast, on average, reach a fifteen to twenty percent decrease in safety stock, which translates to a large inventory reduction throughout the whole supply chain (Pierce, 2013).

Although it is near impossible to create a forecast with one hundred percent accuracy, it is still helpful to have some understanding of what demand could be in order to best prepare the distribution centers (DCs) and manufacturing plants. Without a forecast, it is impossible to plan for labor requirements, building size requirements, and production plans for any product (Bozarth & Handfield, 2019), any of which can cause major issues in the supply chain if they are not addressed well. If a firm over-hires labor, too much cash on hand will be tied up in salaries. If a building will not meet demand requirements in the long term, the company will be affected by capacity constraint or, in other words, restricted by what the facility is able to produce and therefore being unable to meet demand. When a company is restricted by capacity constraint, they risk their competitors stepping in and taking over their portion of the market share (D'Aveni, 2010). Additionally, not having an accurate picture of the production plan will lead to either an overage in raw materials, which is a costly way to tie up cash, or, a shortage of raw materials, which causes plants to sit idle and unproductive while a delivery is on the way.

Forecasting Methods

There are multiple widely used forecasting methods typically chosen based on the nature of the company and how volatile consumer demand is for the product. Time series forecasting models are utilized mainly when chronological order is important to create the forecast. In these models, the future demand is seen as a function of time (Bozarth & Handfield, 2019). Simple moving average, weighted moving average, exponential smoothing, and linear regression are the four widely accepted time series models and their use is dependent on several factors of the forecast that is being created.

Simple moving average (SMA) is widely used for companies seeing a relatively low amount of demand variation, as this method works well to smooth the data over the short period it takes into account (Langley et al., 2020). Typically, the most recent three to four months of data are averaged to produce the next month's forecast as seen in equation 1, where D_t is the demand in month *t*, and N is the total number of months being used. However, more or less months can be utilized.

Equation 1. Simple Moving Average

$$SMA = \frac{D_t + D_{t-1} + \cdots + D_{t-N+1}}{N}$$

Weighted moving average (WMA) is a more complex version of SMA, taking recent seasonality into account when assigning weights to the months, seen in Equation 2. For this reason, WMA is more applicable to companies that experience more seasonality than constant demand. In the equation below (Equation 2), w_t is equal to the weight assigned to the most recent month and

D_t is the demand in month *t.* As long as the weights are equal to 1, more months can be utilized in the formula, but the industry standard is to utilize three to four months of data to create this forecast.

Equation 2. Simple Moving Average

$$WMA = w_t * D_t + w_{t-1} * D_{t-1} + w_{t-2} * D_{t-2} + w_3 * D_{t-3}$$

Exponential smoothing takes the previous month's forecast and combines it with the actual demand from the previous month to create the new demand, seen in Equation 3. By taking the forecast into account, some randomness is added back into the mix instead of relying solely on what the demand was in the past. This randomness helps to account for some seasonality and consumer preference but is better suited for companies that face less seasonality with their products and more constant demand. Equation 3 has the variable $\propto$ which is the smoothing constant used to weight the demand and the forecast for the previous month. D_1 is equal to the demand for the previous month and F_1 is equal to the forecast for the same month. Comparing the actual demand against the forecasted demand allows the company to utilize continuous revision to check and adjust weights should the need arise.

Equation 3. Exponential Smoothing

$$Exponential\ Smoothing = \propto D_1 + (1 - \propto) F_1$$

In order to identify which method works best for a company in the animal pharmaceutical market, it is necessary to compare forecasting methods via error terms in order to see what method is the most accurate historically and should therefore be used to predict future demand. With more data collected and available for the analysis, it is easier to correct for seasonality and randomness for future forecasts.

Choosing an Appropriate Forecast

Once the forecast has been created, error terms serve as a way to see which method was the closest to the actual demand. There are five commonly used error terms, bias (CFE), mean absolute deviation (MAD), mean squared error (MSE), mean absolute percent error (MAPE), and tracking signal. Before looking at the data, it may seem that just bias, or the difference between the forecast and the actual demand, would be sufficient to judge. However, with deeper analysis utilizing the five error terms, a method different to the method indicated by bias could show as the most accurate forecast. Only utilizing one piece of data when there are more resources available creates a forecast that is not performing to its highest potential (Langley et al., 2020). Because error terms utilize actual demand in comparison to the forecast, they need to be calculated after the actual demand is known. When deciding on a forecasting method, it is important to use historical data and create "forecasts" to be able to measure against what demand was in reality. Increasing the amount of data that is utilized in creating forecasts lends itself to omitting randomness and variability that can negatively impact the accuracy of a forecast. With more data, there is more points to average, and the outliers are normalized.

In May 2018, Company Z modified the data tracking process in order to prepare for better analytics and visibility into the company. Prior to this research, no forecasting method was being utilized meaning they were going into the months with very limited visibility into what they would be moving through DCs which causes many problems including, but not limited to, labor and transportation schedules (both inbound and outbound). Being able to visualize an estimate of what will be moving out of the distribution center will allow Company Z to be more prepared and not run into labor shortages or excessive scheduled labor. While Company Z estimated demand based on the previous year's data, the seasonality and fluctuations in buying cycles, as well as increase in demand from consumers, cause too much uncertainty to be able to forecast accurately enough to schedule workers and truckload shipments.

Chapter 3

Methodology & Analysis

The key to creating the forecast is ensuring that the correct data has been collected and analyzed. After a series of discussions with the subject matter expert (SME) for Company Z's data, it was determined that each line should be counted as one unit and by aggregating all lines, the total demand for the month can be determined. The data that was used for this project was in excel files, separated by month. After aggregating the data by months, the sub-category of warehouse is needed to have more visibility at each warehouse.

Because warehouses are dynamic and new ones can open rapidly while others can close quickly, it is important to determine if the warehouse will be useful or not prior to using it as a base. For example, if a warehouse is showing that it has zero lines of data for multiple months and suddenly jumps to having 100+ lines of data, it should be temporarily removed from the data set to avoid miscalculations from the zero months. It is also good to note that not all warehouses will receive the same volume, even while across the network seasonal trends can be seen. It is also important to note that a large reason for the high variability between warehouses is due to the locations of these warehouses and the different markets they serve. The centralized warehouses are likely to see exponentially higher levels of volume because they are not only used for customer orders but also utilized to fill orders for other warehouses. To test the forecast model, a central DC was used.

Figure 1. Aggregated Data *warehouse names have been removed to protect anonymity

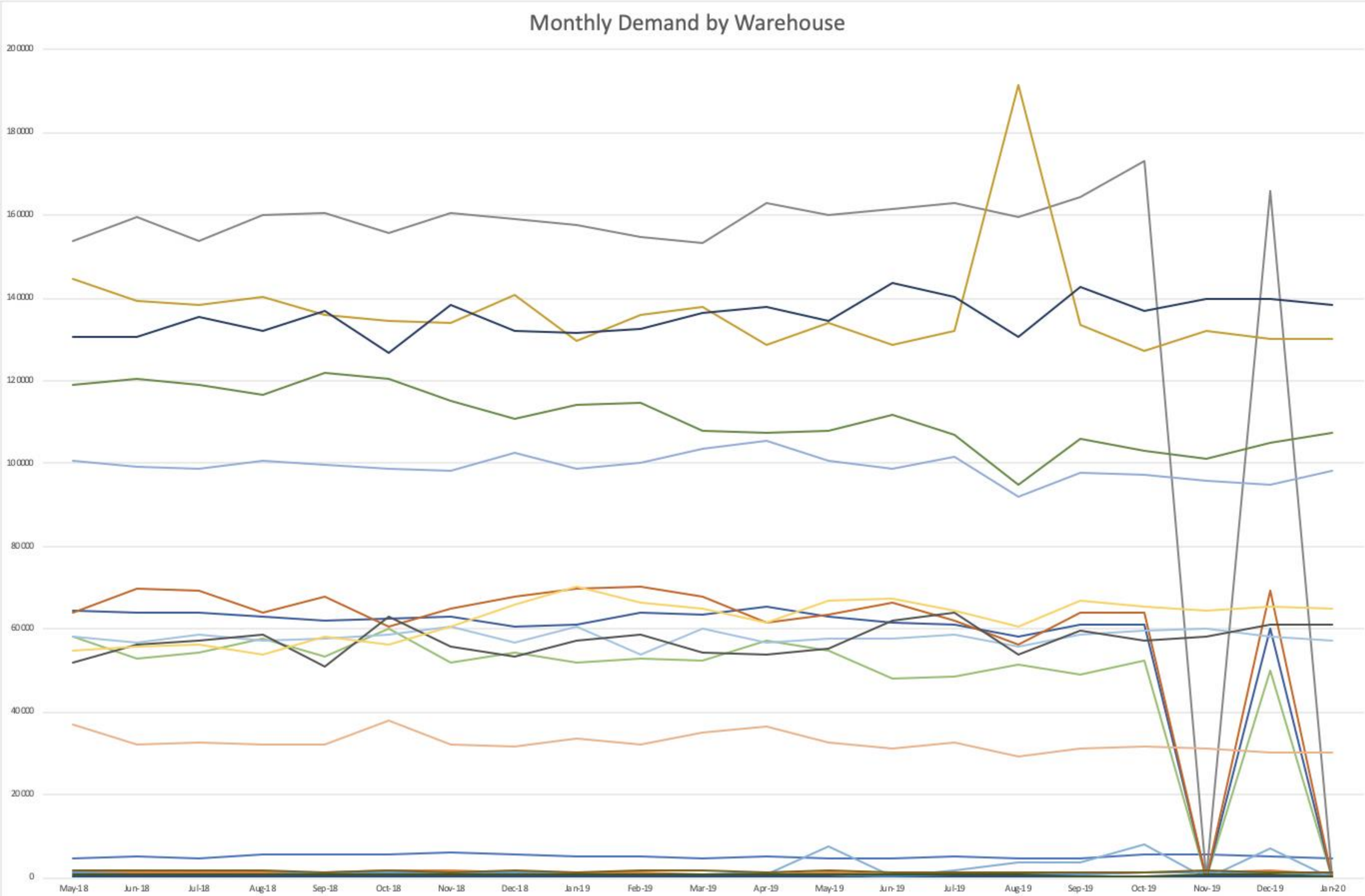
May-18	Jun-18	Jul-18	Aug-18	Sep-18	Oct-18	Nov-18	Dec-18	Jan-19	Feb-19	Mar-19	Apr-19	May-19	Jun-19	Jul-19	Aug-19	Sep-19	Oct-19	Nov-19	Dec-19	Jan-20
4689	5044	4872	5728	5521	5679	6032	5810	4977	5123	4621	5136	4571	4735	5425	4501	4778	5465	5811	5370	4807
1284	1569	1211	1539	1239	1738	1590	1499	1576	1179	935	1024	1105	776	1035	1158	817	1102	1424	1682	1076
199	223	269	292	196	315	251	316	313	263	241	285	230	194	369	317	247	398	267	353	243
47	27	46	77	34	61	55	62	64	69	26	42	60	36	39	38	23	62	50	20	48
1182	867	937	1029	1172	1172	1524	1328	981	1091	905	1356	132	765	912	742	922	1246	1309	1102	948
24	15	22	21	26	30	30	21	17	10	5	12	9	11	7	14	20	19	24	20	21
155	142	156	134	153	218	181	193	163	109	128	158	111	103	80	138	98	170	164	128	93
37	18	13	18	11	45	27	25	35	13	26	20	24	12	19	5	15	12	20	32	5
47	82	9	11	102	77	43	72	85	18	20	24	45	57	98	45	10	45	26	0	12
0	0	0	0	0	0	0	0	0	0	0	1077	7579	500	1959	3888	3840	8281	0	7063	0
58231	53113	54368	57584	53310	60237	51979	54414	52012	52941	52700	57485	54906	48085	48398	51305	49175	52370	0	50108	0
64468	64216	63966	63146	61999	62782	63237	60477	61392	64247	63581	65710	62940	61680	61283	58441	60930	61206	0	60414	0
63975	69684	69488	64173	68074	60662	64965	68104	69958	70269	68023	61508	63416	66266	61879	56334	64145	63899	0	69329	0
153754	159461	153811	160081	160561	155852	160662	159263	157467	154680	153433	162747	160056	161535	162774	159656	164383	172974	0	165754	0
144649	139060	138177	140340	136010	134595	134203	140826	129783	135888	138011	128906	133816	128549	132060	191385	133514	127136	132076	130111	130302
0	0	0	0	0	0	0	0	87	255	203	296	309	241	230	304	194	323	143	102	97
118824	120399	118967	116441	121774	120722	115060	110711	114437	114831	107902	107589	108171	111923	106971	94925	105910	103034	101327	104813	107275
100861	99482	98861	100703	99615	98551	98531	102472	98880	100333	103589	105408	100708	98572	101834	91908	97710	97256	96052	94913	98197
37150	32089	32545	32189	32237	37869	32091	31499	33790	32302	35329	36466	32900	31369	32868	29512	31016	31957	31373	30069	30173
0	0	0	6	0	0	8	8	0	0	0	0	0	0	0	1	0	0	0	0	0
7	8	13	33	0	22	38	24	15	41	24	53	4	98	2	3	22	32	76	52	21
58058	56883	58766	57314	57771	58748	60654	56699	60661	53904	60402	57032	57762	57648	58843	55688	58735	59781	59992	58105	57469
295	183	147	137	161	151	135	141	150	148	111	138	137	69	123	141	91	100	136	99	91
130470	130843	135409	131848	136871	126665	138111	132288	131454	132375	136246	137798	134404	143404	140075	130578	142600	136664	139778	139762	138492
5	2	19	13	8	0	6	13	7	5	11	5	0	7	5	16	0	29	0	27	0
51985	56371	57420	58899	50890	63008	55683	53309	57202	58600	54369	54074	55450	62233	63950	53949	59931	57370	58058	61187	61174
1803	1678	1710	1615	1435	1742	1531	1802	1513	2011	1596	1357	1672	1518	1502	1567	1337	1129	1623	1561	1441
497	478	429	505	498	470	550	462	493	484	409	492	435	309	473	508	384	441	392	409	366
805	884	673	782	737	723	738	665	688	767	727	650	680	620	618	662	480	605	616	619	547
0	0	74	84	0	0	0	66	92	0	75	0	78	2	0	81	81	0	100	0	74
7	6	3	5	3	4	4	5	1	0	5	0	3	6	5	4	0	1	2	5	7
3	7	3	6	1	4	3	6	8	5	4	0	3	5	2	2	2	2	7	3	4
55050	55726	56167	53795	58149	56413	60627	65962	70250	66595	64902	61713	66849	67231	64720	60742	67155	65452	64397	65312	65246
10	7	12	19	16	17	19	20	20	15	11	13	9	12	9	16	9	12	12	13	9

In Figure 1, above, each line represents the volume seen at each warehouse in Company Z's supply chain. At the time of this project Company Z was able to provide data for the previous eighteen months due to the changing of systems that occurred in May 2018. While forecasts were able to be modeled utilizing this quantity of data, yearly trends are not able to be seen as clearly as they would be with five plus years of data. That being said, Figure 2, seen below, shows that the warehouses, while seeing independent levels of demand, stay relatively constant throughout the course of the year.

The November 2019 data creates an outlier for the majority of the warehouses which is why analyzing the data prior to entering it into the forecasting tool is so important. Monitoring to ensure that these data points do not negatively impact the accuracy of the forecast is a key step in having an accurate forecast. It is also a check point to ensure that data is being loaded in the correct format and the forecast does not fall to human error. In many cases, these outliers can be explained by normal operations, such as a routine warehouse closure, supply rerouting or a warehouse upgrade. For these reasons, it is beneficial to have someone familiar with the business reviewing the data and ensuring its integrity. In this case, it was an example of human error and information entered incorrectly. While this is an example of a simple fix on the data sheet, it could result in an inaccurate forecast for this month. This one month of inaccurate forecasting creates many more months of inaccurate forecasts due to the interconnectivity of the forecasts and using forecasts versus the actual demand to create the error terms.

Some warehouses, depending on location, have the potential to be significantly busier than others and see a higher volume. Because of this volume fluctuation, diving down to the warehouse level is very important to create an accurate forecast. The next part of the analysis was taking the

Figure 2. Demand Across All Warehouses



warehouse data and using it to create the actual forecast. As discussed in Chapter 2, there are a number of different forecasting techniques that are widely accepted and used in industry.

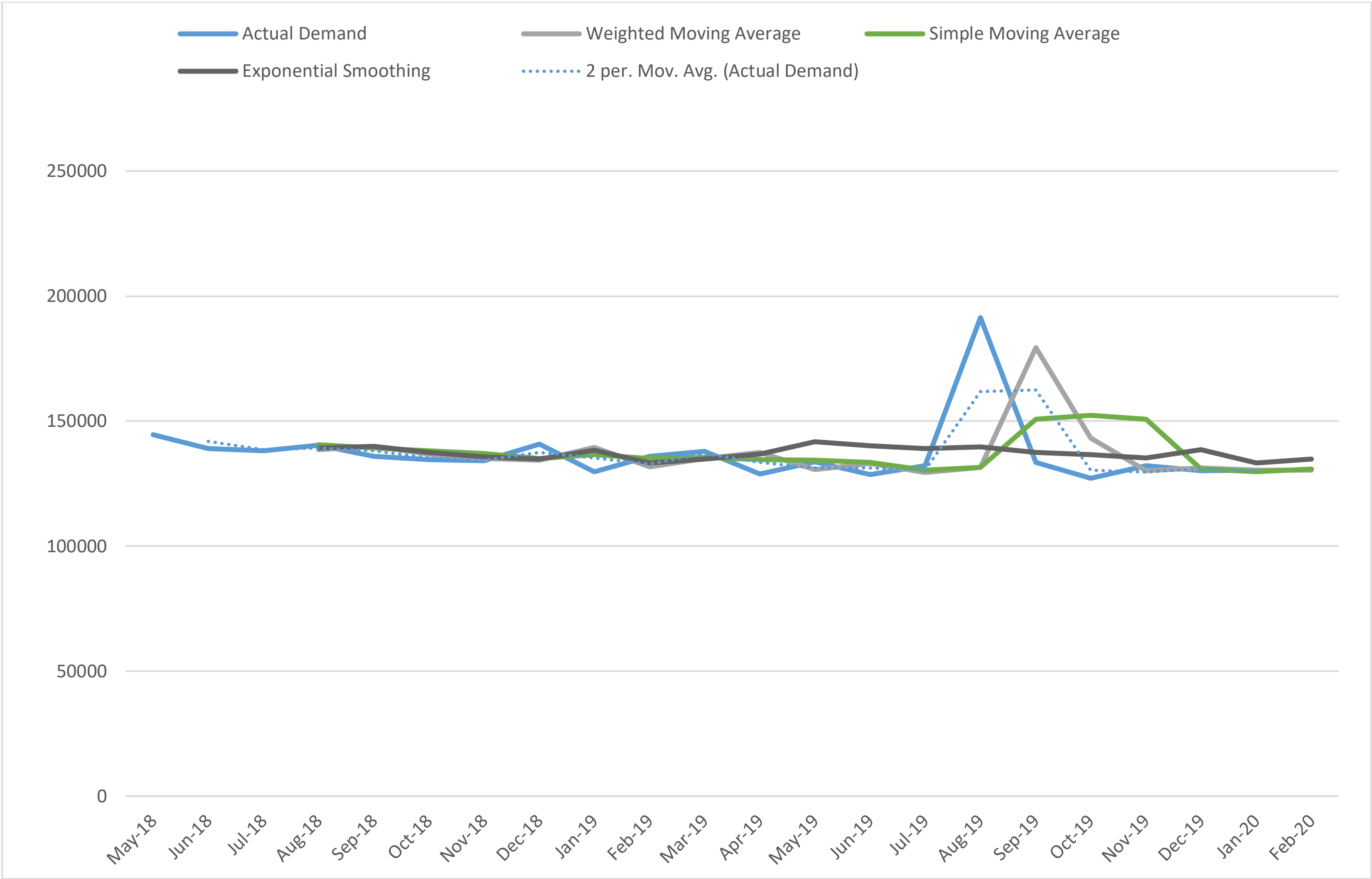
In the calculation tab of the model, each forecast technique is calculated utilizing the forecasts from Chapter 2. Each column utilizes the formulas examined in chapter two to create a forecast and in following columns, error terms that assist in choosing the most accurate formula are calculated. Figure 3 shows the top of the excel sheet where the error terms are calculated in a table and the most accurate method is identified.

Figure 4 is a graphical depiction of the forecast for each method produced. As the dark grey line shows, exponential smoothing stays relatively flat and close to the actual demand. As weighted moving average (light grey) reacts to the demand spike one month late, it creates large inconsistencies between the actual demand and the forecasted demand, throwing the forecasted numbers off for months to come. Simple moving average (green) reacts with less intensity than the weighted moving average but the higher numbers for the surprise month continue to incorrectly increase the forecast for months to come before it returns to following actual demand. If Figure 5 illustrated the following year, 2020, exponential smoothing would see an increased forecast in an attempt to hedge against the demand spike that occurred in 2019 but the weight that is seen in the equation (Equation 3) helps to restrict the spike from being too severe to be useful.

Figure 3. Error Table

	CFE (bias)	MAD	MSE	MAPE	Tracking Signal
Weighted Moving Avg	558.39	9778.39	347480194.7	6.80%	0.057
Simple Moving Avg	1002.17	8938.28	280171483.7	6.42%	0.110
Exponential Smoothing	818	7995.45	184419927.3	5.78%	0.1

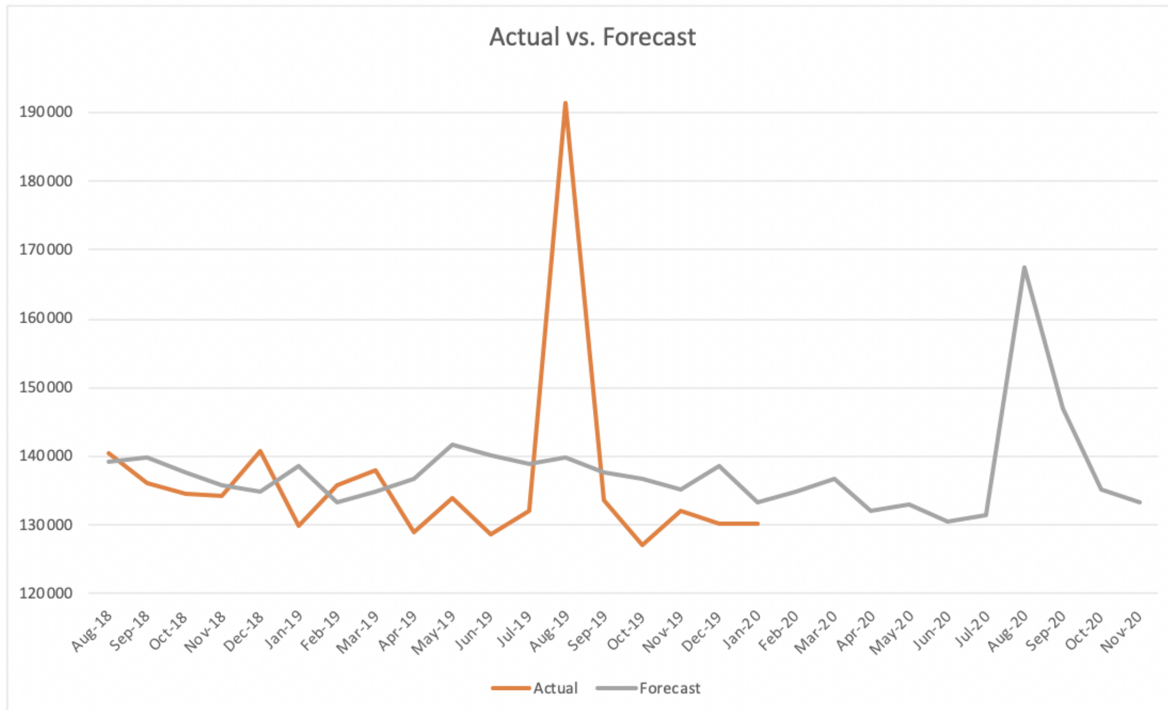
Figure 4. Graphed Forecasts



As seen in Figure 3, for this company, exponential smoothing is the best method as it has three out of five error terms that are closest to zero. Although there is some seasonality seen in the data, the data is relatively stable for the majority of the year which aligns with what was discussed in Chapter 2. Something evident in Figure 3 is how inaccurate each forecasting technique appears. Although the most accurate technique is easily identifiable, Figure 3 does show large discrepancies between the forecast and the actual demand. The alternative to creating forecasts is essentially going into each month blind and not utilizing history to attempt to predict at least some randomness. In Figure 5 there is a large spike in demand in August 2019 as depicted by the orange line. Looking at this data set and utilizing it for next year's forecast, an attempt can be made to offset any sudden jumps in demand, such as the one seen in the previous year. While there could be explanations made for why such a large increase in demand was seen, this data gives insight into something that could potentially happen again in the future and helps prepare for it. Additionally, as this database continues to grow, the increase in data that is used in creating the forecasts will help to avoid large spikes by averaging more of historical tendencies. Using the past to predict the future is never going to totally account for the randomness that occurs in the world but it helps to create a baseline to look at so there is at least somewhere to start from instead of starting from the beginning every month.

Figure 5. Projections

Month	Actual	Forecast	Projected Increase
May-18	144649		
Jun-18	139060		
Jul-18	138177		
Aug-18	140340	139158	0%
Sep-18	136010	139868	0%
Oct-18	134595	137554	0%
Nov-18	134203	135779	0%
Dec-18	140826	134834	0%
Jan-19	129783	138430	0%
Feb-19	135888	133242	0%
Mar-19	138011	134830	0%
Apr-19	128906	136739	0%
May-19	133816	141751	0%
Jun-19	128549	140137	0%
Jul-19	132060	138961	0%
Aug-19	191385	139789	0%
Sep-19	133514	137522	0%
Oct-19	127136	136615	0%
Nov-19	132076	135168	0%
Dec-19	130111	138563	0%
Jan-20	130302	133295	0%
Feb-20	0	134851	0%
Mar-20	0	136747	0%
Apr-20	0	132043	0%
May-20	0	133107	0%



As the data continues to evolve, the continued evaluation of the forecasts allows for growth and higher accuracy for future months. In order to fully utilize this tool and analysis, the data needs to be updated monthly as new information is gathered. Adding actual values will benefit accuracy by determining if the forecast is correctly predicting what the demand will be. Company Z will continue to monitor the forecasting tool to determine if the method of exponential smoothing remains the same as new data continues to be logged. If with more data a different method achieves a more accurate forecast, the forecast can be reevaluated and changed to this method if need be. The most accurate forecast is then pulled to a different sheet in the file. This sheet allows the user to adjust for any projected increases or decreases that marketing and sales is projecting. It also graphs the actual demand versus the forecasted demand which allows the user to visually identify how accurate the forecast has been historically and the trend of where demand is projected to go in the future.

Chapter 4

Conclusion & Recommendations

The forecast model hinges on inputting correct data and ensuring that outliers are removed, as is the case with most data models. The correct data input leads to an analysis that builds upon itself. Having more data to include in the forecast will help better predict for the future which also means that the preferred forecasting method is subject to change. Because the data is relatively easy to clean and shape into the format the tool requires, utilizing Excel for the analysis leaves it in a simple state that can be constantly updated to reflect the best information.

The Methodology section describes the steps taken to create the forecast and how to continue to update the data set. As proven by this analysis, exponential smoothing is the best method to account for constant demand with light adjustments to seasonality. This company, prominent in the animal pharmaceutical industry, has constant demand that is impacted minimally, yet still impacted, by the seasonality of some of their products.

A limitation to this research is the limited amount of data that was able to be obtained. As mentioned before, the more data there is, the more accurate a forecast will be as outliers are normalized and patterns occur. The recommendation that has been made to Company Z is to utilize the model that has been built with the data and continue to update this model month by month. When five years of data has been collected, it is suggested that Company Z recreates the forecast and a trendline is added to forecast and normalize all of the data. Until more data is able to be collected and stored, Company Z will utilize this forecast model, updating the data month by month and identifying what forecast to follow and plan for at their facilities.

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- Trained 15 contract managers and category specialists to use dashboard

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- Condensed shipping procedure documentation by 33% via optimization of documents
- Utilized PowerBI to create reports used in daily and quarterly reviews of budget center expenses

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Teaching Assistant, Intro to Supply Chain for Non-Business Majors - Prof. Frank Chelko January 2020 - Present
Lead Mentor, Sapphire Leadership Academic Program August 2016 - Present
Inventory Coordinator April 2019 - Present
Penn State THON Supply Logistics Committee

- Managed 4 Inventory Liaison Captains in administration and allocation of THON's inventory of 125,000+ items
- Built on previous experience as a THON captain to create more efficient processes to manage and track THON's inventory

Inventory Liaison Captain September 2018 - February 2019
Penn State THON Supply Logistics Committee

- Managed THON's inventory system of 125,000+ items**;** allocated inventory between 16 different committees for 50+ events throughout the year
- Collaborated with 11 donor contacts to ensure maximum amount of funds were directed towards Four Diamonds as opposed to buying inventory and supplies

Security Leader/Education Liaison, Penn State THON September 2016 - February 2018

Spanish Experience

Penn State International Student, Sevilla, Spain June 2017 - August 2017
Rotary International Exchange Student, Coronel Oviedo, Paraguay August 2015 - June 2016

- Fulfilled all course requirements in Spanish
- Lived with host families to maximize opportunities of learning new cultures

Skills

Advanced knowledge of PowerBI; Expert level of Microsoft Excel; Fluent in Spanish