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Forecasting Demand for an Overseas Beverage Company

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Abstract: This study analyzes an alcohol beverage company based in Scotland that holds approximately 3% of the $2.3 billion whiskey industry in the United Kingdom. In addition to expected growth in the U.K., the alcohol industry in the U.S. is continuing to thrive, with a current market share of 1.65% of the economy (Abladmin, 2018). Because of this, the alcohol beverage company expanded their portfolio to the United States in 2016 (Eads, 2015). However, supply chain leaders in the organization have struggled to design forecasts that accurately predict the sales of two U.S.-sold products. This report presents forecasting models for the two products, with the intent to improve the company's ability to forecast demand and streamline operations along the robust supply chain from Scotland to the U.S. Based on results, the company should utilize a three-quarter moving average model for Bourbon and quarterly models for Scotch to best improve their current forecasting techniques.

Keywords: Forecasting, Seasonality, Bullwhip Effect, Supply Chain

1. Background

1.1 Introduction

The alcohol industry is complex with the dynamic aspects of production, wholesaling, and distribution. The company under research is an alcohol beverage company headquartered in Scotland holding approximately 3% of the United Kingdom's $2.3 billion whiskey industry. As of 2016, the company expanded their portfolio to the United States with hopes to recognize revenue growth from the alcohol industry's 1.65% market share in the U.S. economy. However, two of their products, Scotch and Bourbon, are new to the 2016 portfolio and the supply chain leaders have struggled to design forecasts that accurately represent the sales of these two products. The company's global supply chain manager seeks to improve the current forecasting techniques that have an average accuracy of 2%.

1.2 Problem Identification

The company provided a dataset containing performance data by month from 2016 to 2021 for two product families, Scotch and Bourbon, and their corresponding sub-products which included several stock keeping units (SKUs). Variables within the dataset included volume sold, cases sold, net sales, and cost of sales for each product's SKUs. Because these key performance indices (KPIs) are what the company most readily uses, the forecasts generated in this research and referenced in section 2 below make exclusive use of them as inputs into the model. The company liaison noted that the forecast methods currently used by the global supply chain team produced an average accuracy of just 2%. This accuracy is well below the industry standard of 80% (Doe, 2020). According to the global supply chain manager, a current struggle the team is having is high variations in the data which is common in new products. The problem this paper will focus on is improving the forecasting methods to achieve higher accuracy that will enable the global supply team to streamline operations.

1.3 Exploratory Data Analysis of Scotch and Bourbon Products

In the data the company provided, Scotch has 110 different SKUs and Bourbon has 111 different SKUs (Doe, 2020). These SKUs can vary for many reasons, from things as small as different types of labels to significant differences such as age in the cask. With so many different SKUs, predicting demand for all of them was outside the scope of what the company was interested in. Further, producing a singular model that is accurate enough to provide valuable insight for all of the SKUs would have over-simplified the problem. Instead, exploratory analysis was conducted to determine the most impactful SKUs within the two product families, as measured in terms of profit. In finding the most profitable SKUs, historical data was analyzed and cleaned to ensure it provided the depth and reliability required to build mathematically-sound forecasts. This proved to be a challenge as the data was incomplete, necessity some assumptions to be made.

The most impactful SKUs were determined through analysis on each SKUs profit-per-case KPI. The top 10 profit-per-case SKUs were then investigated to determine if enough historical data existed to build a forecast. Many of the key SKUs did not have data outside of 2020 due to Scotch and Bourbon being new brands. This limits the ability to apply more advanced forecasting methods and, based on conversations with the global supply chain manager, it was determined that only three Scotch SKUs and three Bourbon SKUs should be further analyzed, thereby establishing a baseline for the company to build off in the future. With these SKUs selected, the next step was to examine the data to determine if any seasonality or trends existed. Case output versus time series by year was charted to recognize seasonality. Trends were similarly investigated. This analysis resulted in two of the three Bourbon SKUs displaying trends, and four of the six SKUs showing seasonality at the end of the 2nd quarter and again in the 4th quarter.

Additionally, these graphs clearly showed the SKUs exhibited a significant bullwhip effect. This occurs when information flow from the distribution centers to the supply teams lags, resulting in large variances in the data (Lee, 1997). An example of the bullwhip affect for one SKU can be seen in Figure 1 below. The farther away the supply team is from gathering point of sales data, the larger the variance will be (Lee, 1997). Because of the impact of the bullwhip effect, smoothing methods will have to be applied to reduce this variance in the data (Lee, 1997). This is important to recognize early, as various smoothing methods are applicable in these types of supply chain situations, including moving averages.

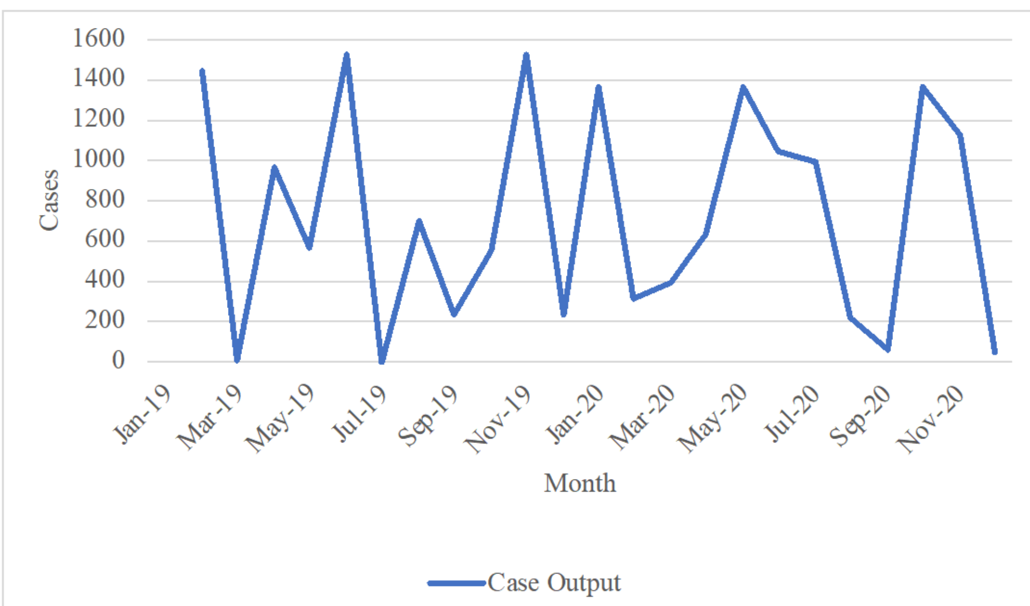

Figure 1: Bullwhip Effect Variations

2. Methodology

2.1 Determining Accuracy and Model Success

Before selecting forecast models for research, it is important to understand the key performance indicator (KPI) the forecasts will be evaluated with. Accuracy for these models is calculated utilizing a formula provided by the alcohol beverage company global supply chain manager (equation 1) (Doe, 2020). The equation utilizes the actual demand for a time period (in this case months) and the forecasted demand.

$$Forecast\ accuracy = 1 - (Abs\ (Actual - Forecast)\ /\ Actual)\ \% \tag{1}$$

When using this KPI, a constraint must be applied to prevent negative accuracies from skewing the data downward. Therefore, in line with common practices, a constraint forcing accuracies to be between 0 and 100% was applied (Chockalingam, 2019). The skewing in the accuracy is heavily derived from actual case values of 0 being in the denominator, leading to negative accuracy values in the thousands. When speaking with the global supply chain manager about why actual case values would be 0, he explained that backlog of inventory at the distribution center from a previous time period's overorder would cause them to not need cases in the next period. Utilizing this constraint, however, requires an assumption to be made that the distribution centers have unlimited carrying capacity (Chockalingam, 2019). The risk of this assumption is that the distribution center may not be able to store the forecasted volume of supply at a specific time of year. While the company accepted this assumption, it is important to note that overhead expenses could increase in the form of higher storage and insurance costs.

Further, it is necessary to acknowledge that many supply chain managers traditionally use different KPIs to measure accuracy in forecasting methods. Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD) are the most common (Winston, 2004). For this research, however, it was determined that using the company's organic accuracy KPI was more appropriate. This enabled the results of the research to be directly compared to the results of the company's current forecasting methods.

2.2 The Forecasting Process

With the method for determining accuracy identified along with the six SKUs and their corresponding trends and seasonality, focus could be turned to researching which forecasting models would be most appropriate. The data provided by the global supply chain manager was limited, with only 20 to 24 months of data available for the key SKUs. Research indicates that with a limited volume of data, naïve forecasting models are most applicable. This is because they use only the most recent data rather than using the many historical data points required of the more advanced forecasting models.

Because of the limited data constraint, the following models were selected for analysis: year prior, three month moving average models, month prior, two-year average, and Holt and Winter's method. Although Holt and Winter's method is commonly classified as an advanced model, it can be used with limited data when a product has seasonality and trends (Winston, 2004). Year prior and two-year average models are utilized when seasonality is present because they capture what happened in a specific time period by using that time periods historical data (Chen, 2003). Month prior and three-month moving averages are utilized when a trend is present because they capture the most recent data (Johnston, 1999).

Before constructing the forecasting models, several additional assumptions are required, the most significant being how to adjudicate situations where historical data was missing. To handle these situations, an average of the prior three months was taken. The associated risk in this assumption is that with the bullwhip effect in the data, the actual value could deviate significantly higher or lower than the calculated average. Because of the implications of this assumption, discussions took place with the global supply chain manager to ensure the missing data points could not be recreated and that, in the worst case, taking the average of the preceding three months was the best possible course of action for the situation.

With the input data solidified, the models previously mentioned were investigated. Initially, the forecasts resulted in accuracies ranging from 5-43%. Further analysis of the data concluded that the bullwhip effect variations were happening on a monthly basis based on how the supply chain was setup, with orders being requested month to month, but that quarters generally had low variation in demand. The models forecasting data by month were ineffective at capturing sporadic variations in the data. When speaking to the global supply chain manager about why one month's case output would be approximately 1,500 cases and the next be 100 cases, he described how the data is based upon the outgoing shipments to distribution warehouses, meaning sometimes they have a full restock and other times they only restock a small fraction of supply. With this knowledge, we transitioned to forecast on a quarterly basis to assist in smoothing the abrupt variations seen from the distribution center resupply request. Mathematically, using quarter methods accounted for three monthly data points rather than one which accurately represented the bulk of the resupply that was happening on a quarterly basis and not a monthly basis. Research backed this transition indicating that forecasting by quarter aides in accounting for seasonality that is not central around one time period (Lee, 1997). The resupply characteristics seen in the data and described by the client could be classified under this eccentric seasonality due to the inventory turnover happening on a quarterly basis.

Transitioning to quarterly forecast further limited the types of models that could be applied to the products since many of the SKUs had a limited amount of data available due to the short lifespan of the product. What was once 24 data points in monthly models reduced to only 8 data points in quarterly models. However, quarterly models proved to be more accurate than monthly methods and accuracies were being produced well above the original forecasting methods used by the alcohol beverage company. This increase in accuracy is attributed to the smoothing effects quarterly methods provide and the identification of seasonality occurring in the quarter rather than the month. It is expected that quarterly methods will increase the accuracy since it spreads the data out, however this level of accuracy in a quarterly forecast will allow the company to transition into quarterly order request to lower their likelihood of under or over producing.

Additionally, the quarterly forecasts alluded to the ability to apply one specific model across all SKUs for Bourbon. This is significant because the alcoholic beverage company has 110 and 111 different SKUs for Scotch and Bourbon respectively. Without being able to apply one model, the resources of time and money become costly. The initial monthly forecast models did not provide this capability.

3. Results and Recommendations

3.1 Bourbon Results and Recommendations

Forecasting the three key Bourbon SKUs resulted in a Naïve three Quarter Moving Average forecast yielding the highest accuracy for two out of the three SKUs and with a Quarterly Year Prior Average model yielding the highest for SKU one. The forecasting accuracy results can be seen in Table 1 below.

Table 1: Bourbon Forecast Accuracy Results

Bourbon SKU Name	Forecast Method	Accuracy
Key SKU 1	**Quarterly Year Prior**	**57%**
	2 Year Average	57%
	3 Month Moving Average	43%
	3 Quarter Moving Average	38%
	Monthly Year Prior	27%
Key SKU 2	**3 Quarter Moving Average**	**62%**
	Quarter Prior	50%
	Month Prior	39%
	Holt and Winters	34%
	3 Month Moving Average	31%
Key SKU 3	**3 Quarter Moving Average**	**67%**
	Month Prior	41%
	3 Month Moving Average	33%
	Monthly Year Prior	29%
	Quarter Prior	27%
	Quarterly Year Prior	15%

With the results in Table 1, it is recommended that the alcohol beverage company's global supply chain team utilize a three Quarter Moving Average model across all Bourbon SKUs as their primary forecasting method. This recommendation is drawn through the analysis of three Quarter Moving Average models being the most accurate method in two out of the three key SKUs. Although it was not the dominate model for SKU one, it did produce a 38% accuracy for that SKU. The three Quarter Moving Average proved to effectively smoothen the variance seen in data and accurately predict demand with seasonality in the quarters accounted for. As an example, the smoothing effect can be seen for SKU three in Figure 2 below, showing the actual case output in comparison to the forecasted case output. This allows the company to produce and distribute their products at a steady rate to limit their potential of underproducing or overcompensating. The company, utilizing this model, can transition to fulfilling orders accurately on a quarterly basis.

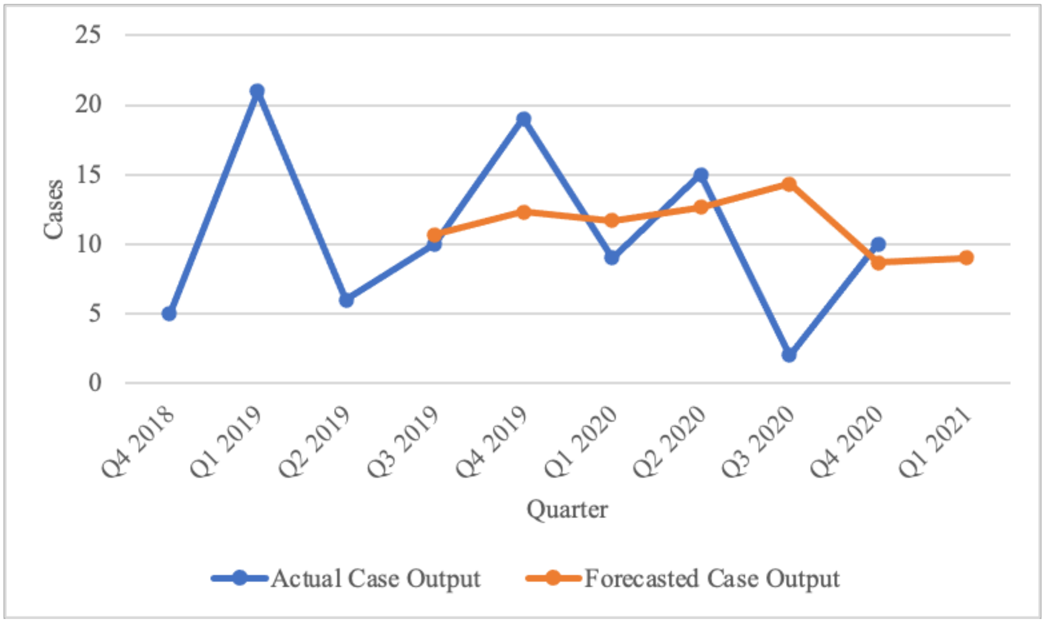

Figure 2: Key SKU three Naïve three Quarter Moving Average Forecast with 67% Accuracy

3.2 Scotch Results and Recommendations

Forecasting the three key Scotch SKUs resulted in no single model being applicable across all SKUs. Forecasting using quarterly methods did yield the highest accuracy in two out of the three key SKUs. The forecast accuracy results can be seen in Table 2 below.

Table 2: Scotch Forecast Accuracy Results

Scotch SKU Name	Forecast Method	Accuracy
Key SKU 1	**Month Prior**	**39%**
	3 Month Moving Average	29%
	Monthly Year Prior	17%
Key SKU 2	**Quarter Prior**	**47%**
	Month Prior	40%
	Quarterly Year Prior	25%
	Monthly Year Prior	20%
	Monthly 2 Year Average	5%
Key SKU 3	**Quarterly Year Prior**	**88%**
	Quarter Prior	41%
	3 Month Moving Average	38%
	Month Prior	27%
	Holt and Winters	25%
	Monthly Year Prior	23%

With the results in Table 2, it is recommended that the alcohol beverage company's global supply chain team utilize quarterly methods across all SKUs. This recommendation is drawn through the analysis of two out of the three SKUs validating quarterly methods as the best method in terms of accuracy. With the Scotch product, there was no particular quarterly model that dominated others. Additionally, the Quarterly Naïve Year Prior model only had three data points, thereby making it prone

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to being easily skewed. Although the analysis does not result in a blanketing model to prevent additional use of time and money, it does result in a recommendation of quarterly methods that accurately predict demand with seasonality in the quarters currently represented. This allows the company to proceed with a solution of higher accuracy in forecasting to streamline operations. Figure 3 shows how the Quarterly Naïve Year Prior model effectively smoothens variations and accounts for the seasonality seen in quarter two of 2019 to predict quarter 2 in 2020 to maximize accuracy.

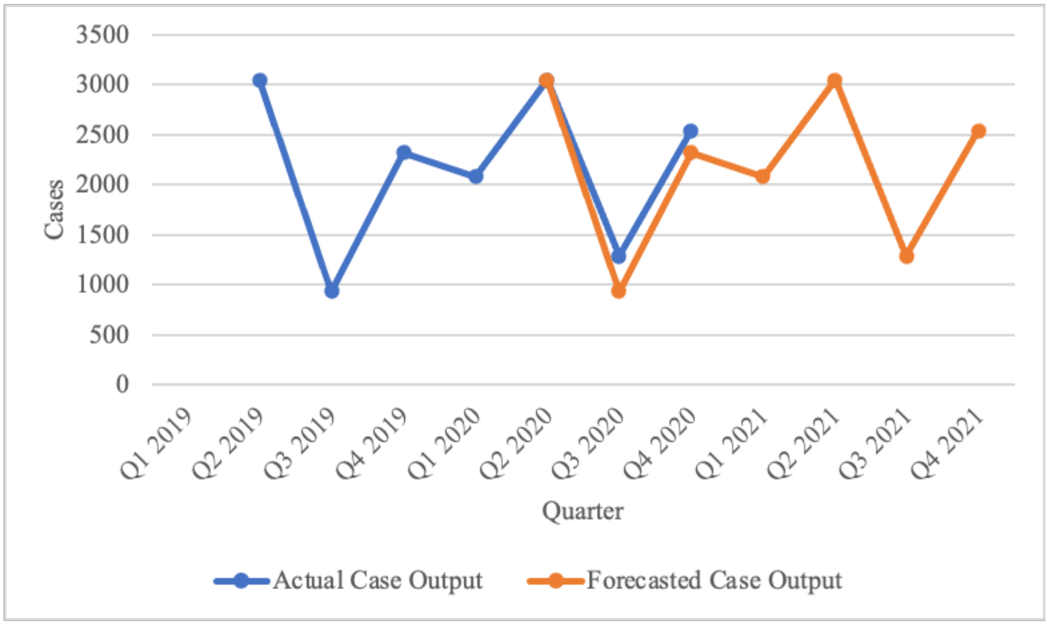

Figure 3: Key SKU 3 Quarterly Naïve Year Prior Forecast with 88% Accuracy

4. Conclusions

The alcohol beverage company sought to improve their forecast accuracies to be more efficient and render higher profits by minimizing over or under production. This report presents the company with forecasting methods that increase their ability to forecast demand utilizing naïve models in a quarterly manner. Utilizing the forecasting methods in this report provides the company the capability to transition to fulfilling orders to the distribution center accurately on a quarterly basis. It also provides the capability to apply one model for all Bourbon SKU's which increases efficiency in production operations by reducing resources needed to generate demand predictions.

With limited data, the alcoholic beverage company must utilize naïve forecasting methods. It is important that the alcoholic beverage company forecasts in a quarterly manner due to the structure of the resupply requests being sporadic within the quarters. Research shows that forecasting in the quarter accurately represents eccentric seasonality which is shown in both the Scotch and Bourbon SKUs. A significant takeaway for Bourbon SKUs is that three Quarter Moving Average models performs best overall and should be applied across all Bourbon SKUs. A significant takeaway for Scotch SKUs is quarterly methods prove best overall, however, quarterly methods will have to be applied at an individual level for each Scotch SKU.

By utilizing the logic and methods provided in this report, the alcoholic beverage company can capitalize on accurate forecasting to improve their supply chain. The ability to represent demand accurately allows the company to minimize losses from opportunity cost derived from miscalculations in production.

5. Future Work

Beyond the forecasting conducted in this paper, three key areas for future work include revalidating these models once more data is provided, gathering point of sales data from the distribution centers, and determining a maximum production capacity that each distribution center can allow. These three areas of study will aid in managing the supply chain at the alcohol beverage company and are essential moving forward.

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Currently, the data available for each product SKU is limited. This hindered the ability to investigate more advanced models and apply one model to all Scotch SKUs. With more data, the company can revalidate the models presented and scale specific models to all SKUs. By doing so, they can efficiently manage production with little cost in resources. Additionally, revalidating the models will allow them to possibly generate higher accuracies as these new products age more and become more gravitated to patterned demand levels with less variation. This will further limit over or under production and increase efficiency in storage of inventory at the distribution center.

The lack of information flow from the distribution center to the supply team is hindering the ability to forecast with consistency. The distribution center currently only provides data based on their demand rather than the retail point of sale demand. This is causing a larger observed variance in the demand data as it strays further away from the point of sale, known as the bullwhip effect (Lee, 1997). It is recommended that the alcohol beverage company gather data from the distribution center on the point of sale demand in stores that they are observing. The more data the alcohol beverage company can collect from the point of sale, the more accurate their data will be, thereby rendering more accurate forecasts and the ability to use more advanced forecasting methods.

When forecasting utilizing quarterly methods, it is imperative to know a maximum capacity the distribution centers can hold. A quarter's worth of supply will have to be stored at the front end of every quarter. It is important that the alcohol beverage company know what levels of volume the distribution centers can hold to ensure they do not overload the distribution centers. If quarterly methods cannot feasibly be used due to this storage capacity, monthly methods will have to be used independently for each SKU as no monthly method was dominant in either product.

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