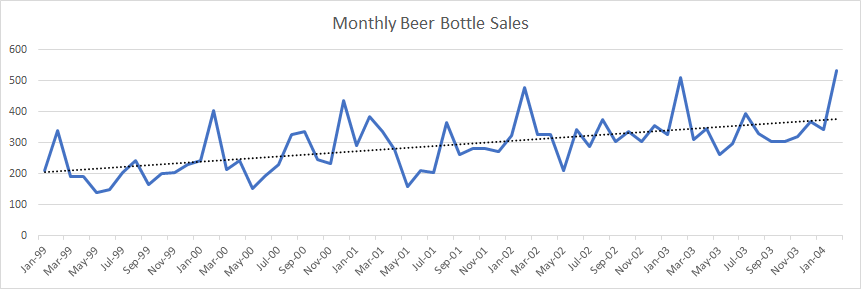
# **Executive Summary**

In our project, we conducted a thorough analysis for the demand of beer bottles at Titanium Brewery, located in the southern Caribbean Island of Trinidad. To suffice our forecasting values, we collected the monthly historical data from January 1999 to February 2004 (in thousands of cases). Then, we have utilized the application “Forecast Pro” to get actionable insights for any possible trend, seasonal, or cyclical patterns.

Per requirement, we withheld 9 months of data, from June 2003 – Feb 2004, and performed the Exponential Smoothing method to produce a forecast. From our analysis, we have narrowed down some possible forecasting methods, and then we ranked each method based on their fit and accuracy measures. By observing MAPE for all the methods, a measure of predicting accuracy of a forecasting method, the Custom Exponential Smoothing method with no trend and an additive seasonality has the lowest value of 8.01%. Hence, the Custom Exponential Smoothing method with no trend and an additive seasonality appeared to be the most accurate and fits the data correctly. As the purchasing managers at Banged-Tail Bikes, **we recommend ……………………………………………….……………………………………………………………………………………………………………………………** The following report demonstrates our analysis in a detailed manner, explaining each step of our study and how we reached our conclusion.



# **Objective**

The forecasting problem for the Titanium Brewery is that the covered storage space for empty bottles is tight and a bottle design change is expected in 2005 and 2006. So, they want to forecast the number of beer bottles to order in the year 2004 which would accommodate the year’s supply comfortably along with minimizing the year end inventories. Both under-forecasting and over-forecasting are going to be expensive situations hence, careful forecast is needed as a strong base before placing the order of beer bottles. The cost of under production and losing sales is much higher than the cost of over stock. If sales exceed, Titanium Brewery must expand their storage space. They must also consider by how much the quarterly sales exceed, for how many quarters the sales will exceed, and finally whether exceeding the sales in a year will be a short-term situation or if it will be a permanent state. They should also record if sales increase in a particular season. For instance, generally beer sales are more in summer than in winter except during carnivals. These decisions could be taken after proper forecasting of Titanium brewery business.

***Below is a graphical framework that illustrates how our decision making is related to forecasting.***

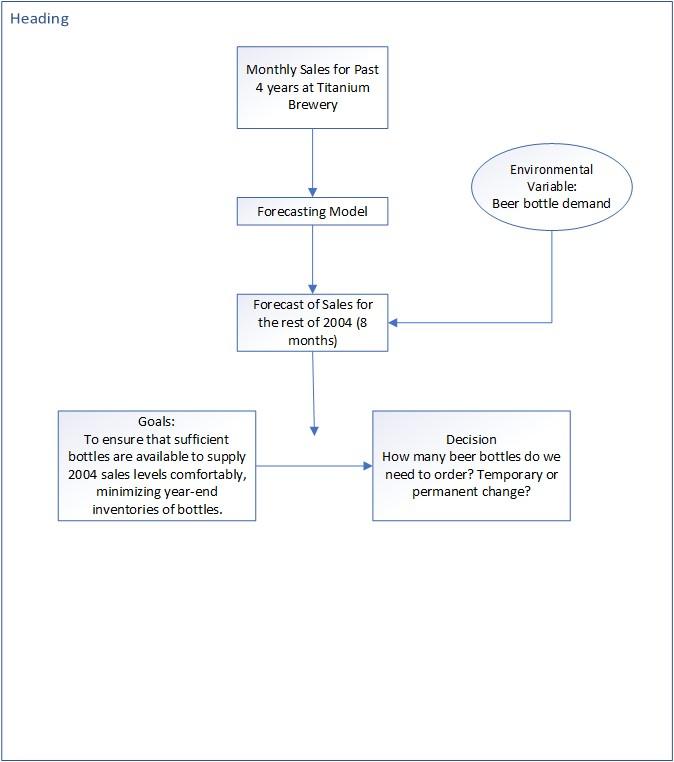


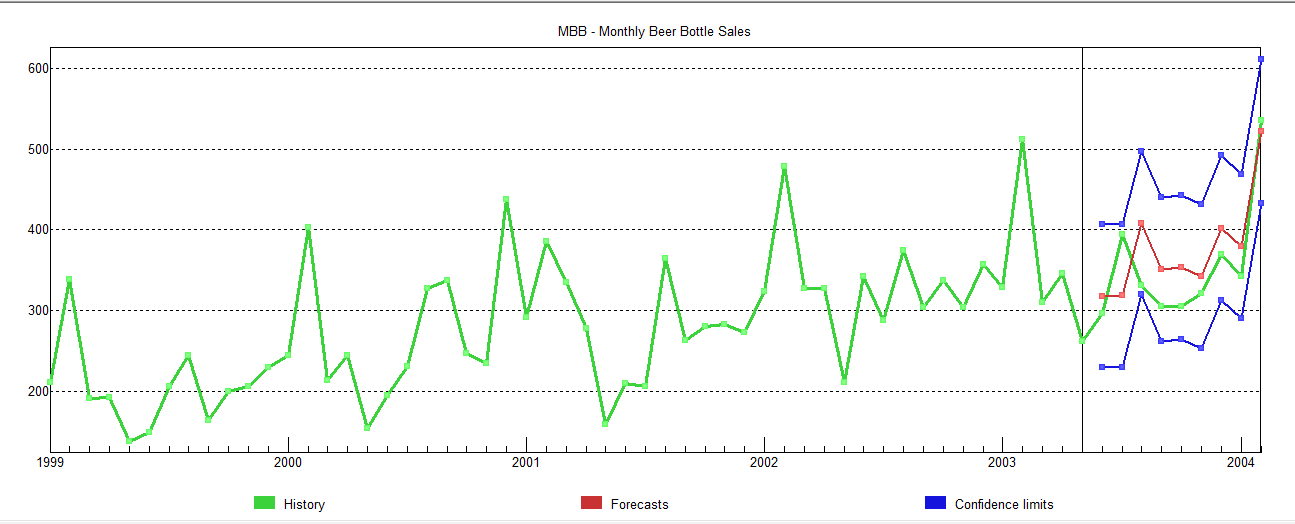
Figure : Relation between forecasts and decision

# **Data Patterns**

Before identifying the number of bottles, we wanted to determine the patterns within our data such as seasonality, trend, stationarity, or irregularity. This would help us come up with better decision and recommendations.

If we visualize the below time series, we observe that our data has no trend since there is no long term peak or depression within the series. Now, the rises and fall are not of fixed period. As a result, we can also infer that the series is cyclic. There is an increase in every February which is clear from consistent peaks during February repeated annually. Hence, the pattern of our time series also has seasonality, in fact, additive seasonality. We can say this from the seasonal variations which are independent of the level.

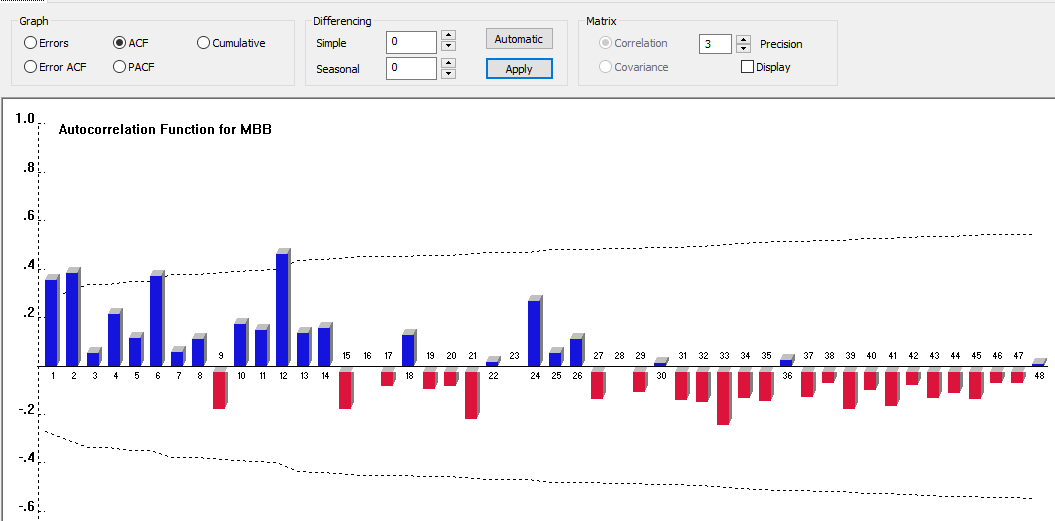
The time series lacks stationarity since mean and variance are not constant over time.



**Determining Patterns in time series using Autocorrelation Analysis**

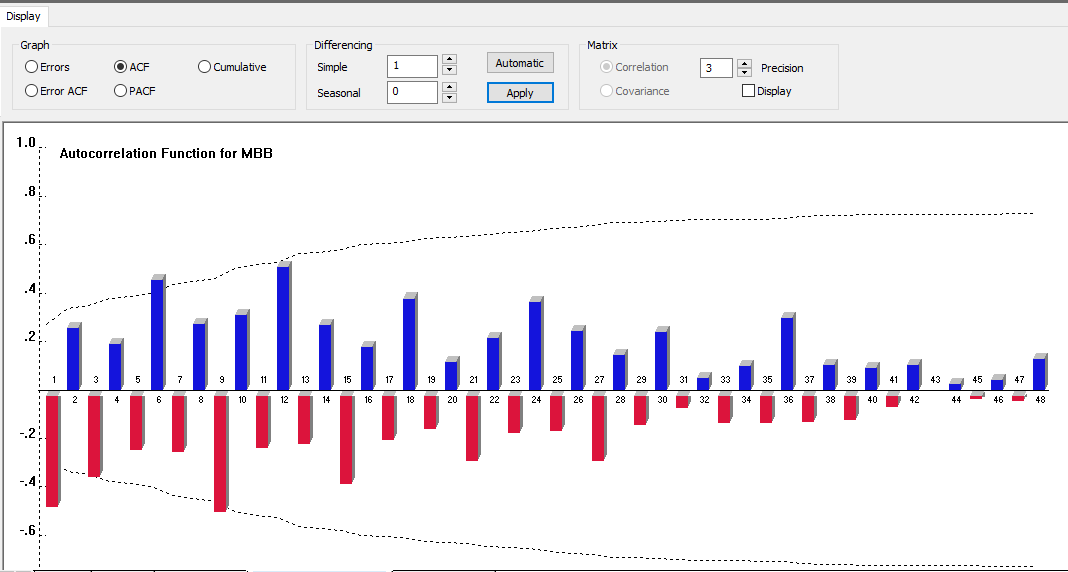
We performed autocorrelation to confirm on the above data patterns which we observed via visualizing the time series. We modified ‘Simple Differencing’ and ‘Seasonal differencing’ to determine the patterns in the data.

* **Patterns observed when no differencing was applied**



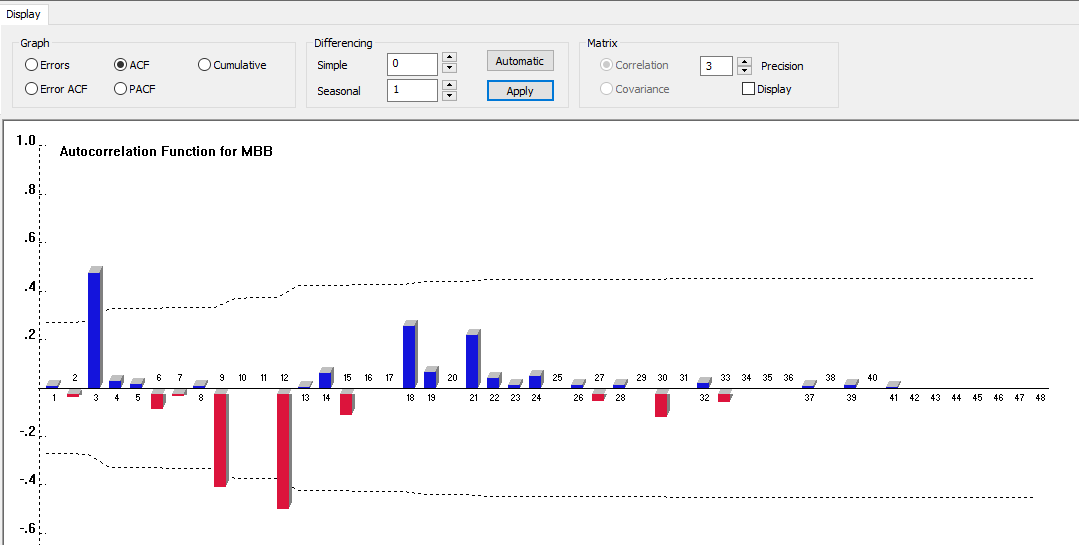
From the figure above, we observe that the autocorrelation function gradually drops to 0. As a result, we can infer that the time series is non-stationary. Also, there is no trend within the series since there is no long term increase or decrease in data.

* **Patterns observed when first order simple differencing was applied**



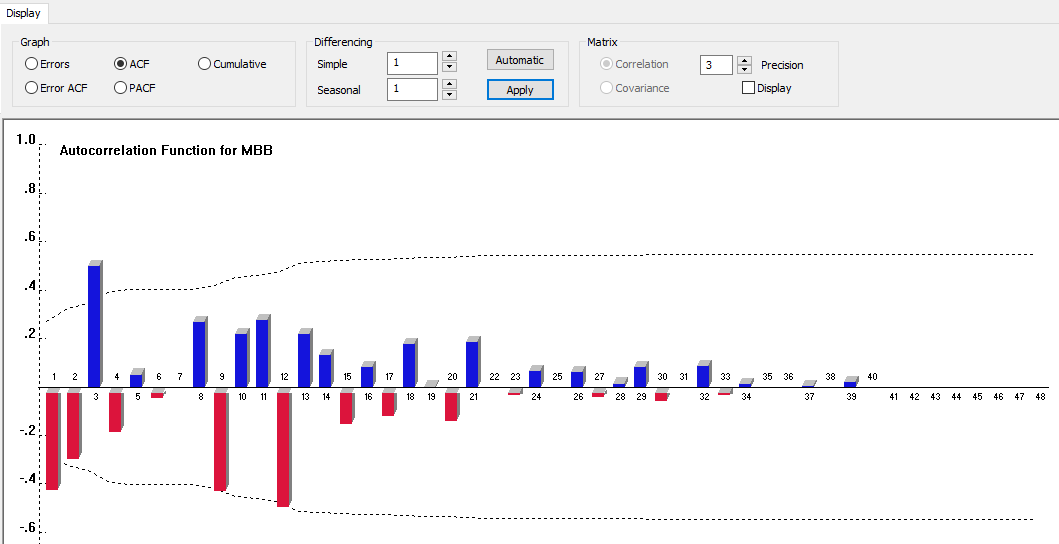
The figure shows that the series has seasonality which can be observed by increase of sales every February and also by a significant autocorrelation coefficient occurring in lags of 12 months.

* **Patterns observed when first order seasonal differencing was applied**



We see that the peak and depressions are not repeated after fixed periods. Therefore, the pattern within the series is cyclic.

* **Patterns observed when both first order seasonal and simple differencing were applied**



Non-stationary data should be converted to stationary so that further statistical analysis can be done. So, we applied both first order Simple and Seasonal differencing in order to make the series stationary. We can observe that the series is moving towards stationarity with constant mean and variance. Moreover, the autocorrelation above immediately drops to 0 which happens when the series is stationary.

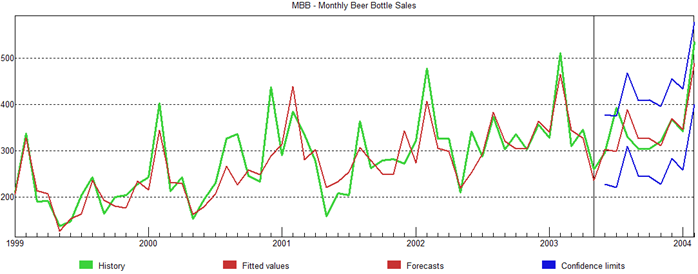
# **Model Selection**

Per the requirement, we can use only the methods from the class of exponential smoothing models. The below table lists all the methods (including all custom smoothing methods). There are total 8 methods that we are considering. **(add a line retaining to no seasonality in relation to time series).** From the data pattern analysis, explained further in the report, we acknowledged that the data shows an additive seasonality and implies no trend whatsoever. In light of this, a Custom Exponential Smoothing with a no trend and an additive seasonality should perform the best. Also, the time series does indicate a possible cyclical pattern.

Exhibit Number summarizes the calculated MAPE values comparing holdout forecasts (9 months) with actual data for the 8 methods that we are considering.

|  |  |  |
| --- | --- | --- |
| **Type of Exponential Smoothing** | **Method** | **MAPE** |
| Custom Exponential Smoothing | No Trend /Additive Seasonality | 8.01% |
| Custom Exponential Smoothing | No Trend /Multiplicative Seasonality | 8.03% |
| Custom Exponential Smoothing | Linear Trend / Additive Seasonality | 12.16% |
| Winters Exponential Smoothing | Linear Trend / Multiplicative Seasonality | 12.46% |
| Custom Exponential Smoothing | Damped Trend / Additive Seasonality | 9.76% |
| Custom Exponential Smoothing | Damped Trend / Multiplicative Seasonality | 12.35% |
| Custom Exponential Smoothing | Exponential Trend /Additive Seasonality | 12.16% |
| Custom Exponential Smoothing | Exponential Trend /Multiplicative Seasonality | 8.47% |

The MAPE indicates the prediction accuracy of a forecasting method in statistics, for example in estimation of the best model. Thus, from the above chart we can see that custom exponential smoothing with no trend and an additive seasonality produced a considerably low MAPE value*. Its MAPE is 8.01%, this means that the mean absolute error for the 9 months forecasted was 8.01% of the actual beer sales data.*



The (the above image number) time series is for the custom exponential smoothing with no trend and an additive seasonality. We can see from the time series that the fitted value (red line) is a good fit for our history data (green line).

**###################################**

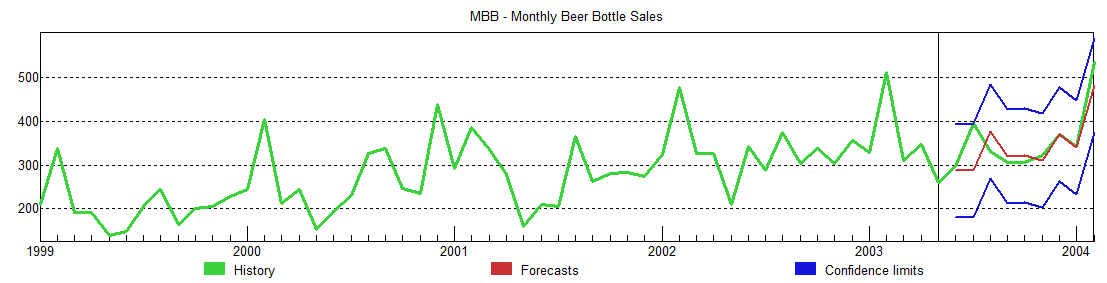
The above is Sanchit’s Model selection and as per the professor.

Also, in the above explanation we are missing the answer for “Your report should also provide and interpret the seasonal indexes” from the 4th point (Model Selection).

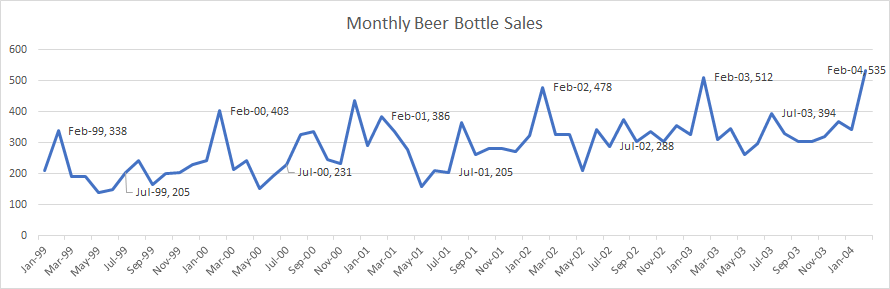
**###################################**

**We tried different approaches for comparison to select the best exponential smoothing process for forecasting. Below were the MAPE % error values obtained after applying forecasting models taking the seasonality into consideration.**

|  |  |  |
| --- | --- | --- |
| **Method** | **Model Type** | **MAPE %** |
| **Exponential smoothing** | **Non linear, Additive seasonality** | **8.01** |
| **Non linear, Multiplicative seasonality** | **8.03** |
| **Linear, Additive seasonality** | **12.16** |
| **Linear, Multiplicative seasonality** | **12.46** |

As per our analysis in the data patterns section, we could identify that the data pattern exhibits additive seasonality with cyclic trend. Hence, we decided to manipulate the Alpha, Beta and Gamma factors for handling the irregularities during forecasting. We took the Linear trend Additive seasonality exponential smoothing method as the base model and then changed the above factors to tune the model. We got the best result with a MAPE of 7.5% using the values alpha = 0.38, beta = 0.02, gama = 0.267. ****

**In the data patterns section we applied simple differencing to the dataset in order to analyze the seasonality. We could see significant positive correlation in the ACF plot for the lags of 6, 12, 18, 24 and so on. This shows that there is a significant seasonality occuring in a period of 6 months. We also notice that the seasonality exhibited in the lag intervals of 12, 24, 36 are prominent whereas the seasonalities at 6 and 12 gradually decreases. We can see similar observation from the plots below. Our time series ends at February ‘04 and we can see that the most prominent periodic peaks are in February (lag=12) and there is a constant low in the months of July (lag=6).**

****

**5. Forecast for rest of 2004 - Period (March ‘04 to December ‘04)**

**Now we move towards the final goal to predict the sales for the rest of the year 2004. Based on our analysis and model evaluation illustrated above, we have applied the Exponential smoothing method for No trend and an additive seasonality.**

**The forecasted values are given in the table below:**

***Table 2***

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Month** | **2.5% Lower** | **Forecast** | **Quarterly** | **Annual** | **97.5% Upper** |
| 2004-Mar | 255 | 346 | Q1, 1,223 | 4,205 | 436 |
| 2004-Apr | 258 | 350 | Q2, 916 | 442 |
| 2004-May | 163 | 256 | 350 |
| 2004-Jun | 214 | 309 | 405 |
| 2004-Jul | 236 | 333 | Q3, 1,039 | 430 |
| 2004-Aug | 279 | 378 | 477 |
| 2004-Sep | 228 | 328 | 429 |
| 2004-Oct | 227 | 329 | Q4, 1,028 | 431 |
| 2004-Nov | 219 | 322 | 426 |
| 2004-Dec | 271 | 377 | 482 |

**In our hold out analysis we got a MAPE error of 8.01% This is a crucial factor to take a call on the actual bottle levels to be maintained in the inventory. On** an average monthly forecast errors of the model are 8% of the monthly beer sales. The holdout analysis indicates that the forecast MAPE error is 8%, and the comparison of numbers from the holdout analysis in the table below shows that it would be ideal for the us to take the upper forecast limit of 97.5% into consideration. We can clearly see below that the actual values are majorly falling below the upper forecast limit of 97.5 %. This gives us a positive indication that the confidence limits can further be explored to optimize the space constraints as per the business decisions. A proposal can be made to discuss on the impact to decide the decision.

|  |  |  |  |
| --- | --- | --- | --- |
| **Month** | **Forecast** | **97.5% Upper** | **Actual** |
| Jun-03 | 304 | 393 | 296 |
| Jul-03 | 299 | 391 | 394 |
| Aug-03 | 390 | 484 | 331 |
| Sep-03 | 328 | 424 | 305 |
| Oct-03 | 328 | 426 | 305 |
| Nov-03 | 312 | 413 | 321 |
| Dec-03 | 370 | 473 | 369 |
| Jan-04 | 346 | 451 | 342 |
| Feb-04 | 490 | 596 | 535 |

**Conclusion and Recommendations**