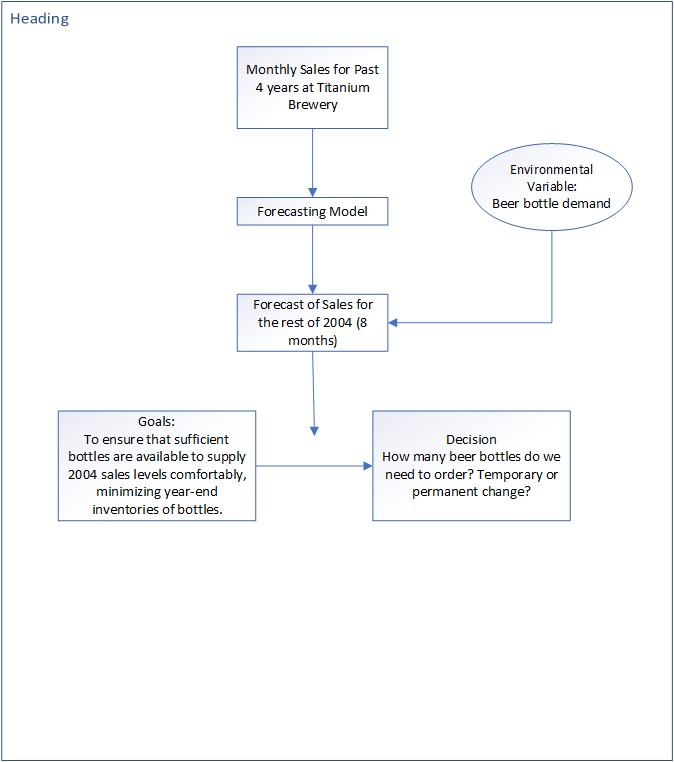
# **Executive Summary**

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 8 months of data 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 Winter’s Exponential Smoothing method has comparatively the lowest value of 10.36%. Also, Hence, Winter’s Exponential Smoothing method with 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 they are trying to determine how many beer bottles to order in the year 2004, accommodating the year’s supply comfortably while minimizing the year end inventories. Because the covered storage space for empty bottles is tight and a bottle design change is expected in 2005 and 2006. The under-forecasting or over-forecasting (sales) both could be costly situations and hence we need to be to have a good basis before making any order. If sales do 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 an year will be a short-term situation or if it will be a permanent state. Below is a graphical frame work that illustrates how our decision making is related to forecasting.



There is a huge impact of the forecast on the accuracy of the decision to be taken to plan the warehouse strategy for the upcoming months. There is a warehouse cost involved if there is excess inventory whereas the company loses sales in case of under production. The cost of under production and losing sales is much higher than the cost of over stock. Therefore, most of the forecasting decisions are made after carefully analyzing the impact of the forecast interval. The forecast interval shows us the possibility of the forecast number of the beer bottles to go above and below the forecast limits. The upper forecast limit of 97.5 indicates that there is a 2.5 % chance that the actual demand of bottles is above the upper limit.

We have set the upper limit as 97.5 for our forecast interval. It is very important to justify the impact of the forecasting in the form of cost involved based on the MAPE error %. Let us analyze the implications of over / under forecasting by converting the errors into dollar values. Let us evaluate the monthly sales based on the expert selection forecast for analysis. We have done the calculation based on Case volume of 1,00,000 cases. Below are the assumptions used for calculations.

1 case = 10 bottles (22 oz. each)

1 pallet = 50 cases

Average beer cost = $1 per bottle

Warehouse holding cost = $10 per pallet

Average profit margin = $5 per case

1. **Cost of 1% over production**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Product** | **Case volume** | **Case excess** | **Pallet excess** | **Product cost** | **Holding cost** | **Total inventory cost per month** |
| Titanium beer | 100,000 | 1,000 | 20 | $10,000 | $200 | **$10,200** |

Table 1.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Product** | **Case volume** | **1% Case short** | **1% Pallet short** | **Total loss per month** |
| Titanium beer | 100,000 | ,1000 | 20 | **$5,000** |

Table 2.

Our calculations in Table 1 and Table 2 show that a 1% over forecasting error will result in a loss of $10,200. An under forecasting of 1 % results in a loss of $5,000 for a case volume of 100,000. This calculation has been shown for a case volume of 1,00,000.

Let us consider the result of the holdout analysis that we performed using the expert selection method of forecast pro in our analysis.

The statistics represented in Table 3 below shows the comparison of our forecast generated by using the holdout analysis and the actual sales numbers. The accuracy is tested by using the last 8 months of observations. We are using the observation for the months of November and December 2003 to explain the cost of forecasting errors below.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Period** | **2.5 Lower limit** | **Point Forecast** | **97.5 Upper limit** | **Actual sales** | **MAPE %** |
| Nov-03 | 253 | 341 | 429 | 321 | 15.8 |
| Dec-03 | 312 | 401 | 489 | 369 | 14.59 |

Table 3. *\*\* Sales numbers are in thousands*

|  |  |  |  |
| --- | --- | --- | --- |
| **Period** | **Cost of 1 % over forecast** | **MAPE %** | **Total Cost** |
| Nov-03 | 10,200 | 15.8 | $ 161,160 |
| Dec-03 | 10,200 | 14.59 | $ 148,818 |

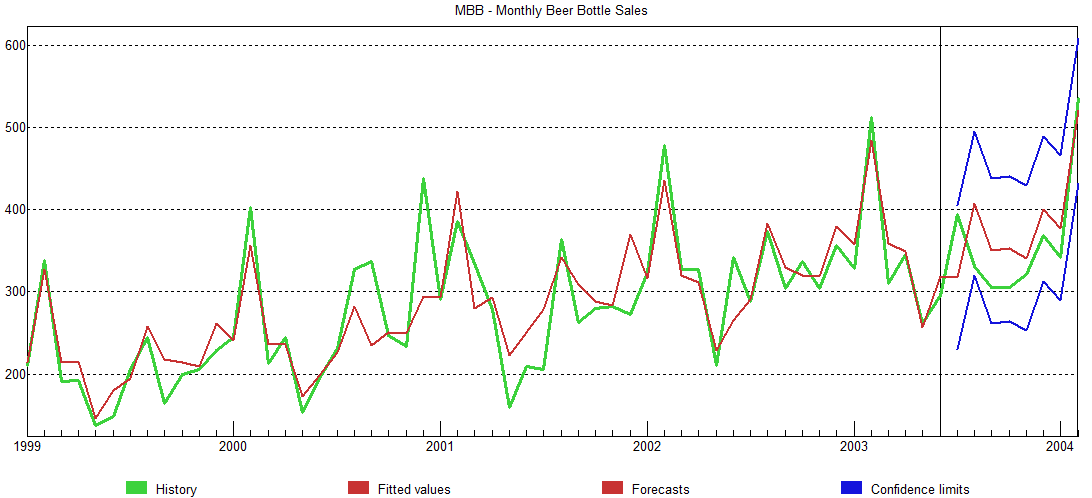
Table 4.

Based on the assumptions and the calculations illustrated above, the actual cost of the errors is $161,160 for November 2003 and $148,818 for December 2003. We know that the 1% cost was calculated assuming the case volume to be 100,000. Our actual case volumes for Nov-2003 and Dec-2003 are 321,000 and 369,000 respectively. Hence, our actual cost of over-forecasting is $ 516,000 and $ 537,233 for November and December of 2003 respectively.

The above numbers are staggering, and we can surely tell that the expert selection method is not a good method to generate forecast due to the cost of the forecast errors and a high error percentage. Hence, we need to analyze the historical data by detecting patterns and the factors such as trend and seasonality. Considering the above factors and by deeply analyzing the correlogram of the data will help us to recommend a model that will give a better and accurate forecast for our monthly sales data.

# **Data Patterns**

As per time-series, our model shows Linear trend since the

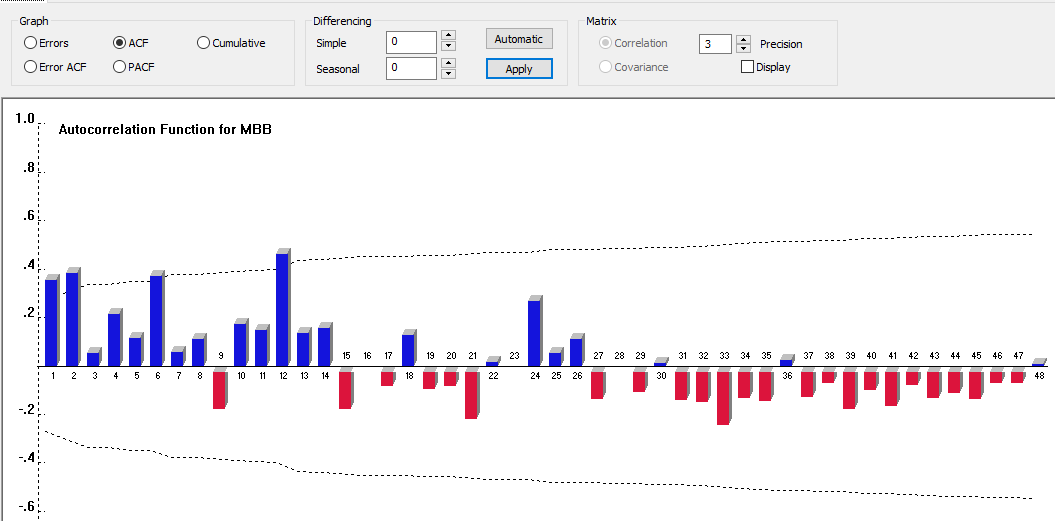


s(Explanation would be here)

**Determining Patterns in time series using Autocorrelation**

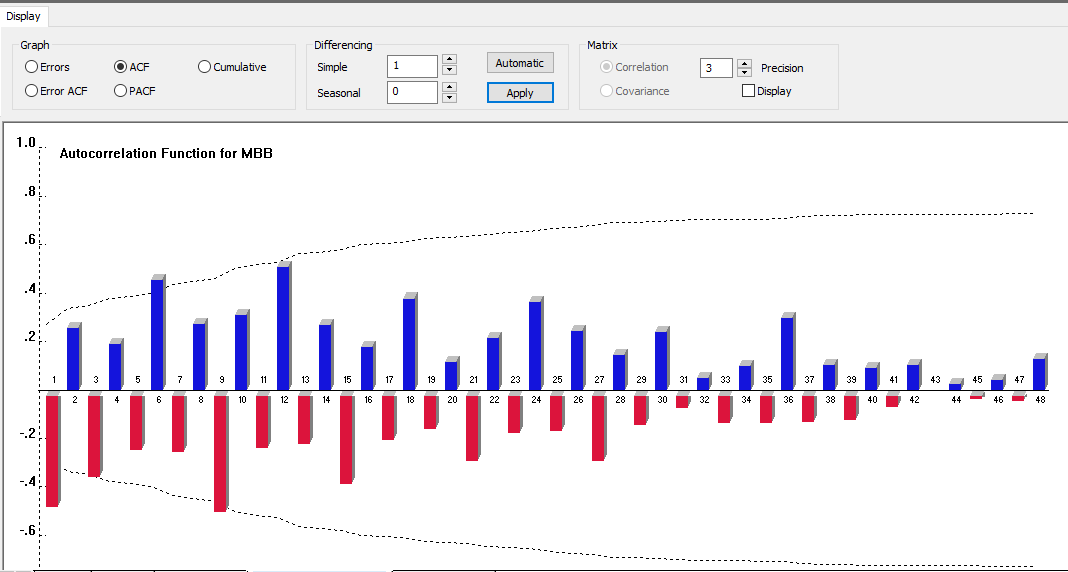
We performed autocorrelation and modified ‘Simple Differencing’ and ‘Seasonal differencing’ to determine the patterns in the data.

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



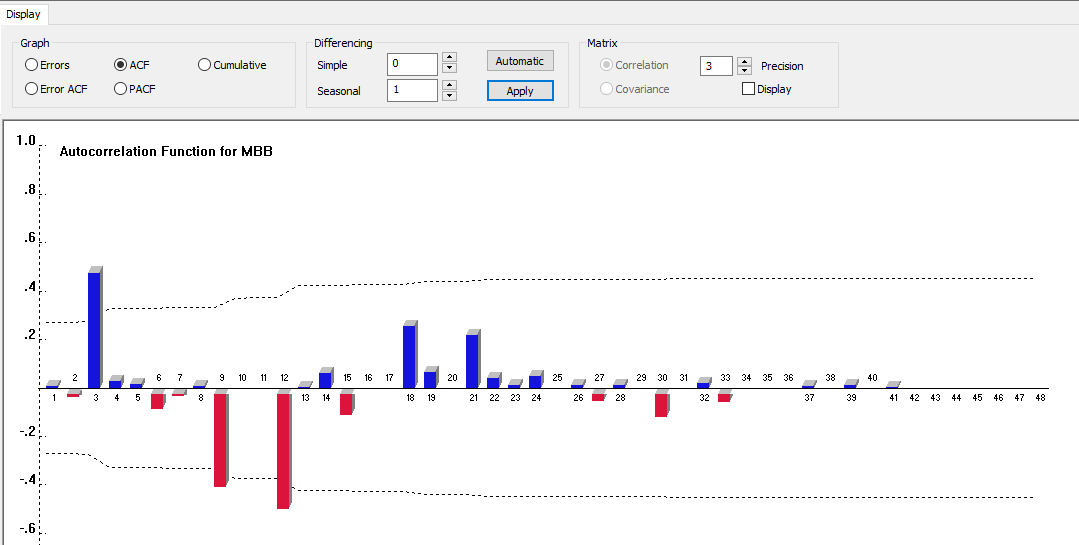
From the figure above, we observe that the autocorrelation function gradually drops to 0. As a result, we can infer that the time series is non-stationary. Also, high correlation can be seen among the observations with initial lags being significantly different from 0 and then gradually dropping to 0 which explains the trend within the series.

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



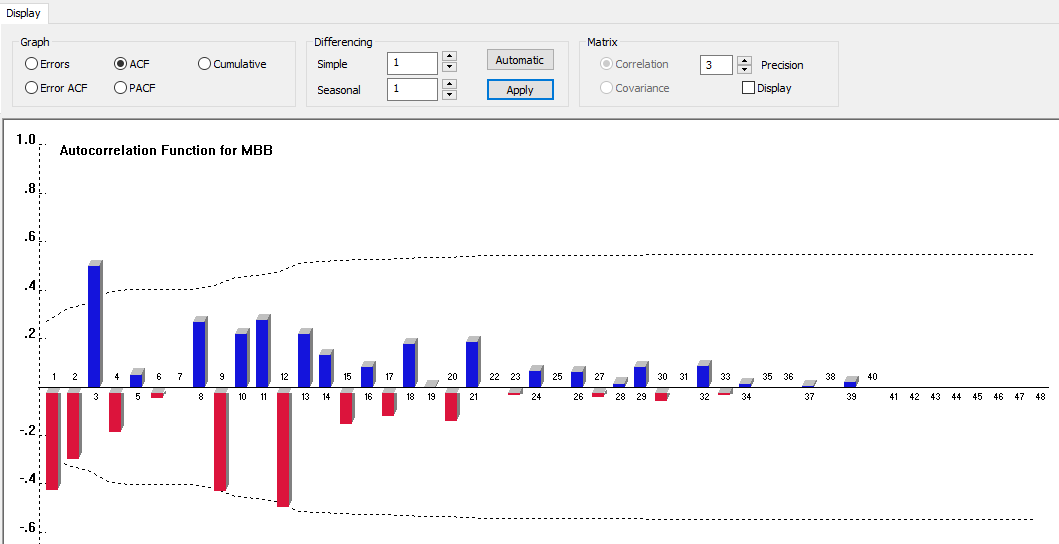
The figure shows that the series has seasonality which can be observed by increase of sales every February and also by a significant autocorrelation coefficient occurring in lags of 12 months.

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



We see that the trend is not repeated after fixed periods. Therefore, the trend within the series is cyclic.

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



This differencing is applied in order to make the series stationary. We can determine that the series is moving towards stationary with constant mean and variance. Moreover, the autocorrelation immediately drops to 0 which happens when the series is stationary.