Forecasting Model Accuracy Assessment in a Bottled Water Supply Chain

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Abstract
This study presents an accuracy assessment of various classical time series forecasting methods to determine the most accurate forecasting method for predicting demand of the 50cl product of a bottled water supply chain. The classical time series forecasting methods compared are the moving average, weighted moving average, exponential smoothing, adjusted exponential smoothing, linear trend line, Holt's model, and Winter's model. The Mean Absolute Percent Deviation (MAPD) value was determined for the various forecasting methods to find the forecasting method with the least MAPD and hence the highest forecasting accuracy. The tracking signal measure was also used to determine the forecasting models which were biased. The results showed that though the weighted moving average method began to underforecast demand in the final period, it had the lowest MAPD value of 2.25%, making it the forecasting method with the highest accuracy for predicting the 50cl bottled water demand. On the other hand, though the exponential smoothing forecasting method had the highest MAPD value of 3.43% and least accuracy for predicting the bottled water demand, its forecasts were consistently within the tracking signal control limits. This study will aid supply chain analysts in implementing accuracy assessment of classical time series forecasting models.

Keywords*: Demand Forecasting, Moving Average, Exponential Smoothing, Mean Absolute Percent Deviation, Tracking Signal.*

1. Introduction

Forecasting is an essential aspect of planning and making decisions within manufacturing companies. It is concerned with making future predictions based on historical data. Forecasting provides a broad perspective which manufacturing companies can use in benchmarking. Therefore, the manufacturing companies can compare actual demand for products with forecasted demand to obtain a clear view of trends in demand. However, forecasting is limited by the fact that it involves the future which is basically unknowable, making forecasting an educated guessing process. Even with this limitation, forecasting still helps managers and analysts to decide on crucial issues about the future.

Supply chains are networks of facilities that aid in the distribution of products and services to consumers (Lummus et al., 2001). Mentzer et al. (2001) have described a supply chain as a linkage of multiple firms both upstream (supply) and downstream (distribution) that produce value in the form of products and services delivered to the ultimate consumer. They further explained that a supply chain is a set of three or more organizations or individuals directly involved in the upstream and downstream flows of products, services, finances and information from a source to a customer. Similarly, Janvier-James (2012) explained that the role of supply chains is to add value to a product by transporting it from one location to another, after the good must have been changed through processing. Stock and Boyer (2009) developed a consensus definition for supply chain management, describing the term as the management of a network of relationships within a firm and between interdependent organizations and business units consisting of material suppliers, purchasing, production facilities, logistics, marketing and related systems facilitating both forward and reverse flows of materials, services, finances and information from producer to customer with the benefits of adding value, maximising profitability and achieving customer satisfaction.

Klimberg et al. (2010) have pointed out that inaccurate forecasts can result in increased costs and decreased customer satisfaction. As forecasting is necessary for predicting sales and demand amongst other values in the supply chain, when more than one method is utilised in the forecasting process, accuracy assessment of the methods becomes necessary. This is in order to compare the forecasting methods and determine the method with the highest accuracy of predicting the values in question. Several measures of forecasting accuracy exist, with the aim of determining the forecasting method with the least error (Koutsandreas et al., 2021). The aim of this study is to assess a number of classical forecasting methods to determine the method with the highest accuracy of predicting demand of the 50cl product of a bottled water supply chain.

Some researchers have carried out studies on forecasting model accuracy assessment. Klimberg et al. (2010) conducted a research which introduced a practical forecast performance measure called percentage forecast error (PFE) and compared this measure to traditional performance measures. Rossi and Sekhposyan (2011) proposed a new methodology to identify the sources of forecasting models' performance by decomposing the models' forecasting performance into asymptotically uncorrelated components which measure instabilities in the forecasting performance, predictive content and overfitting.

Lean Six Sigma process improvement methodology has been utilised in preceding studies to improve the manufacturing echelon of the bottled water supply chain (Wofuru-Nyenke *et al.*, 2019; Wofuru-Nyenke, 2021). Therefore, this study is a forerunner to another study that will propose discrete event simulation models for optimising inventory of manufacturing supply chains as outlined in Wofuru-Nyenke *et al.* (2022).

2. Methodology

The forecasting methods being compared are the moving average, weighted moving average, exponential smoothing, adjusted exponential smoothing, linear trend line, Holt's model, and Winter's model. The mean absolute deviation (MAD) method has already been used to determine the most accurate forecasting method to be the weighted moving average method in Wofuru-Nyenke and Briggs (2022). This study utilises the MAPD measure of forecasting accuracy to check if the results of the current study agree with those of Wofuru-Nyenke and Briggs (2022).

2.1 Mean Absolute Percent Deviation

The mean absolute percent deviation (MAPD) determines the absolute error as a percentage of demand rather than per period, thereby eliminating the problem of interpreting the measure of accuracy relative to the magnitude of the demand and forecast values, like the mean absolute deviation (MAD) method does. The equation for MAPD, was obtained from Russel and Taylor (2011) as

$$\mathrm{MAPD} = \frac{\sum|\mathrm{D_t} - \mathrm{F_t}|}{\sum \mathrm{D_t}} \times 100\% \quad (1)$$

where t is the period number, D_t is the demand in period t and F_t is the forecast for period t.

A lower MAPD value implies a more accurate forecast. Also, the forecasting technique having the lowest MAPD value is the most accurate.

2.2 Tracking Signal

The tracking signal checks if the forecast is consistently biased high or low. The equation for the tracking signal at period t, TS_t, was obtained from Chopra and Meindl (2016) as

$$\mathrm{TS_t} = \frac{\sum_{t=1}^{n} e_t}{\mathrm{MAD_t}} \quad (2)$$

where e_t is the difference between the demand in period t, D_t, and the forecast for period t, F_t and MAD_t is the mean absolute deviation at period t.

The equation for the mean absolute deviation, MAD, was obtained from Russel and Taylor (2011) as

$$\mathrm{MAD} = \frac{\sum|\mathrm{D_t} - \mathrm{F_t}|}{n} \quad (3)$$

where t is the period number, D_t is the demand in period t, F_t is the forecast for period t and n is the total number of periods.

The smaller the value of MAD when compared to the data values, the more accurate the forecast. Also, the forecasting technique having the lowest MAD value is the most accurate.

For each period t, a forecasting method with $-4 \leq TS_t \leq 4$ indicates that the forecast is unbiased. $TS_t < -4$ indicates biased underforecasting, while $TS_t > 4$ indicates biased overforecasting.

3. Results and Discussion

The total 50cl bottled water demand obtained from 200 retailers for each of January, February, March, April, May, June, July, August, September, October, November and December are 70,027 bottles, 65,491 bottles, 62,759 bottles, 61,801 bottles, 64,765 bottles, 67,838 bottles, 64,972 bottles, 66,134 bottles, 66,643 bottles, 66,561 bottles, 66,415 bottles and 72,697 bottles, respectively. The moving average (MA), weighted moving average (WMA), exponential smoothing (ES), adjusted exponential smoothing (AES), linear trend line (LTL), Holt's model, and Winter's model time series forecasting methods were applied on the historical data, and Table 1 shows the results of the various forecasting methods. The procedure for determining the number of retailers as well as the equations for the various forecasting methods utilised are contained in Wofuru-Nyenke and Briggs (2022).

Table 1: Forecast of 50cl Bottled Water Demand Using MA, WMA, ES, AES, LTL, Holt's and Winter's forecasting models.

Period	Month	Monthly Demand (Bottles)	3-Month MA Forecast (Bottles)	3-Month WMA Forecast (Bottles)	ES Forecast (Bottles)	AES Forecast (Bottles)	LTL Forecast (Bottles)	Holt's Model Forecast (Bottles)	Winter's Model Forecast (Bottles)
1	January (2021)	70,027	—	—	—	—	64,616	64,615	65,606
2	February (2021)	65,491	—	—	70,027	70,027	64,930	65,524	65,275
3	March (2021)	62,759	—	—	68,213	66,580	65,244	65,889	63,216
4	April (2021)	61,801	66,092	64,805	66,031	63,905	65,557	65,912	65,594
5	May (2021)	64,765	63,350	62,690	64,339	62,604	65,871	65,797	68,024
6	June (2021)	67,838	63,108	63,427	64,509	64,489	66,185	65,978	66,443
7	July (2021)	64,972	64,801	65,857	65,841	67,037	66,499	66,468	64,332
8	August (2021)	66,134	65,858	65,944	65,493	65,300	66,813	66,607	66,502
9	September (2021)	66,643	66,315	65,983	65,750	65,961	67,126	66,844	69,365
10	October (2021)	66,561	65,916	66,214	66,107	66,450	67,440	67,106	68,215
11	November (2021)	66,415	66,446	66,526	66,289	66,486	67,754	67,328	65,637
12	December (2021)	72,697	66,540	66,500	66,339	66,404	68,068	67,504	67,722

Figure 1 shows a time series plot of the actual 50cl bottled water monthly demand and the various forecasts against months of year 2021. These forecasts aid in the comparison between the forecasted demand and the actual demand.

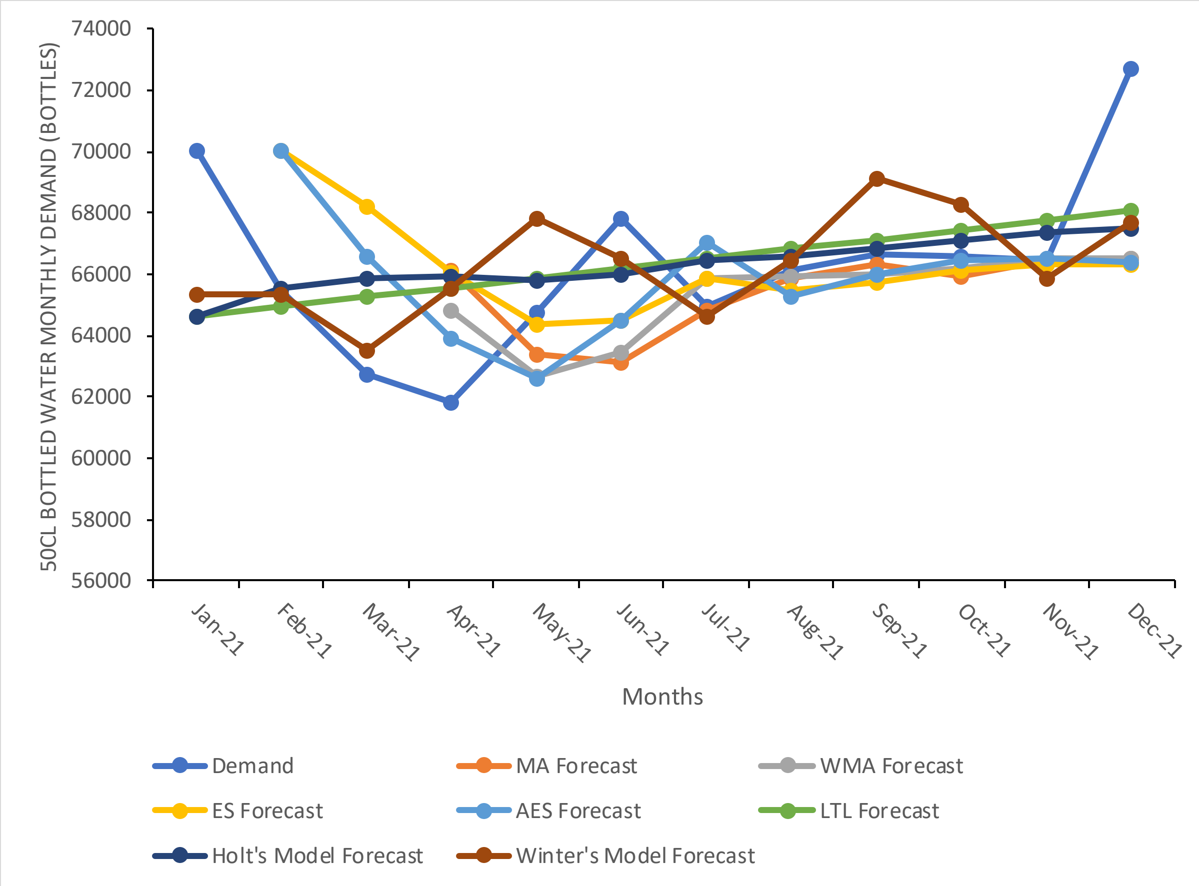

Figure 1: Plot of actual 50cl bottled water monthly demand and the various forecasts against months of year 2021.

From Figure 1, several of the forecasting methods seem to follow the actual 50cl bottled water demand. However, the most accurate forecasting method can only be determined using the various forecasting performance measures outlined in section 3.

The MAPD measure of forecasting accuracy was used in determining the most accurate forecasting method for predicting the 50cl bottled water demand. Using equation 1 and Microsoft Excel, the MAPD values for the MA, WMA, ES, AES, LTL, Holt's and Winter's forecasting models were evaluated to be 2.27%, 2.25%, 3.43%, 3.27%, 3.08%, 3.06% and 3.03%, respectively. Since the WMA forecasting method has the lowest MAPD value, it is the most accurate method for forecasting the 50cl bottled water demand. This agrees with the results of Wofuru-Nyenke and Briggs (2022) where the WMA forecasting method was found to be the most accurate method for forecasting the 50cl bottled water demand, using the MAD measure of forecasting accuracy. Figure 2 shows a bar chart of the various MAPD values of the forecasting methods.

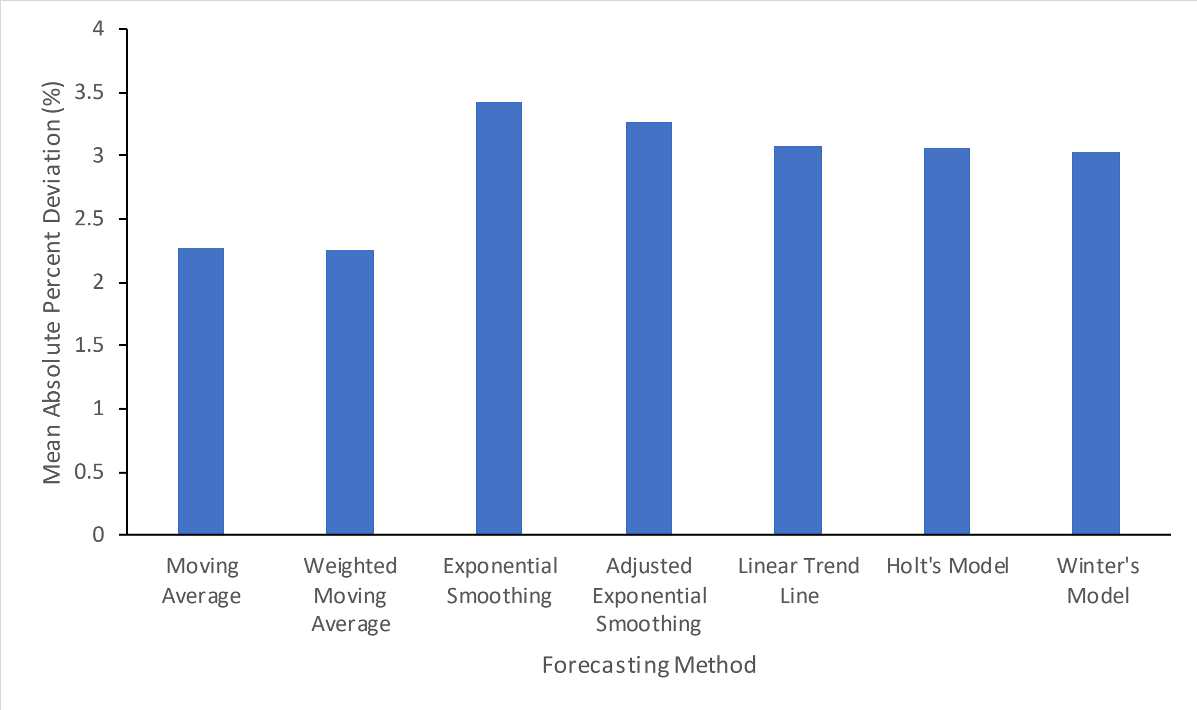

Figure 2: Comparison of Mean Absolute Percent Deviation (MAPD) values for various 50cl bottled water forecasting methods.

From Figure 2, the exponential smoothing forecasting method possesses the highest MAPD value of 3.43%, therefore it is the least accurate forecasting method for forecasting demand of the 50cl bottled water. On the other hand, the weighted moving average forecasting method possesses the lowest MAPD value of 2.25%, therefore it is the most accurate forecasting method for forecasting demand of the 50cl bottled water.

Using Microsoft Excel and equation (2), the tracking signal was evaluated for each forecasting method at each period of the year. This was carried out in order to determine forecasting methods which were biased and either overforecasting or underforecasting. Figure 3 shows the plot of tracking signal against periods of year 2021.

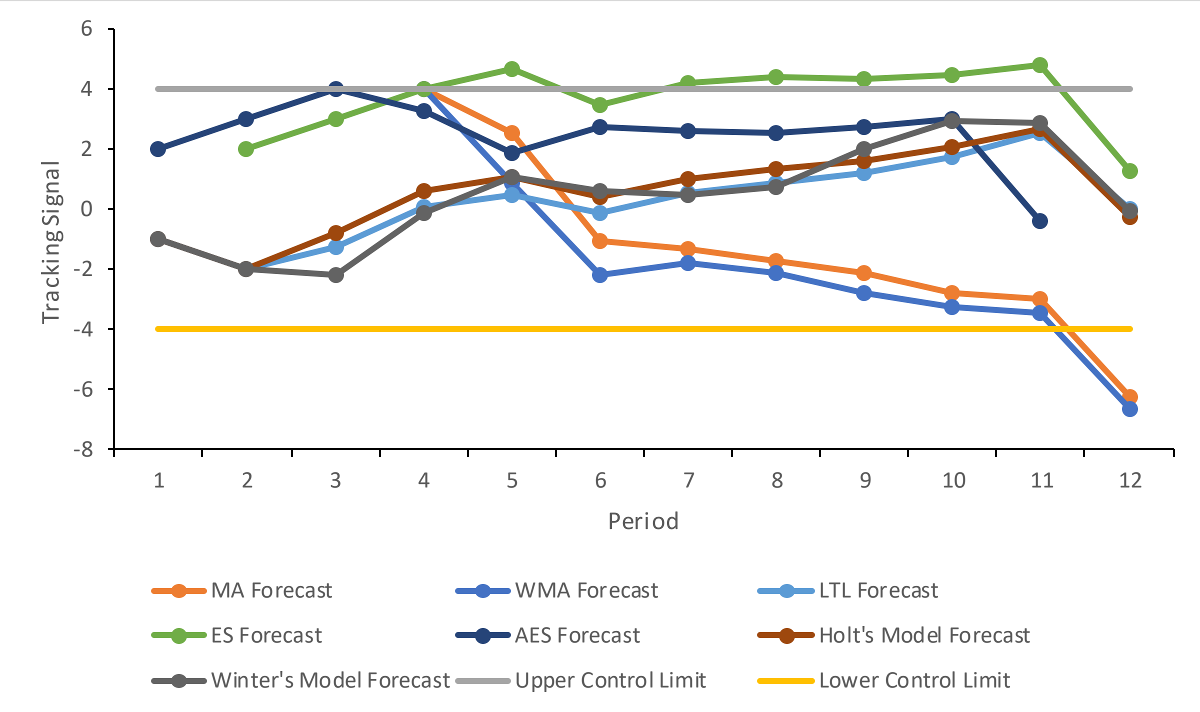

Figure 3: Plot of Tracking Signal against Periods of Year 2021.

From Figure 3, the forecasts of the MA, WMA forecasting methods were well within the upper and lower control limits, except for period 12 when these methods began to underforecast demand. On the other hand, even though the LTL, AES, Holt's and Winter's methods were inappropriate for forecasting the demand for the 50cl bottled water, the forecasts of these methods remained consistently within the control limits. However, the ES forecasting method was majorly overforecasting the 50cl bottled water demand.

4. Conclusions

This research has conducted an accuracy assessment of various classical time series forecasting methods namely the moving average (MA), weighted moving average (WMA), exponential smoothing (ES), adjusted exponential smoothing (AES), linear trend line (LTL), Holt's model, and Winter's model. The Mean Absolute Percent Deviation (MAPD) and Tracking Signal methods were used to perform this assessment for forecasting 50cl bottled water demand at different periods of year 2021. The results showed that the MAPD values for the MA, WMA, ES, AES, LTL, Holt's and Winter's forecasting models were 2.27%, 2.25%, 3.43%, 3.27%, 3.08%, 3.06% and 3.03%, respectively. Since the WMA forecasting method had the lowest MAPD value, it was determined to be the most accurate method for forecasting the 50cl bottled water demand. Moreover, by evaluating the tracking signal, it was found that even though the LTL, AES, Holt's and Winter's methods were inappropriate for forecasting the demand for the 50cl bottled water, the forecasts of these methods remained consistently within the control limits. While, the ES method majorly overforecasted demand, and the demand forecasts of the MA and WMA methods remained consistently within the control limits except for period 12 when they began to underforecast the bottled water demand.

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