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Predicting demand in a bottled water supply chain using classical time series forecasting models

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C H R O N I C L E

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A B S T R A C T

In this paper, various classical time series forecasting methods were compared to determine the forecasting method with the highest accuracy in 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. These methods were evaluated to determine the method with the least Mean Absolute Deviation (MAD) value and hence the highest forecasting accuracy. From the results, the weighted moving average forecasting method had the lowest MAD value of 1,987, making it the forecasting method with the highest accuracy for predicting the 50cl bottled water demand. While the exponential smoothing forecasting method had the highest MAD value of 2,483, making it the forecasting method with the least accuracy for predicting the 50cl bottled water demand. This research provides a procedure for aiding supply chain analysts in implementing demand forecasting using classical time series forecasting models.

1. Introduction

Forecasting refers to the process of predicting a future occurrence. In order to meet future customer needs on time, product demand forecasts need to be made to enable the organizations to determine the amount of inventory required in each echelon of the supply chain, the amount of product to make, the amount of material to purchase from suppliers as well as the kind of transportation needed, the location of plants, warehouses, and distribution centres. Inaccurate forecasts or absence of forecasting can lead to the organization's finances being tied down in excess stocks of costly inventory being stored at the individual echelons of the supply chain to compensate for the irregularities in customer demand. On the other hand, if there are inadequate inventories from inaccurate forecasts or absence of forecasting, customer service levels decline as a result of late deliveries and stockouts, which can be detrimental to an organization's bottom line in today's competitive global business environment, where customer service and on-time delivery are critical factors.

Russel and Taylor (2011) have pointed out that though accurate forecasts are necessary, it is not possible to make completely accurate forecasts, and the core function of forecasting is to decrease the uncertainty associated with the future occurrence as much as possible. Therefore, forecasting serves to stem the occurrence of the bullwhip effect within the supply chain. The bullwhip effect occurs when minor variabilities in demand of a product or service is magnified as information moves back upstream in the supply chain (Russel & Taylor, 2011). Similarly, Nakade and Aniyama (2019) described the bullwhip effect as demand fluctuation propagation from downstream to upstream of a supply chain, under stochastic demand. According to Russel and Taylor (2011), when each echelon of the supply chain cannot ascertain the actual demand for the succeeding member it supplies, and instead makes its own demand forecasts, then it will attempt to create a security blanket of inventory by stockpiling extra inventory to compensate for uncertainty, leading to the bullwhip effect.

In selecting a suitable time series forecasting model, one has to consider the properties of the time series data. According to Brownlee (2018), simple classical methods perform better than sophisticated machine learning and deep learning methods

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for one-step or multi-step forecasting on univariate datasets. Since the demand forecasting carried out in this study is for one step, and involves a univariate dataset, the classical methods were chosen as the appropriate methods for predicting demand. Therefore, the main objective of this research is to compare various classical forecasting methods, in order to determine the forecasting method with the highest accuracy of predicting demand in 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. These methods will be evaluated to determine the method with the least Mean Absolute Deviation (MAD) value and hence the highest forecasting accuracy.

2. Literature Review

A number of researchers have utilised classical time series forecasting models for making predictions. Lee *et al.* (2012) compared the moving average method with other forecasting methods for predicting sales of fresh food in a point of sales database for convenience stores. Their main objective was to find an efficient forecasting model that can aid in increasing volume of sales and reduce wastes at such convenience stores. Mateia (2013) compared the simple moving average and linear regression forecasting models in order to find the more accurate prediction method and observed that the moving average model generated values closer to the initial values. Shih and Tsokos (2008) used a weighted moving average forecasting model for predicting daily stock closing prices of a company, with the aim of comparing the accuracy of the weighted moving average method and other forecasting models. Yu *et al.* (2020) have attested to the efficacy of the weighted moving average method in a study where they applied the method to 18 real time series datasets from public data repositories. They observed that the two-stage exponential weighted moving average is useful for analysing complex time series data that are non-stationary and noisy. Ekhosuehi *et al.* (2016) compared the moving average, weighted moving average and exponential weighted moving average forecasting models for predicting economic time series data. They observed that the weighted moving average model performed better at smoothing the time series data but the simple moving average model performed better at future forecasting. Nakade and Aniyama (2019) have analysed the bullwhip effect on weighted moving average forecast considering stochastic lead time, observing that the larger the variance of lead time, the greater the bullwhip effect, even when expected lead time is small.

Billah *et al.* (2006) compared various approaches for selecting exponential smoothing models based on real time series data. The exponential smoothing models considered were simple exponential smoothing, trend corrected exponential smoothing and seasonality corrected exponential smoothing. They observed that the information criterion approach was best for selecting exponential smoothing models, with the Akaike information criteria having an edge over other information criteria counterparts. Rendon-Sanchez and Menezes (2018) have compared seasonal exponential smoothing forecasting models for predicting peak electricity demand and evaluated their performance using various measures of forecasting accuracy such as mean squared error, symmetric mean absolute percentage error and geometric mean relative absolute error. Adamuthe *et al.* (2015) utilised double exponential smoothing for medium term forecasting of cloud computing providers. By using forecasting accuracy measuring models such as mean absolute deviation and root mean square error, they assessed the performance of exponential smoothing models with two smoothing constants and one smoothing constant. The results showed that double exponential smoothing with two smoothing constants is better fitted than double exponential smoothing with one smoothing constant. Segura and Vercher (2001) utilised spreadsheet modelling and the Holt-Winters model for optimal forecasting of airline passengers, pesticide demand and population growth. Similarly, Grubb and Mason (2001) have used the Holt-Winters model for long lead-time forecasting of airline passengers of the United Kingdom. Their results showed that the Holt-Winters model is very suitable for univariate forecasting where the forecast depends only on the past of the series and not on relationships between the series and exogenous variables subject to uncertainty.

The manufacturing echelon of the bottled water supply chain has been improved using Lean Six Sigma process improvement methodology in preceding studies (Wofuru-Nyenke *et al.,* 2019; Wofuru-Nyenke, 2021). However, the bottled water supply chain is still experiencing difficulties in meeting customer demand on time. Therefore, this study serves as a precursor to another study that will utilise discrete event simulation for optimising the entire bottled water supply chain as outlined in Wofuru-Nyenke *et al.* (2022).

3. Methodology

Forecasting can be conducted with the aid of time series methods. Time series forecasting methods provide a useful set of statistical techniques for predicting future demand with the aid of historical demand data accumulated over a period of time. The time series methods utilised for forecasting in this study are moving average, weighted moving average, exponential smoothing, adjusted exponential smoothing, linear trend line, Holt's model, and Winter's model.

3.1 Determining Minimum Sample Size

The equation for the minimum sample size, n_s, was obtained from George *et al.* (2005) as

$$n_s = \left(\frac{1.96s}{\Delta}\right)^2 \tag{1}$$

where 1.96 is a constant representing a 95% confidence interval, s is an estimate of standard deviation of the data, Δ is the difference (level of precision desired from the sample) or margin of error.

The equation for determining the sample standard deviation, s, was obtained from Montgomery *et al.* (2011) as

$$s = \sqrt{\frac{\sum_{i=1}^{n_s}(x_i - \bar{x}_s)^2}{n_s - 1}} \quad (2)$$

where x_i is an observation or data point, $\bar{x}$ is the sample mean and n_s is the number of observations in the sample.

The equation for determining the sample mean, $\bar{x}_s$, was obtained from Montgomery *et al.* (2011) as

$$\bar{x}_s = \frac{\sum_{i=1}^{n_s} x_i}{n_s} \quad (3)$$

where x_i is an observation or data point and n_s is the number of observations in the sample.

3.2 Moving Average

The equation for moving average, MA_n, was obtained from Russel and Taylor (2011) as

$$MA_n = \frac{\sum_{i=1}^{n} D_i}{n} \quad (4)$$

where n is the number of periods in the moving average and D_i is the demand in the ith period.

3.3 Weighted Moving Average

The equation for weighted moving average, WMA_n, was obtained from Russel and Taylor (2011) as

$$WMA_n = \sum_{i=1}^{n} W_i D_i \quad (5)$$

where n is the number of periods in the weighted moving average, W_i is the weight for the ith period and D_i is the demand in the ith period.

3.4 Exponential Smoothing

The equation for exponential smoothing was obtained from Russel and Taylor (2011) as

$$F_{t+1} = \alpha D_t + (1 - \alpha)F_t \quad \text{for } 0 \leq \alpha \leq 1 \quad (6)$$

where F_{t+1} is the forecast for the next period, α is a weighting factor referred to as the smoothing constant, D_t is the actual demand in the current period, F_t is the previously determined forecast for the current period.

The forecast for period 1 can be assumed to be equal to the demand for period 1. Therefore, $F_1 = D_1$. Also, the value of α that minimizes the forecast error can be obtained by utilising Microsoft Excel Solver.

3.5 Adjusted Exponential Smoothing

The equation for adjusted exponential smoothing was obtained from Russel and Taylor (2011) as

$$AF_{t+1} = F_{t+1} + T_{t+1} \quad (7)$$

where AF_{t+1} is the adjusted forecast for the next period, F_{t+1} is the forecast for the next period given by Eq. (6) and T_{t+1} is the exponentially smoothed trend factor for the next period.

The equation for the exponentially smoothed trend factor for the next period, T_{t+1}, was obtained from Russel and Taylor (2011) as

$$T_{t+1} = \beta(F_{t+1} - F_t) + (1 - \beta)T_t \quad \text{for } 0 \leq \beta \leq 1 \quad (8)$$

where β is a smoothing constant for trend, F_{t+1} is the forecast for the next period given by Equation (6), F_t is the previously determined forecast for the current period and T_t is the previously determined trend factor for the current period.

The exponentially smoothed forecast for period 1, F_1 will be assumed to be equal to the demand for period 1, and the trend factor for period 2, T_2 will be assumed to be equal to 0 while that of period 1, T_1 is undefined. Also, the values of α and β that minimize the forecast error can be obtained by utilising Microsoft Excel Solver.

3.6 Linear Trend Line

The equation for the linear trend line was obtained from Russel and Taylor (2011) as

$$y = a + bx \tag{9}$$

where y is the forecast for demand for period x, a is the intercept (at period 0), b is the slope of the linear trend line and x is the time period.

The equation for the slope of the linear trend line, b, was obtained from Russel and Taylor (2011) as

$$b = \frac{\sum xy - n\bar{x}\bar{y}}{\sum x^2 - n\bar{x}^2} \tag{10}$$

where x is the time period, y is the forecast for demand for period x, n is number of periods, $\bar{x}$ is the mean of the x values (time periods) and $\bar{y}$ is the mean of the y values (demands).

The equation for the mean of the time periods, $\bar{x}$, was obtained from Russel and Taylor (2011) as

$$\bar{x} = \frac{\sum x}{n} \tag{11}$$

where x is the time period and n is the number of periods.

The equation for the mean of the demands, $\bar{y}$, was obtained from Russel and Taylor (2011) as

$$\bar{y} = \frac{\sum y}{n} \tag{12}$$

where y is the demand at each time period and n is the number of periods.

The equation for the intercept (at period 0), a, was obtained from Russel and Taylor (2011) as

$$a = \bar{y} - b\bar{x} \tag{13}$$

where $\bar{x}$ is the mean of the x values (time periods), b is the slope of the linear trend line and $\bar{y}$ is the mean of the y values (demands).

3.7 Holt's Model

Holt's model for forecasting is also known as the trend-corrected exponential smoothing forecasting model or the double exponential smoothing model. The model is suitable in situations where past data of the observation to be predicted exhibits a trend.

The equation for Holt's model was obtained from Chopra and Meindl (2016) as

$$F_{t+1} = L_t + T_t \tag{14}$$

where F_{t+1} is the forecast for the next period, L_t is an estimate of the level factor for the current period and T_t is an estimate of the trend factor for the current period.

The equation for the estimate of the level factor for the next period, L_{t+1}, was obtained from Chopra and Meindl (2016) as

$$L_{t+1} = \alpha D_{t+1} + (1 - \alpha)(L_t + T_t) \quad \text{for } 0 \le \alpha \le 1 \tag{15}$$

where α is a smoothing constant for the level, D_{t+1} is the demand for the next period, L_t is an estimate of the level factor for the current period and T_t is an estimate of the trend factor for the current period.

The equation for the estimate of the trend factor for the next period, T_{t+1}, was obtained from Chopra and Meindl (2016) as

$$T_{t+1} = \beta(L_{t+1} - L_t) + (1 - \beta)T_t \quad \text{for } 0 \le \beta \le 1 \tag{16}$$

where β is a smoothing constant for the trend, L_{t+1} is the estimate of the level factor for the next period, L_t is the estimate of the level factor for the current period and T_t is the estimate of the trend factor for the current period.

The initial estimates of the level factor, L_0, and trend factor, T_0, are obtained by using linear regression. L_0 is given by the intercept coefficient and T_0 is given by the variable coefficient (slope) of the regression equation that relates the time period (independent variable), with the quantity to be forecasted (dependent variable). Also, the values of α and β that minimize the forecast error can be obtained by utilising Microsoft Excel Solver.

3.8 Winter's Model

Winter's model for forecasting is also known as the trend-and-seasonality-corrected exponential smoothing forecasting model, Holt-Winters model or the triple exponential smoothing model. The model is suitable in situations where past data of the observation to be predicted exhibits trend and seasonality.

The equation for Winter's model was obtained from Chopra and Meindl (2016) as

$$F_{t+1} = (L_t + T_t)S_{t+1} \tag{17}$$

where F_{t+1} is the forecast for the next period, L_t is an estimate of the level factor for the current period, T_t is an estimate of the trend factor for the current period and S_{t+1} is an estimate of seasonal factor for the next period.

The equation for the estimate of the level factor for the next period, L_{t+1}, was obtained from Chopra and Meindl (2016) as

$$L_{t+1} = \alpha\left(\frac{D_{t+1}}{S_{t+1}}\right) + (1-\alpha)(L_t + T_t) \qquad \text{for } 0 \leq \alpha \leq 1 \tag{18}$$

where α is a smoothing constant for the level, D_{t+1} is the demand for the next period, S_{t+1} is an estimate of the seasonal factor for the next period, L_t is an estimate of the level factor for the current period and T_t is an estimate of the trend factor for the current period.

The equation for the estimate of the trend factor, T_{t+1}, was obtained from Chopra and Meindl (2016) as

$$T_{t+1} = \beta(L_{t+1} - L_t) + (1-\beta)T_t \qquad \text{for } 0 \leq \beta \leq 1 \tag{19}$$

where β is a smoothing constant for the trend, L_{t+1} is an estimate of the level factor for the next period, L_t is an estimate of the level factor for the current period and T_t is an estimate of the trend factor for the current period.

The equation for the estimate of the seasonal factor, S_{t+p+1}, was obtained from Chopra and Meindl (2016) as

$$S_{t+p+1} = \gamma\left(\frac{D_{t+1}}{L_{t+1}}\right) + (1-\gamma)(S_{t+1}) \qquad \text{for } 0 \leq \gamma \leq 1 \tag{20}$$

where p is the periodicity or number of periods in a seasonal cycle, γ is a smoothing constant for the seasonality, D_{t+1} is the demand for the next period, L_{t+1} is an estimate of the level factor for the next period and S_{t+1} is an estimate of the seasonal factor for the next period.

The initial estimates of the level factor, L_0, and trend factor, T_0, are obtained by using linear regression. L_0 is given by the intercept coefficient and T_0 is given by the variable coefficient (slope) of the regression equation that relates the time period (independent variable), with the deseasonalized quantity to be forecasted (dependent variable). Also, the values of α, β and γ that minimize the forecast error can be obtained by utilising Microsoft Excel Solver.

The equation for the deseasonalized demand, $\overline{D}$, was obtained from Chopra and Meindl (2016) as

$$\overline{D}_t = \begin{cases} \left[D_{t-\left(\frac{p}{2}\right)} + D_{t+\left(\frac{p}{2}\right)} + \sum_{i=t+1-\left(\frac{p}{2}\right)}^{t-1+\left(\frac{p}{2}\right)} 2D_i\right] \Big/ 2p & \text{for p even} \quad (21) \\ \sum_{i=t-\frac{(p-1)}{2}}^{t+\frac{(p-1)}{2}} \frac{D_i}{p} & \text{for p odd} \quad (22) \end{cases}$$

where p is the periodicity or number of periods in a seasonal cycle, $D_{t-\left(\frac{p}{2}\right)}$ is the demand for period $t-\left(\frac{p}{2}\right)$, $D_{t+\left(\frac{p}{2}\right)}$ is the demand for period $t+\left(\frac{p}{2}\right)$ and D_t is the demand for period t.

The regression equation for deseasonalized demand was obtained from Chopra and Meindl (2016) as

$$\overline{D}_t = L + Tt \tag{23}$$

where $\overline{D}_t$ is the deseasonalized demand at period t, L is the level factor of the deseasonalized demand at period 0 and T is the trend factor of the deseasonalized demand at period 0. Regression analysis will be conducted with the aid of Microsoft Excel.

The regression equation for deseasonalized demand is used to obtain values of the deseasonalized demand for each period, t. Then the seasonal factor, $\overline{S}_t$ is calculated for each period t using Equation (24) obtained from Chopra and Meindl (2016) as

$$\overline{S}_t = \frac{D_t}{\overline{D}_t} \tag{24}$$

where D_t is the demand at period t and $\overline{D}_t$ is the deseasonalized demand at period t.

The equation for the overall seasonal factor for corresponding periods, S_i, was obtained from Chopra and Meindl (2016) as

$$S_i = \frac{\sum_{j=0}^{r-1} \overline{S}_{jp+i}}{r} \tag{25}$$

where r is the number of seasonal cycles in the data and $\overline{S}_{jp+i}$ is the seasonal factor for period $(jp + i)$. Equation (25) provides the initial values of the seasonal factors used in evaluating Winter's model.

3.9 Measuring Forecasting Accuracy

The moving average, weighted moving average, exponential smoothing, adjusted exponential smoothing, Holt's model, Winter's model and linear trend line methods will be compared to determine the most accurate forecasting method for predicting customer demand. The method used in this study for determining the accuracy of the forecasting methods utilised is the Mean Absolute Deviation (MAD) method.

The equation for the Mean Absolute Deviation, MAD, was obtained from Russel and Taylor (2011) as

$$MAD = \frac{\sum |D_t - F_t|}{n} \tag{26}$$

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.

4. Results and Discussion

Moving upstream of the water bottling supply chain, demand data were obtained from a number of retailers. In order to obtain the minimum sample size, n_s, of respondents from the retailer echelon, at 95% confidence interval and a precision, Δ, of demand of 10 bottles of water (50cl) in a month, a preliminary study of 50 retailers was conducted. From the preliminary study, the calculated standard deviation, s, using equations (2) and (3) was 65 bottles of water (50cl) and Eq. (1) was used to determine the minimum sample size as follows,

$$n_s = \left(\frac{1.96 \times 65}{10}\right)^2 = 163 \text{ retailers}$$

Since the minimum sample size is 163 retailers, a sample size of 200 retailers was chosen.

Therefore, the data of 50cl bottled water demand for January, February, March, April, May, June, July, August, September, October, November, December of year 2021 were obtained for 200 retailers. The demand data from the 200 retailers were added together to obtain a single demand quantity at the retailer echelon, for each month. The total 50cl bottled water demand 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. Various time series forecasting methods were applied on the historical data, and their accuracies evaluated, in order to determine the specific forecasting method with the highest prediction accuracy.

The equation for moving average, MA_n given by Equation (4), was used in forecasting the demand for 50cl bottled water for the months of year 2021. A period of three (3) months was chosen. The calculations were conducted in Microsoft Excel, and the Moving Average forecasted demand of 50cl bottled water for various months of 2021 are shown in Table 1.

Table 1
Three-Month Moving Average Forecast for 50cl Bottled Water Demand at the Retailer.

Period	Month	Demand per month (Bottles)	3-Month Moving Average Forecast (Bottles)
1	January (2021)	70,027	—
2	February (2021)	65,491	—
3	March (2021)	62,759	—
4	April (2021)	61,801	66,092
5	May (2021)	64,765	63,350
6	June (2021)	67,838	63,108
7	July (2021)	64,972	64,801
8	August (2021)	66,134	65,858
9	September (2021)	66,643	66,315
10	October (2021)	66,561	65,916
11	November (2021)	66,415	66,446
12	December (2021)	72,697	66,540

Fig. 1 shows the time series plot of the actual 50cl bottled water monthly demand and the 3-month Moving Average forecast against the month of the year. These forecasts aid in the comparison between the forecasted demand and the actual demand. The accuracy of the Moving Average forecasting method was evaluated using Equation (26) in Microsoft Excel, and the MAD value for the Moving Average forecasting method was evaluated to be 2,005.

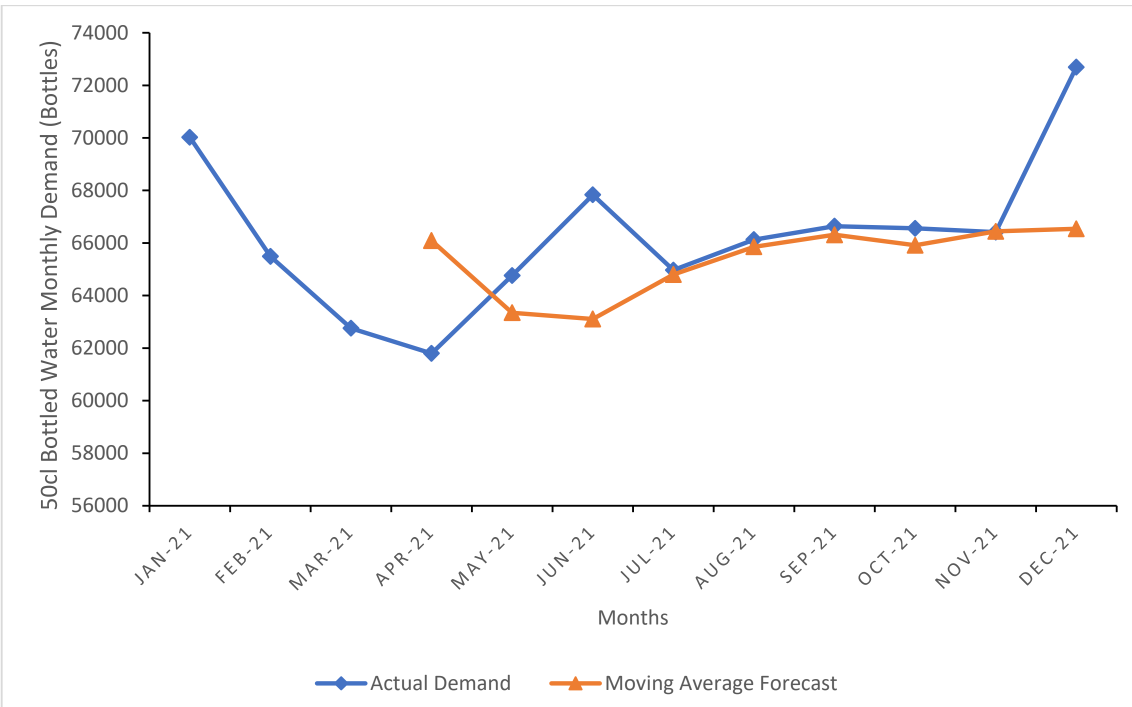

Fig. 1. Plot of actual 50cl bottled water monthly demand and the 3-month Moving Average forecast against months of the year

From Fig. 1, the lowest actual demand for 50cl bottled water occurred in the month of June, 2021, with a total demand of 61,801 bottles. On the other hand, the lowest 3-month Moving Average forecasted demand of 50cl bottled water occurred in the month of June, 2021 with a total forecasted demand of 63,108 bottles. Moreover, the highest actual demand for 50cl bottled water occurred in the month of December, 2021, with a total demand of 72,697 bottles. Whereas, the highest 3-month Moving Average forecasted demand occurred in the month of December, 2021 with a total forecasted demand of 66,540 bottles. Though the 3-month moving average plot closely reflects the most recent actual demand data, it can also be noticed that the 3-month moving average plot is consistently below the actual demand data, except for the months of April, 2021 and November, 2021, where the 3-month Moving Average forecast exceeds the total actual demand.

The equation for Weighted Moving Average, WMA_n, given by Equation (5), was used in forecasting the demand for 50cl bottled water for the months of year 2021. A period of three (3) months was chosen. 50%, 35% and 15% weights were selected for the most recent demand data, the median demand data and the earliest demand data, respectively. The calculations were conducted in Microsoft Excel, and the Weighted Moving Average forecasted demand of 50cl bottled water for various months of 2021 are shown in Table 2.

Table 2
Three-Month Weighted Moving Average Forecast for 50cl Bottled Water Demand at the Retailer

Period	Month	Demand per month (Bottles)	3-Month Weighted Moving Average Forecast (Bottles)
1	January (2021)	70,027	—
2	February (2021)	65,491	—
3	March (2021)	62,759	—
4	April (2021)	61,801	64,805
5	May (2021)	64,765	62,690
6	June (2021)	67,838	63,427
7	July (2021)	64,972	65,857
8	August (2021)	66,134	65,944
9	September (2021)	66,643	65,983
10	October (2021)	66,561	66,214
11	November (2021)	66,415	66,526
12	December (2021)	72,697	66,500

Fig. 2 shows the time series plot of the actual 50cl bottled water monthly demand and the 3-month Weighted Moving Average forecast against the month of the year. These forecasts aid in the comparison between the forecasted demand and the actual demand. The accuracy of the Weighted Moving Average forecasting method was evaluated using Eq. (26) in Microsoft Excel, and the MAD value for the Weighted Moving Average forecasting method was evaluated to be 1,987.

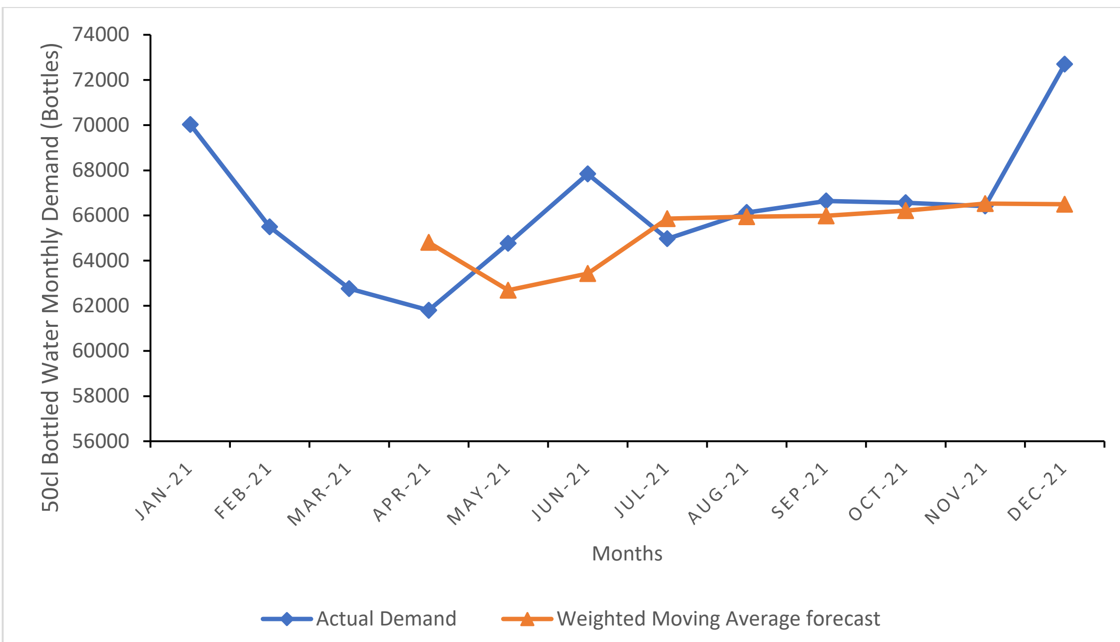

Fig. 2. Plot of actual 50cl bottled water monthly demand and the 3-month Weighted Moving Average forecast against months of the year

From Fig. 2, the lowest actual demand for 50cl bottled water occurred in the month of June, 2021, with a total demand of 61,801 bottles. On the other hand, the lowest 3-month Weighted Moving Average forecasted demand of 50cl bottled water occurred in the month of May, 2021 with a total forecasted demand of 62,690 bottles. Moreover, the highest actual demand for 50cl bottled water occurred in the month of December, 2021, with a total demand of 72,697 bottles. Whereas, the highest 3-month Weighted Moving Average forecasted demand occurred in the month of December, 2021, with a total forecasted demand of 66,500 bottles.

The equation for Exponential Smoothing given by Equation (6), was used in forecasting the demand for 50cl bottled water for the months of year 2021. Using Microsoft Excel Solver, the smoothing constant, α, was chosen as 0.4, by determining the value of α for which the Mean Absolute Deviation (MAD) given by Equation (26) is minimum. The exponential smoothing formula required a forecast for January, 2021. Therefore, the demand for period 1 was used as the demand as well as the forecast for period 1. The calculations were conducted in Microsoft Excel, and the Exponential Smoothing forecasted demand of 50cl bottled water for various months of 2021 are shown in Table 3.

Table 3
Exponential Smoothing Forecast for 50cl Bottled Water Demand at the Retailer

Period	Month	Demand per month (Bottles)	Exponential Smoothing Forecast (Bottles)
1	January (2021)	70,027	—
2	February (2021)	65,491	70,027
3	March (2021)	62,759	68,213
4	April (2021)	61,801	66,031
5	May (2021)	64,765	64,339
6	June (2021)	67,838	64,509
7	July (2021)	64,972	65,841
8	August (2021)	66,134	65,493
9	September (2021)	66,643	65,750
10	October (2021)	66,561	66,107
11	November (2021)	66,415	66,289
12	December (2021)	72,697	66,339

Fig. 3 shows the time series plot of the actual 50cl bottled water monthly demand and the Exponential Smoothing forecast against the month of the year. These forecasts aid in the comparison between the forecasted demand and the actual demand. The accuracy of the Exponential Smoothing forecasting method was evaluated using Eq. (26) in Microsoft Excel, and the MAD value for the Exponential Smoothing forecasting method was evaluated to be 2,483.

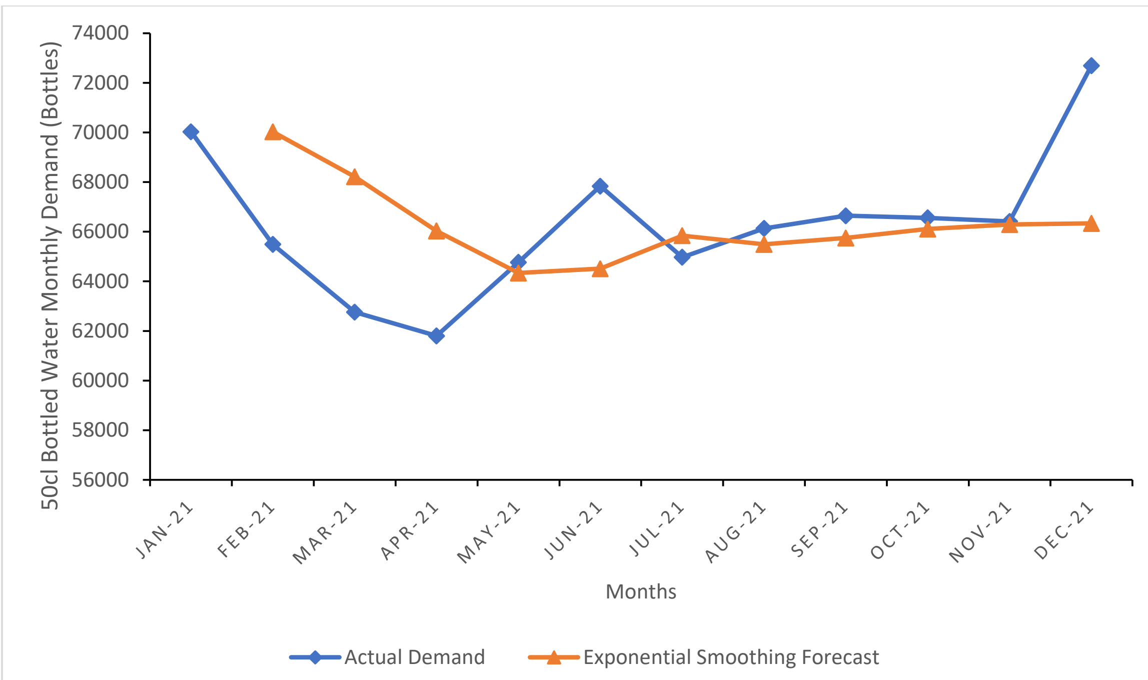

Fig. 3. Plot of actual 50cl bottled water monthly demand and the Exponential Smoothing forecast against months of the year.

From Fig. 3, the lowest actual demand for 50cl bottled water occurred in the month of June, 2021, with a total demand of 61,801 bottles. On the other hand, the lowest Exponential Smoothing forecasted demand of 50cl bottled water occurred in the month of May, 2021 with a total forecasted demand of 64,339 bottles. Moreover, the highest actual demand for 50cl bottled water occurred in the month of December, 2021, with a total demand of 72,697 bottles. Whereas, the highest Exponential Smoothing forecasted demand occurred in the month of February 2021, with a total forecasted demand of 70,027 bottles.

The equations for Adjusted Exponential Smoothing given by Equation (7) and Equation (8), were used in forecasting the demand for 50cl bottled water for the months of year 2021. Using Microsoft Excel Solver, the smoothing constant for level, α and trend, β, were chosen as 0.4 and 0.9 respectively, by determining the value of α and β for which the Mean Absolute Deviation (MAD) given by Equation (26) is minimum. The Adjusted Exponential Smoothing formula required a forecast for January, 2021, and an initial value for T_1 to start the computational process. T_1 was assumed to be 0 and the forecast for January, 2021, was assumed to be the same as the demand i.e. 70,027 bottles. The calculations were conducted in Microsoft Excel, and the Adjusted Exponential Smoothing forecasted demand of 50cl bottled water for various months of 2021 are shown in Table 4.

Table 4
Adjusted Exponential Smoothing Forecast for 50cl Bottled Water Demand at the Retailer

Period	Month	Demand per month (Bottles)	Adjusted Exponential Smoothing Forecast (Bottles)
1	January (2021)	70,027	—
2	February (2021)	65,491	70,027
3	March (2021)	62,759	66,580
4	April (2021)	61,801	63,905
5	May (2021)	64,765	62,604
6	June (2021)	67,838	64,489
7	July (2021)	64,972	67,037
8	August (2021)	66,134	65,300
9	September (2021)	66,643	65,961
10	October (2021)	66,561	66,450
11	November (2021)	66,415	66,486
12	December (2021)	72,697	66,404

Fig. 4 shows the time series plot of the actual 50cl bottled water monthly demand and the Adjusted Exponential Smoothing forecast against the month of the year. These forecasts aid in the comparison between the forecasted demand and the actual demand. The accuracy of the Adjusted Exponential Smoothing forecasting method was evaluated using Eq.(26) in Microsoft Excel, and the MAD value for the Adjusted Exponential Smoothing forecasting method was evaluated to be 2,169.

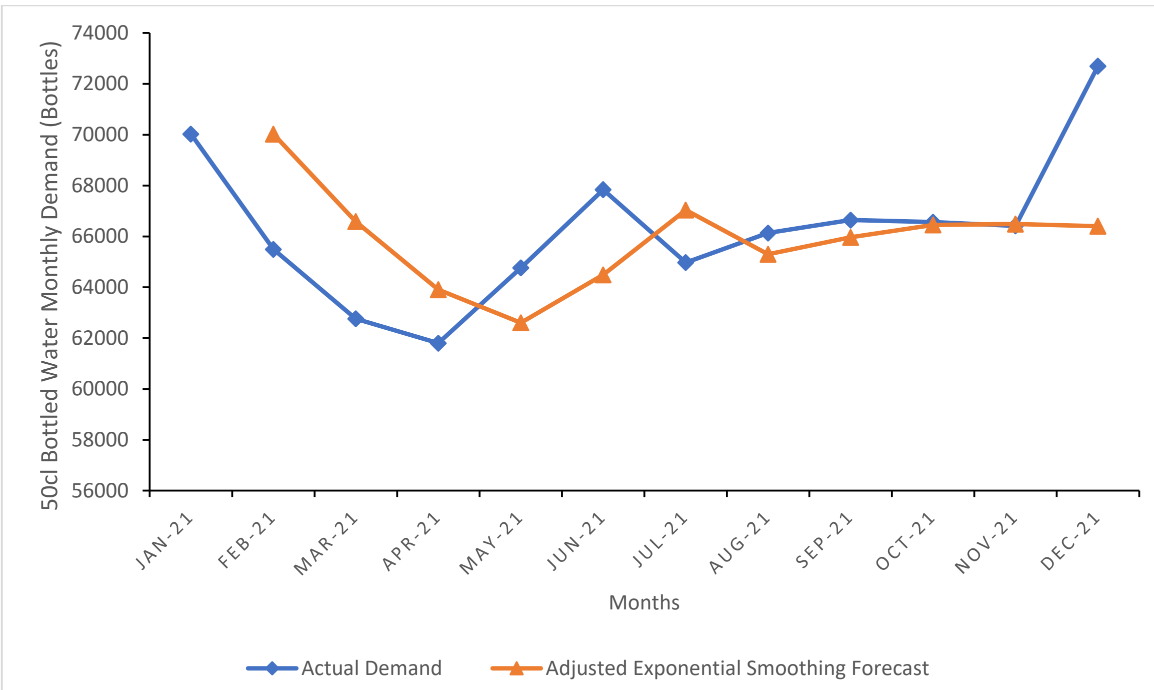

Fig. 4. Plot of actual 50cl bottled water monthly demand and the Adjusted Exponential Smoothing forecast against months of the year

From Fig. 4, the lowest actual demand for 50cl bottled water occurred in the month of June, 2021, with a total demand of 61,801 bottles. On the other hand, the lowest Adjusted Exponential Smoothing forecasted demand of 50cl bottled water occurred in the month of May, 2021 with a total forecasted demand of 62,604 bottles. Moreover, the highest actual demand for 50cl bottled water occurred in the month of December, 2021, with a total demand of 72,697 bottles. Whereas, the highest Adjusted Exponential Smoothing forecasted demand occurred in the month of February, 2021, with a total forecasted demand of 70,027 bottles.

Using Microsoft Excel, equations (9), (10), (11), (12) and (13) were used in determining the linear trend line for use in forecasting the demand for 50cl bottled water for the months of year 2021. The parameters for the linear trend line given by Equation (9) as obtained from Microsoft Excel were a = 64,301 and b = 314. Therefore, the linear trend line is given by

$$y = 64{,}301 + 314x$$

The calculations using the linear trend line equation were conducted in Microsoft Excel, and the Linear Trend Line forecasted demand of 50cl bottled water for various months of 2021 are shown in Table 5.

Table 5
Linear Trend Line Forecast for 50cl Bottled Water Demand at the Retailer.

Period (x)	Month	Demand per month (Bottles)	Linear Trend Line Forecast (y) (Bottles)
1	January (2021)	70,027	64,616
2	February (2021)	65,491	64,930
3	March (2021)	62,759	65,244
4	April (2021)	61,801	65,557
5	May (2021)	64,765	65,871
6	June (2021)	67,838	66,185
7	July (2021)	64,972	66,499
8	August (2021)	66,134	66,813
9	September (2021)	66,643	67,126
10	October (2021)	66,561	67,440
11	November (2021)	66,415	67,754
12	December (2021)	72,697	68,068

Fig. 5 shows the time series plot of the actual 50cl bottled water monthly demand and the Linear Trend Line forecast against the month of the year. These forecasts aid in the comparison between the forecasted demand and the actual demand. The accuracy of the Linear Trend Line forecasting method was evaluated using Eq. (26) in Microsoft Excel, and the MAD value for the Linear Trend Line forecasting method was evaluated to be 2,042.

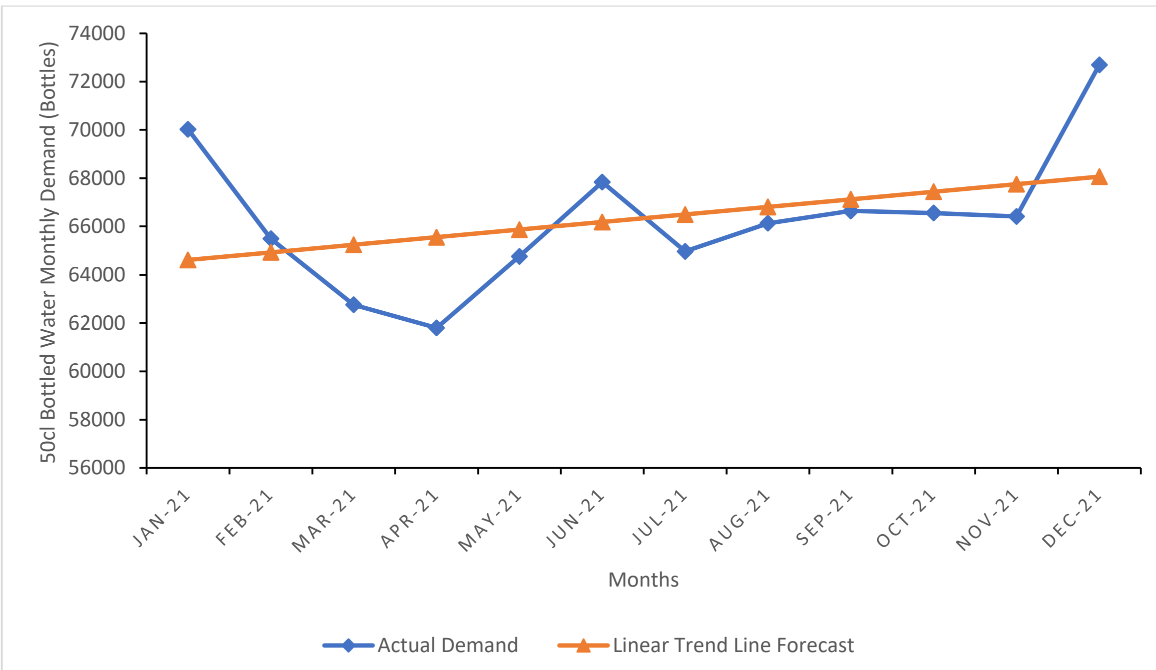

Fig. 5. Plot of actual 50cl bottled water monthly demand and the Linear Trend Line forecast against months of the year

From Fig. 5, the lowest actual demand for 50cl bottled water occurred in the month of June, 2021, with a total demand of 61,801 bottles. On the other hand, the lowest Linear Trend Line forecasted demand of 50cl bottled water occurred in the month of January, 2021 with a total forecasted demand of 64,615 bottles. Moreover, the highest actual demand for 50cl bottled water occurred in the month of December, 2021, with a total demand of 72,697 bottles. Also, the highest Linear Trend Line forecasted demand occurred in the month of December 2021, with a total forecasted demand of 68,069 bottles.

Holt's model or the Trend-corrected Exponential Smoothing forecasting model given by Eq. (14), Eq. (15) and Eq. (16) was also used in forecasting the demand for 50cl bottled water for the months of year 2021. The initial estimates of level, L_o and trend, T_o, were obtained using the linear regression equation of the linear trend line with L_o as the intercept and T_o as the slope. Therefore, $L_o = 64,301$ and $T_o = 314$. Using Microsoft Excel Solver, the smoothing constants for level, α, and trend, β, were chosen as 0.1 and 0.1 respectively, by determining the value of α and β for which the Mean Absolute Deviation (MAD) given by Equation (26) is minimum. The calculations were conducted in Microsoft Excel, and the Holt's model forecasted demand of 50cl bottled water for various months of 2021 are shown in Table 6.

Table 6
Holt's Model Forecast for 50cl Bottled Water Demand at the Retailer

Period	Month	Demand per month (Bottles)	Holt's Model Forecast (Bottles)
1	January (2021)	70,027	64,615
2	February (2021)	65,491	65,524
3	March (2021)	62,759	65,889
4	April (2021)	61,801	65,912
5	May (2021)	64,765	65,797
6	June (2021)	67,838	65,978
7	July (2021)	64,972	66,468
8	August (2021)	66,134	66,607
9	September (2021)	66,643	66,844
10	October (2021)	66,561	67,106
11	November (2021)	66,415	67,328
12	December (2021)	72,697	67,504

Fig. 6 shows the time series plot of the actual 50cl bottled water monthly demand and the Holt's model forecast against the month of the year. These forecasts aid in the comparison between the forecasted demand and the actual demand. The accuracy of the Holt's model forecasting method was evaluated using Eq. (26) in Microsoft Excel, and the MAD value for the Holt's model forecasting method was evaluated to be 2,033.

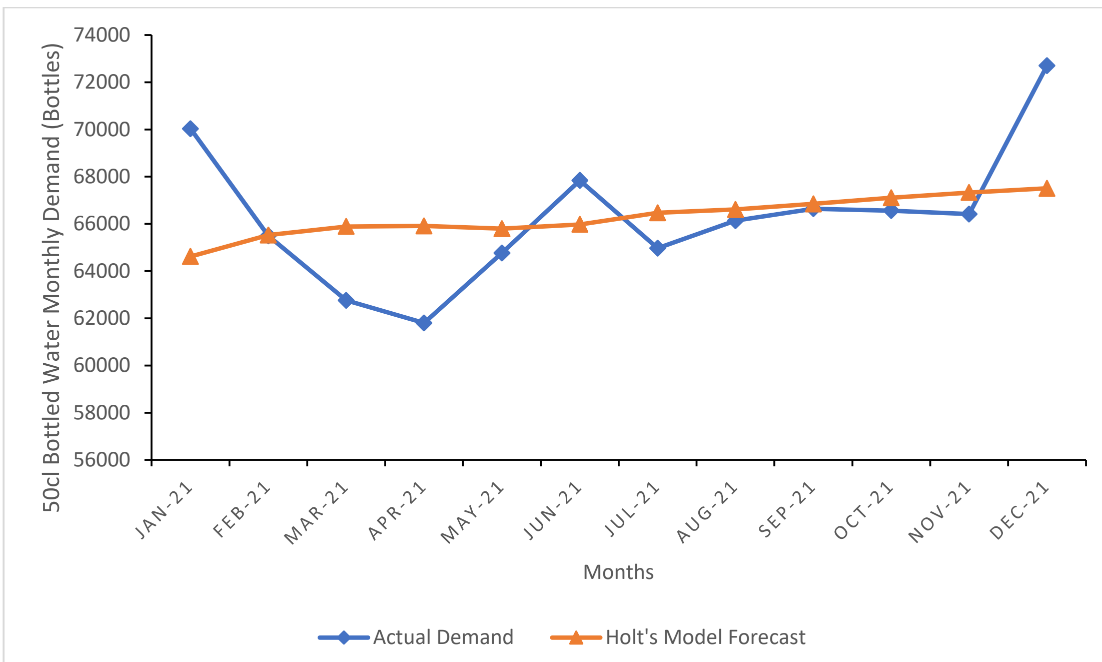

Fig. 6. Plot of actual 50cl bottled water monthly demand and the Holt's model forecast against months of the year

From Table 6 and Fig. 6, the lowest actual demand for 50cl bottled water occurred in the month of June, 2021, with a total demand of 61,801 bottles. On the other hand, the lowest Holt's model forecasted demand of 50cl bottled water occurred in the month of January, 2021 with a total forecasted demand of 64,615 bottles. Moreover, the highest actual demand for 50cl bottled water occurred in the month of December, 2021, with a total demand of 72,697 bottles. Whereas, the highest Holt's model forecasted demand occurred in the month of December 2021, with a total forecasted demand of 67,504 bottles.

Winter's model or the Trend-and-seasonality-corrected Exponential Smoothing forecasting model given by equations (17), (18), (19) and (20) was also used in forecasting the demand for 50cl bottled water for the months of year 2021, assuming that the periodicity, p, for the demand is 4.

Since periodicity, p, is even, Equation (21) will be used for evaluating the deseasonalized demand, $\overline{D}_t$. The calculations for deseasonalized demand for the 50cl bottled water were conducted in Microsoft Excel, and the deseasonalized demands are shown in Table 7.

Table 7
Deseasonalized Demand for 50cl Bottled Water at the Retailer

Period, t	Month	Demand per month, D_t (Bottles)	Deseasonalized Demand, $\overline{D}_t$ (Bottles)
1	January (2021)	70,027	–
2	February (2021)	65,491	–
3	March (2021)	62,759	64,362
4	April (2021)	61,801	63,998
5	May (2021)	64,765	64,568
6	June (2021)	67,838	65,386
7	July (2021)	64,972	66,162
8	August (2021)	66,134	66,238
9	September (2021)	66,643	66,258
10	October (2021)	66,561	67,259
11	November (2021)	66,415	–
12	December (2021)	72,697	–

Using Microsoft Excel, a regression analysis was conducted using the period, t, as the independent variable and the deseasonalized demand, $\overline{D}_t$, as the dependent variable, considering only periods 3 to 10. This was in order to obtain the values of the level factor of the deseasonalized demand, L, and the trend factor of the deseasonalized demand, T, in Equation (23). From the regression analysis, L = 62,637 and T = 445, therefore, Eq. (23) becomes,

$$\overline{D}_t = 62637 + 445t$$

Therefore, the deseasonalized demand for all periods as obtained from the regression equation is shown in Table 8. Also, Table 8 shows the seasonal factors, $\overline{S}_t$, calculated from Eq. (24).

Table 8
Regression Equation Deseasonalized Demand for 50cl Bottled Water at the Retailer.

Period, t	Month	Demand per month, D_t (Bottles)	Deseasonalized Demand, $\overline{D}_t$ (Bottles)	Seasonal Factor, $\overline{S}_t$
1	January (2021)	70,027	63,082	1.11
2	February (2021)	65,491	63,527	1.03
3	March (2021)	62,759	63,972	0.98
4	April (2021)	61,801	64,417	0.96
5	May (2021)	64,765	64,862	1.00
6	June (2021)	67,838	65,307	1.04
7	July (2021)	64,972	65,752	0.99
8	August (2021)	66,134	66,197	1.00
9	September (2021)	66,643	66,642	1.00
10	October (2021)	66,561	67,087	0.99
11	November (2021)	66,415	67,532	0.98
12	December (2021)	72,697	67,977	1.07

Since there are a total of 12 periods, and a periodicity of p = 4, the number of seasonal cycles is r = 12/4 = 3. Therefore, the seasonal factors for each period was calculated from Equation (25) as,

$$S_1 = \frac{\overline{S}_1 + \overline{S}_5 + \overline{S}_9}{3} = \frac{1.11 + 1.00 + 1.00}{3} = 1.04$$

$$S_2 = \frac{\overline{S}_2 + \overline{S}_6 + \overline{S}_{10}}{3} = \frac{1.03 + 1.04 + 0.99}{3} = 1.02$$

$$S_3 = \frac{\overline{S}_3 + \overline{S}_7 + \overline{S}_{11}}{3} = \frac{0.98 + 0.99 + 0.98}{3} = 0.98$$

$$S_4 = \frac{\overline{S}_4 + \overline{S}_8 + \overline{S}_{12}}{3} = \frac{0.96 + 1.00 + 1.07}{3} = 1.01$$

Therefore, the initial estimates of level, trend and seasonal factors are:

$$L_o = 62{,}637,\quad T_o = 445,\quad S_1 = 1.04,\quad S_2 = 1.02,\quad S_3 = 0.98,\quad S_4 = 1.01$$

Using Microsoft Excel Solver, the smoothing constants for level, α, trend, β, and seasonality, γ were chosen as 0.1, 0.1 and 0.1 respectively, by determining the value of α, β and γ for which the Mean Absolute Deviation (MAD) given by Equation (26) is minimum. The calculations were conducted in Microsoft Excel, and the Winter's model forecasted demand of 50cl bottled water for various months of 2021 are shown in Table 9.

Table 9
Winter's Model Forecast for 50cl Bottled Water Demand at the Retailer

Period	Month	Demand per month (Bottles)	Winter's Model Forecast (Bottles)
1	January (2021)	70,027	65,606
2	February (2021)	65,491	65,275
3	March (2021)	62,759	63,216
4	April (2021)	61,801	65,594
5	May (2021)	64,765	68,024
6	June (2021)	67,838	66,443
7	July (2021)	64,972	64,332
8	August (2021)	66,134	66,502
9	September (2021)	66,643	69,365
10	October (2021)	66,561	68,215
11	November (2021)	66,415	65,637
12	December (2021)	72,697	67,722

Fig. 7 shows the time series plot of the actual 50cl bottled water monthly demand and the Winter's model forecast against the month of the year. These forecasts will aid in the comparison between the forecasted demand and the actual demand. The accuracy of the Winter's model forecasting method was evaluated using Eq. (26) in Microsoft Excel, and the MAD value for the Winter's model forecasting method was evaluated to be 2,056.

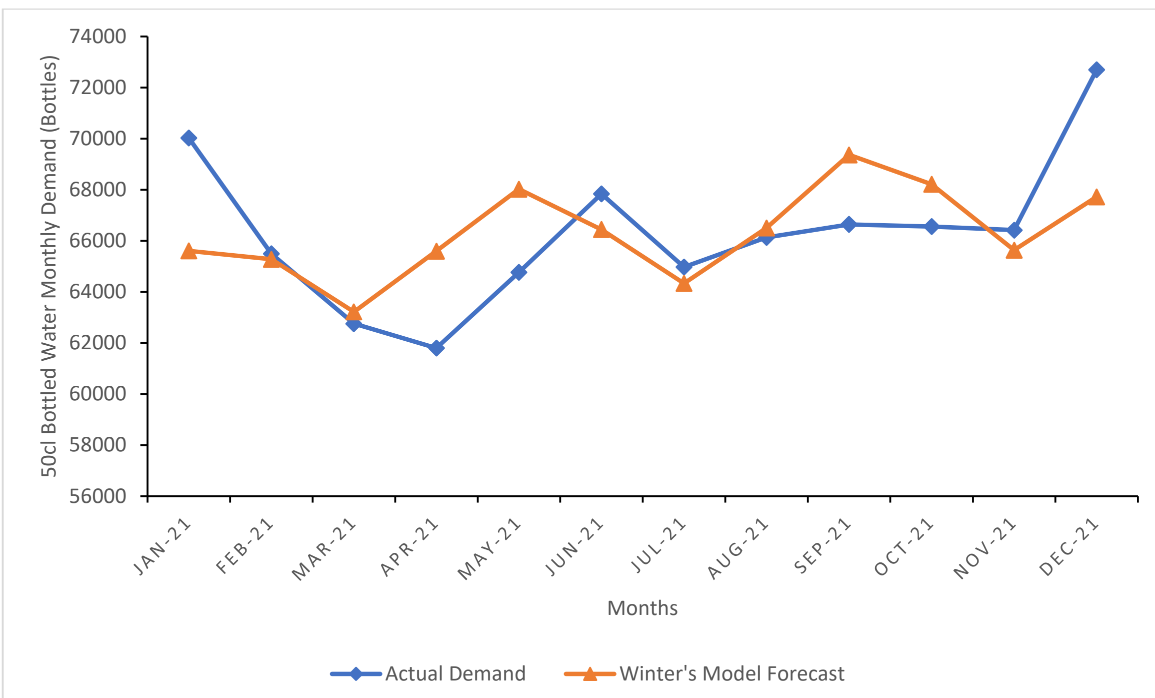

Fig. 7. Plot of actual 50cl bottled water monthly demand and the Winter's model forecast against months of the year

From Table 11 and Fig. 7, the lowest actual demand for 50cl bottled water occurred in the month of June, 2021, with a total demand of 61,801 bottles. On the other hand, the lowest Winter's model forecasted demand of 50cl bottled water occurred in the month of March, 2021 with a total forecasted demand of 63,216 bottles. Moreover, the highest actual demand for 50cl bottled water occurred in the month of December, 2021, with a total demand of 72,697 bottles. Whereas, the highest Winter's model forecasted demand occurred in the month of September 2021, with a total forecasted demand of 69,365 bottles.

Fig. 8 is a bar chart that shows a comparison of the Mean Absolute Deviation (MAD) values for the various methods utilised in forecasting demand of the 50cl bottled water.

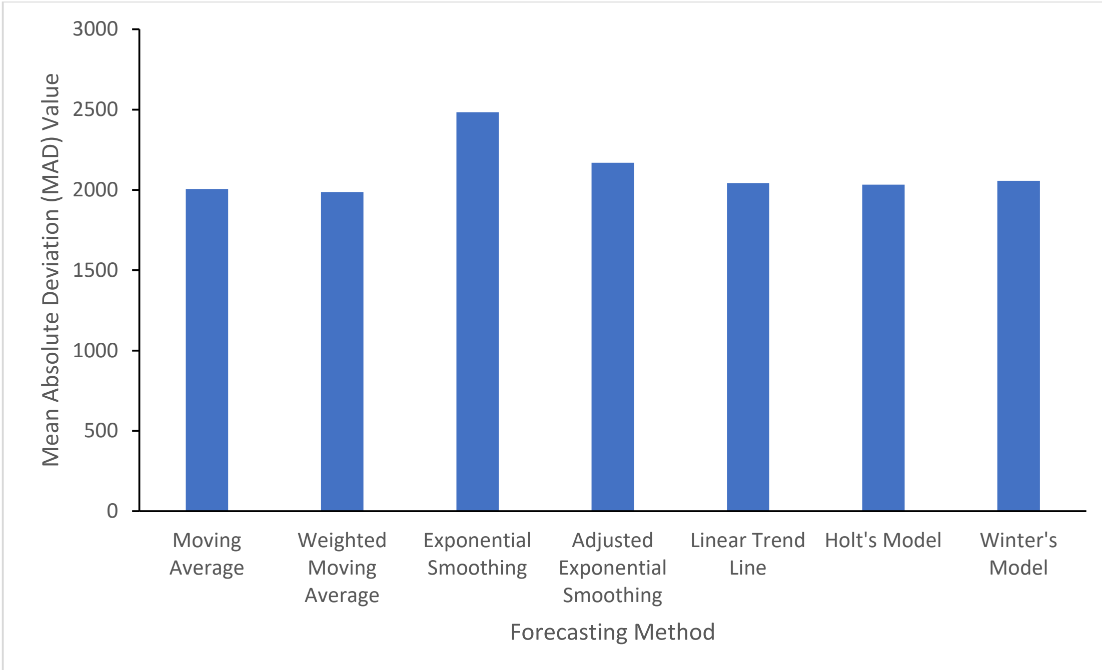

Fig. 8. Comparison of Mean Absolute Deviation (MAD) values for various 50cl bottled water forecasting methods

From Fig. 8, the exponential smoothing forecasting method possesses the highest MAD value of 2,483, 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 MAD value of 1,987, therefore it is the most accurate forecasting method for forecasting demand of the 50cl bottled water.

Using Microsoft Excel and the weighted moving average forecasting method, the forecasted demand for 50cl bottled water in the month of January, 2022 is 69,578 bottles.

5. Conclusions

Forecasting is a very important aspect of managerial activities in organisations for determining the direction of future trends. This paper has compared the performance of various classical time series forecasting methods to determine the method with the highest accuracy in predicting the 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. Moreover, the Mean Absolute Deviation (MAD) method was used in assessing the performance of each of the forecasting methods. The results showed that the moving average, weighted moving average, exponential smoothing, adjusted exponential smoothing, linear trend line, Holt's model, and Winter's model had MAD values of 2,005, 1,987, 2,483, 2,169, 2,042, 2,033 and 2,056, respectively. Since the weighted moving average method had the lowest MAD value of 1,987, it was determined to be the forecasting method with the highest accuracy for predicting the 50cl bottled water demand.

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