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TRIPLE EXPONENTIAL SMOOTHING TECHNIQUES: APPLICATION TO KENYA'S INDUSTRIAL INPUTS PRICE INDEX

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ABSTRACT
A move towards industrialization is an active ingredient in achieving sustainable economic development owing to the derived benefits of the creation of employment opportunities and enhanced international trade. Through its big four agenda launched on December 12, 2017, Kenya aims to foster the manufacturing sector. One of the industrial- agenda is reducing the costs of industrial inputs. Thus, an accurate predictive model that can be used to gauge the cost of manufacturing inputs ought to be developed. The current study compared the pertinence of two Holt-Winter Exponential Smoothing (HWES) techniques in forecasting Kenya's industrial inputs price data. Unlike simple moving average, where past values are weighted equally, exponential functions assign exponentially decaying weights, over time. The study used secondary data on Kenya's monthly industrial inputs price index from January 1980 to June 2018 extracted from the OECD website. The data had 450 observations and was analyzed using R software. The findings indicated that a hybrid of both the additive and multiplicative HWES model efficiently captures the nonlinearity or seasonality of industrial inputs price index series. Specifically, the "optimal" model was a specification of the multiplicative error, additive trend, and multiplicative seasonality ("MAM") with a performance accuracy of 2.3% in terms Mean Absolute Percentage Error (MAPE) in making 24 months step-ahead forecasts. The model outperformed the purely additive (2.44%) or multiplicative HWES model (2.55%). The estimated smoothing of alpha, beta and gamma were; 0.9647, 0.1378, and 0.0004, respectively. The prediction future prices movement is beneficial to producers, consumers and policymakers. The 24-period forecast of the industrial inputs the price index indicates a falling trend, and indication that the industrial agenda shows some prospects in the reduction of the cost of inputs.
Keywords: Industrial Inputs Price Index, Holt-Winter Exponential Smoothing, Additive Model, Multiplicative Model, Forecasting, Kenya

INTRODUCTION
Industrialization is the process by which an economy is transformed from primarily agricultural to one based on the manufacturing of goods. It is an essential ingredient in achieving sustainable economic growth and development through the creation of employment opportunities, enhancing international trade and assure maximum utilization of a country's resources. In, Kenya, Agriculture, industry and the service sectors contributed 15.7%, 21.6% and 62.7% to GDP growth rate of 5.1% in 2017 (AfDB, 2017). Empirical studies have revealed that the manufacturing sector has the highest employment multiplier effect as compared to other sectors. Bivens (2003) showed that every 100 jobs in the manufacturing sector support 291 jobs in other sectors of the economy, compared to 118 in the health sector, and 154 jobs in the service sector. According to Biven (2003), manufacturing production demands for intermediate goods and capital equipment than other sectors. Thus, layoffs in the manufacturing sector have a higher spillover effect on indirect employment loss than in other sectors. According to Berger *et al*. (2017), developing economies can create significant jobs in the non-tradable sectors by shifting towards skill-intensive production. With the world share of manufacturing value added (MVA) as a percentage of GDP is 16%, the Middle East & North Africa and sub-Saharan Africa had 14% and 10% respectively (World Bank, 2018). The African Economic Outlook (2018) report indicated that Eastern African countries like Kenya, Uganda, Tanzania and Rwanda had respective growth in MVA of 4.8%, 5.1%, 8.9%, and 9%. Since most African countries lag in terms of MVA, Africa has been on the move to unlock and enhance its manufacturing potential with the most recent launch of the Africans Continental Free Trade Area (AfCFTA) in March 2018. It should create a single continental market for

goods and services as well as a customs union with free movement of goods through the removal of tariffs (AU, 2020). Likewise, Kenya recently launched its Big 4 Agenda on December 12, 2017, comprising of four pillars; enhancing manufacturing, affordable housing, food and nutrition security, and universal healthcare coverage (The Presidency, 2020). Additionally, the manufacturing sector is an economic pillar under the Vision 2030 long-term development launched in 2008 (Kenya Vision 2030) aiming to transform Kenya to a middle-income country by 2030. Kenya's priority sectors under the manufacturing pillar are textile apparel/cotton, leather, agro-processing (tea, dairy & meat), fish processing, construction materials, oil, Mining and gas iron and steel and information communication and Technology (KAM, 2017).

Even though Africa is a cost-effective location for manufacturers due to its high population size, which is a source of cheap labour (Tate *et al*., 2014), most manufacturing companies in Kenya face challenges of the increased cost of inputs in their production processes (KAM, 2018). Moreover, Kenya's share of the manufacturing sector to GDP has been declining from 11.8% in 2011 to 8.4% in 2017. According to KAM (2018) priority agenda, it is an expectation that MVA will increase from 8.4% in 2017 to 15% by 2022. One of the first pillar under enhancing manufacturing is competitiveness and level playing field with one of its agendas being to lower the cost of imported industrial inputs (KAM, 2018). Therefore, it is imperative to understand how the cost of industrial inputs has been evolving. According to Köppelová & Jindrová (2019), quantitative information knowledge is essential when making policy decisions. The approach relies on and on data analysis, interpretation, and forecasting tools. Thus, time series analysis has become indispensable in the modern world as time-series data is continually rising (Hassani & Mahmoudvand, 2018). Classical models widely used to forecast the economic and financial time series, such as unemployment and stock indices, are based on restrictive assumptions of normality, linearity and the stationarity of the observed data (Hassani & Mahmoudvand, 2018). However, most time-series data do not meet these assumptions. In as much as non- linear models such as cointegration models, Autoregressive Integrated (AR), Moving Average (MA), Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) models have been developed, the data has to be stationary. As well, most economic and financial time series are characterized by non-stationarity caused by exogenous shocks such as; technological change, policy changes, and changes in consumer preference. Such shocks have rendered parametric models inaccurate in modelling and forecasting (Hassani & Thomakos, 2010). Violation of parametric assumptions in classical time series modelling calls for data transformations, e.g., by differencing or log transformation. According to Hassani and Mahmoudvand (2018), such data transformation results in a loss of information. Non-parametric methods can produce a better fit for the data with a higher accuracy performance than parametric methods.

As a non-parametric method, the parametric assumptions relating to normality, stationarity, and linearity do not apply when modelling with Exponential Smoothing Techniques (EST). It is used to isolate trends and seasonality from irregular variation (Chan *et al*., 2011). The technique eliminates the high variations in the signal while maintaining the significant patterns of series (Muhamad & Mohamed Din, 2015). The Holt Winter and Autoregressive Integrated Moving Average (ARIMA) class of models use past values to obtain future values (Hanzak, 2008). However, the two models have some disparity. First, the ARIMA model is capable of describing stationary data by differencing method (Wei, 2006). Secondly, the ARIMA model expresses a series in terms of both lagged values and the error values of the original series, unlike EST which only uses lagged values. While ARIMA class models and Holt Winter Exponential Smoothing (HWES) model integrates both Seasonal and trend data patterns into the model to enhance its performance Syafei, *et al.* (2019), HWES does not consider stationarity of data. Instead, HWES employs iterative steps and past observations are weighted to obtain predictive values (Omane- Adjepong *et al*., 2013). Moreover, unlike the simple moving average models where lagged observations are weighted equally, exponential functions allocate gradually decreasing weights over time (Ostertagová & Ostertag, 2011). The EST has been applied in univariate time series modelling and forecasting of air quality (Nimesh *et al*., 2014), population (Nazim & Afthanorhan, 2014), agrometeorological time series, consisting of air temperature, wind speed (Murat *et al*., 2016), monthly rainfall (Dhamodharavadhani & Rathipriya (2019), students' admission (Himawan & Silitonga, 2019), Chicken Business Profit (Sudirman, 2020). Based on model evaluation criterion such as Mean Absolute Percentage Error (MAPE), the HWES model produced better forecasts compared with single EST, double EST and ARIMA class models. Therefore, the current study compared the pertinence of two HWES; the additive and multiplicative HWES technique in fitting and forecasting Kenya's industrial inputs prices index.

DATA AND METHODS

The current study employed HWES to fit and forecast Kenya's industrial inputs price index data. The price index under consideration aggregates the data for both metals and non-metals (Agricultural) industrial inputs. Metals Price Index is calculated based on the prices of raw materials including Copper, Aluminum, Iron Ore, Tin, Nickel, Zinc, Lead, and Uranium while Agricultural Raw Materials Index, Timber, Cotton, Wool, Rubber, and Hides. No sampling technique is employed in this study since it deals with a univariate time series data. Therefore, secondary data set of Kenya's monthly industrial inputs price index data, over 25 years, from June 1993 to June 2018 (450 observations) obtained from the Organization for Economic Co-operation and Development (OECD) website (https://www.oecd.org/). The period is considered appropriate as it encompasses the pre- and post-industrial agenda towards industrialization in Kenya under the Vision 2030 long-term development launched in 2008. Additionally, this period is inclusive of the global crisis in 2008, which causes structural changes in time series data, making the time series data non-stationary (Hassani & Mahmoudvand, 2018). Thus, the model demonstrates its capability of capturing such structural breaks in a time series data.

Holt-Winters Exponential Smoothing Technique

Exponential Smoothing techniques were first suggested by Brown (1956) and expanded by Holt (1957). Triple exponential smoothing was first suggested by Holt's student, Peter Winters in 1960. It is suitable for time-series data that exhibit both seasonality and trend (Singh *et al*., 2019. The HWES technique comprises of a forecast equation with three smoothing equations. The first is at level; , followed by trend , and lastly for the seasonal component denoted by , with respective smoothing parameters , , and . The Holt-Winters method has two versions, additive and multiplicative, the use of which depends on the characteristics of the particular time series.

Additive Model

The additive method is preferred when the seasonal variations are roughly constant through the series. That is when the seasonal or trend component is not proportional to the level of the series. That is, we can overlay or add the components together to reconstruct the original series. If Y is the price index, the component form for the additive method is: $\hat{}_{+h|}$

$$= + h + \quad (2.1)$$

Where; m denotes the frequency of the series. In this case, m is taken as 12 since the data is monthly and k is an integer such that the estimates of the seasonal indices used for forecasting come from the end year of the sample data. The level equation shows a weighted average between seasonally adjusted observation $-$ $_-$ and non- seasonal forecast $_{-1}+$ $_{-1}$ for time for . Seasonal equation shows a weighted average between current seasonal index, $-$ $_{-1}-$ $_{-1}$ and the seasonal index of the same season last year (h periods ago). The specification of this model takes the form "AAA" denoting the additive error, additive trend, and additive seasonality.

Multiplicative Model

The multiplicative model is preferred when the seasonal variations are changing proportionally to the level of the series. With this model, the seasonal component is expressed in relative terms (percentages), and the series is seasonally adjusted by dividing through by the seasonal component. Annually, the sum of the seasonal components is approximately m. Generally, the additive model is represented as follows:

$$\quad (2.2)$$

The component form for the multiplicative method is: $\hat{}_{+h|} = (+ h \ )\ _{+h-(+1)}$. The multiplicative seasonality model takes the form "MMM". That is, with a multiplicative error, trend, and seasonality.

Data Analysis

Data was be analyzed using the R Statistical Software (R Core Team, 2020). The analysis involved presenting the general descriptive statistics of the series, decomposition of the time series properties of the series using technique and eventually fitting the model.

The procedure of obtaining both the Holt-Winters Triple Exponential Smoothing Additive and Multiplicative models are outlined below;

Step 1: Determining the initial values: For the stationary (S), trend (T) and seasonally (I) components using equations the following equations;

$$= , = \frac{1}{} (_1 + _2 + \dots +) \quad (2.3)$$

$$= \frac{1}{} \left(\frac{(_{+1} - _1)}{} + \frac{(_{+2} - _2)}{} + \dots + \frac{(_+ -)}{} \right) \quad (2.4)$$

$$= \frac{}{} , = 1,2,3, \dots \quad (2.5)$$

Step 2: Choosing the Values for the Smoothing Parameters.

Unlike in single exponential smoothing, TES usually has more than one smoothing parameter. The initial parameters are α, β and γ, ranging between 0 to 1. While the choice of smoothing parameters can be subjective, it can be estimated by minimizing the sum of squared errors (SSE) (Hyndman & Athanasopoulos, 2018). The errors are obtained as $= - _{|-1}, = 1, \dots,$, that is, the one-step-ahead within-sample forecast errors.

The optimum parameters and initial values of the model minimizes the SSE obtained as;

$$= \sum (\; - \; {}_{-1}) = \sum {}^{2} \qquad (2.6)$$

=1 =1

Unlike in linear regression analysis, which uses a formula to calculate the regression coefficients minimizing the SSE directly, it requires a non-linear minimization problem necessitating the use of an optimization tool (Scales, 1985). In this study, the determination of the smoothing parameter (α) is based on trial and error. To determine the value of α, the series are smoothed based on guessed values from 0.1 to 1 by 0.1 as used by Muhamad & Mohamed Din (2015). The best value of α to be used is the one that minimizes the SSE. According to Lazim (2013), a smaller value of α suits a stable time series data while a larger α suits a rapidly changing series.

Step 3: Calculation of TES data stationary with additive and multiplicative method can be performed using equations as used by Siregar, *et al*. (2017).

Additive: $= (- {}_{-1}) + (1 -)({}_{-1} + {}_{-1})$

Where; is the observations of the industrial inputs index series ; smoothing factor, $0 < < 1$

; are the observations of the smoothed data

−1; Trend factor

; initial value index

Step 4: Estimation of the trend data using equations below:

Additive: $= (- {}_{-1}) + (1 -) {}_{-1}$ Multiplicative: $= (+ {}_{-1}) + (1 -)({}_{-1}$

Where; is the trend smoothing factor, $0 < < 1$

Step 5: Estimation of the initial value I is then done using the equation below;

Additive: $= (-) + (1 -) -$

Multiplicative: $= + (1 -)$

Where; is the seasonal smoothing factor, $0 < < 1$

Step 6: After obtaining all the parameter values, then m step ahead forecasts is estimated using the equation 2.7 (Himawan & Silitong, 2019).

$$+ \; = (+) - +) \qquad (2.7)$$

Step 7: The RMSE is then computed based on the fitted values and recorded. Step two to sx, is repeated until a final model which minimizes the SSE (Equation 3.12) is obtained. The model minimizing the prediction error rate is chosen and used for forecasting (Köppelová & Jindrová, 2019).

Step 8: The best model is then used to make m-step-ahead predictions using equation 2.7.

Models Evaluation Criterion

Several performance metrics have been used to evaluate the performance of models based on error measurement (Lazim, 2013). The prediction errors are the differences between the actual and forecasted values. This study employed the Mean Absolute Percentage Error (MAPE), which estimates the square root of the averaged squared prediction errors, to compare the performance of SSA and the two TES additive and multiplicative. The MAPE measures the average absolute error across the periods, expressed aa s percentage of the observation values (Jana, 2016). The MAPE is calculated using the following equation (Himawan & Silitong, 2019).

$$\frac{1}{} \sum_{=1} \frac{\;}{\;}$$

The best model for adoption is the one that minimizes the value of MAPE based on the 24 months step-ahead forecasts covering the period between July, 2018, to July 2022.

RESULTS AND DISCUSSION

The current study looks into the applicability of SSA to monthly industrial inputs price index data from January 1980 to June 2017. The time series plot in figure 1 presents an oscillatory change in the price index in the 1990s followed by a sharp rise from January, 20002. The impact of the recession of 2008/2009 attributed to the banking crisis is evident due to a sharp fall in the industrial inputs price index within this period. This shows that the price index data is elastic and can respond to global economic shocks. Such exogenous shocks make data non-stationary with seasonal fluctuation. Thus, the use of a filtering technique such as SSA could provide better results since it can filter, extract, and model such signals (Silva, Hassani, and Heravi 2018). In general, it is observable that the monthly industrial inputs price index series depicts seasonality and trend pattern. Therefore, the associated harmonic components should be extracted and modelled Holt and Winters Triple Exponential smoothing.

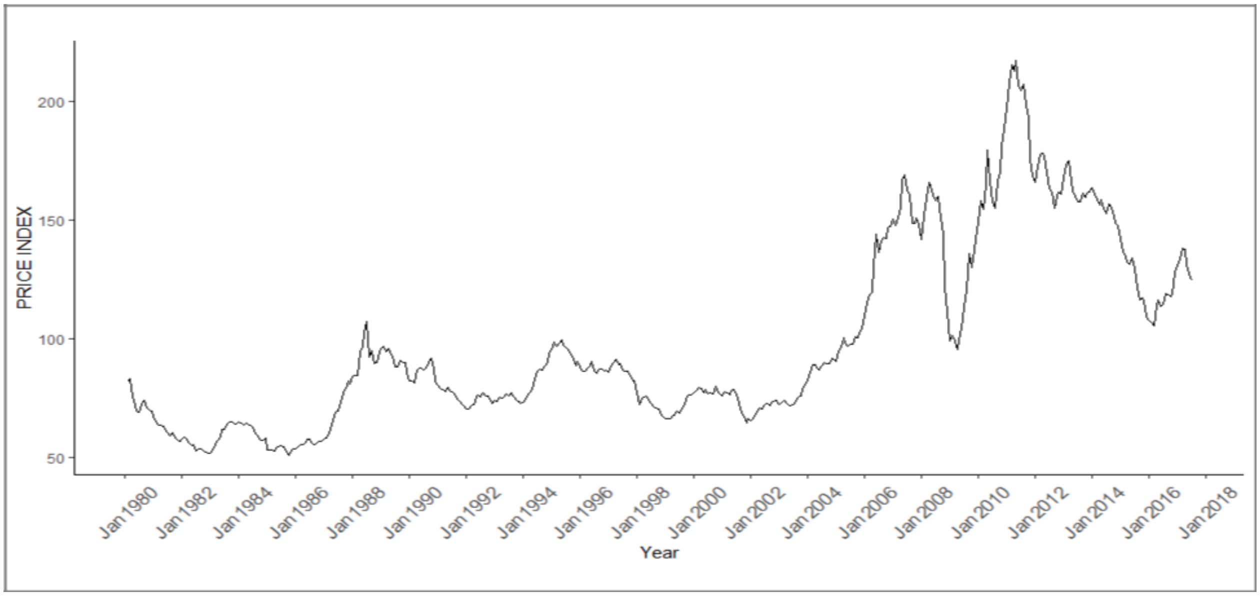

Figure 27: Monthly Industrial Inputs Price Index Data (1982M1–2017M6)

Descriptive Statistics

As shown, in table 1, the least price index was 50.92 recorded in September, 1989, whilst the highest was 217.07, recorded in April, 2014. The priced index between January, 1982 to June, 2019 averaged 98.20 with a standard deviation of 38.40. The measures of dispersion indicate that the data is non-symmetrical to the mean suggesting that the seasonality skews the distribution of the data (Table 1). However, since HWES is a non-parametric method which is da-a adaptive, the distribution of the data is not of the utmost importance.

Table 89: Descriptive Statistics

Min	Mean	SD	Max	Skewness	Kurtosis
Price Index50.92	98.20	38.48	217.07	1.03	0.06

Decomposing the Data

Most time-series data represent an amalgam response of physically interpretable signal of concern ana d certain amount of noise (Rekapalli & Tiwari, 2015). A time series can portray trend, seasonal or irregular component.

- **Seasonal component** refers to variations in a given series concerning the calendar cycles. For example, the demand for ice cream might increase during summer and decrease during winter. Typically, seasonality is the tendency of time-series data to exhibit a behaviour that repeats itself after some fixed interval; say after quarterly, semi-annually or monthly periods.
- **Trend component** is the overall pattern of the series which can either be decreasing or increasing over time.
- **Cycle component** comprises of the decreasing or increasing patterns that are not seasonal.
- **The error or residual component** is the portion of the series that is not explained by seasonality, cyclical, or trend components.

Decomposing the time series is the process of extracting or separating these components. The current study employed the “Seasonal and Trend decomposition using Loess” (STL) decomposition method to decompose the series into its constituents. Here, Loess is a method for estimating nonlinear relationships which estimate the seasonal component of a series using smoothing technique and corrects the initial series by removing seasonality (Cleveland *et al*., 1990). STL is more advantageous over the classical, SEATS (Seasonal Extraction in ARIMA Time Series) and X_{11} decomposition techniques (Dagum and Bianconcini 2016).

(i) The rate of change in the seasonal component and the smoothness of the trend-cycle can be customized.
(ii) In case of the presence of outliers in the data set, robust decomposition can be adopted to minimize the impact of influential observations on the estimates of the trend-cycle and seasonal components.
(iii) 11 specifically handles high varying frequency data such as weekly, intraday series where trading day variation and holiday effects occur

By applying STL decomposition to the price index series, figure 8 depicts the original time series (observed) and its three additive components; the estimated trend, seasonal, and the irregular component. The fitted trend component is oscillatory with both increasing and decreasing trend. A steady increase occurred between 200p to 2009 followed by a sharp rise in 2010.

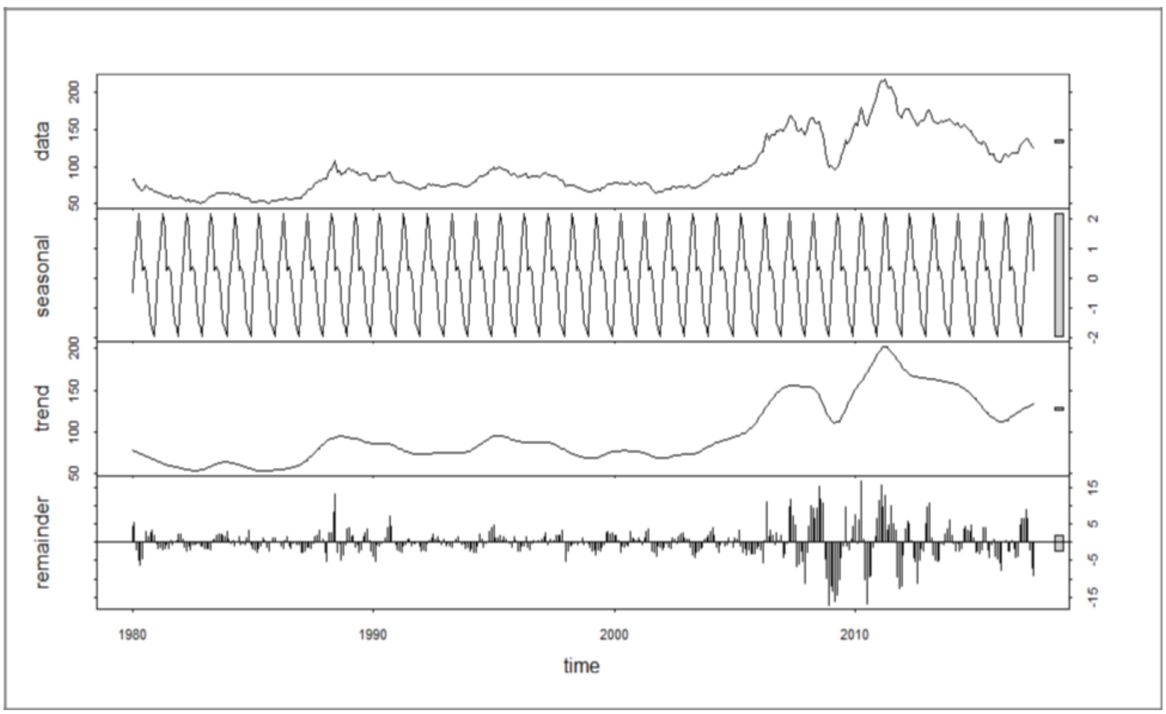

Figure 28: Robust Decomposition of the Industrial Inputs Price Index Series Using STL

Since the series has both seasonality and trend, forecasts can be made using triple exponential smoothing (Holt- Winters exponential smoothing method). The technique estimates the level, slope and seasonal component at the current time point (Holt, 1957 and Winters, 1960). The Holt-Winters seasonal method comprises the forecast equation and three smoothing equations representing the estimates of the level ( ) one for the slope of the trend component ( ), and another for the seasonal component ( ) with corresponding smoothing parameters; alpha ( ), beta ( ), and gamma ( ). All the parameter values range between 0 and 1. Values closer to 0 indicates that relatively little weight is placed on the most recent observations when making forecasts of future values. The resultant components can be described using an additive model or multiplicative.

Figure 4.3 shows the plot the original time series with the forecasted values using the HWT filtering technique. A preliminary evaluation of this technique shows that it can well fit the price index series since the plot depicts that the in-sample forecasts (red line) are congruent with the observed values (black line).

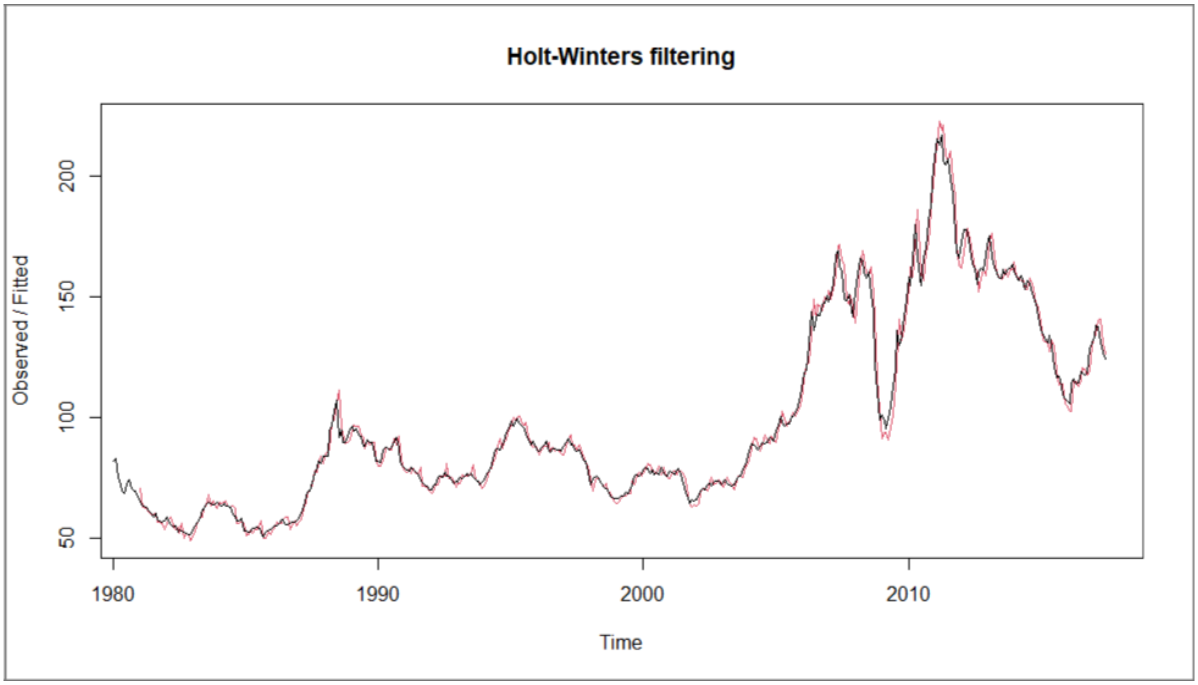

Figure 29: Ho-t Winters Triple Exponential Smoothing (Auto-plot from "HoltWinters" function in R)

To determine the best predictive model, different model specifications are fitted and their accuracy performance evaluated using RMSE. Table 4.2 depicts the accuracy of the two pure additive and multiplicative models with four hybrid model specifications. The predictive accuracy of a purely additive model is better (2.44% based on the MAPE) than a purely multiplicative model (2.55% based on the MAPE). The smaller value of for the purely additive model relative to the multiplicative model implies that the seasonal component in the later changes more with time. The increasing size of the seasonal parameter ( ) for the multiplicative model elicits that the model is more suitable to capture frequently changing seasonality in the series than the additive model.

Conversely, the smaller value of for the purely additive model relative to the purely multiplicative model implies that the slope component of the series described by the additive model barely changes over time. As indicated by the decomposed series (Figure 4.2) the trend component frequently changes over time. Thus, a larger beta, as in the additive model could be appropriate to capture the trend component. Similarly, the error term can best be described by the multiplicative model since it has a relatively small α value. Generally, the best model specification is of the multiplicative error, additive trend, and multiplicative seasonality("MAM"). The model is assumed "optimal" and thus best fit for the data since it minimizes the RMSE of 2.30% by harmonizing all the parameters (Table 4.2)

Table 90: Models Evaluation

	Smoothing Parameters				
Model Specification	**Alpha**	**Beta**	**Gamma**	**Phi**	**MAPE**
ETS (A, Ad, A)	0.9903	0.1411	0.0096	0.8	2.44
ETS (M, Md, M)	0.8024	0.1263	0.1937	0.9365	2.55
ETS (M, Ad, A)	0.9983	0.1412	0.0017	0.8	2.33
ETS (M, Ad, M)	0.9647	0.1378	0.0004	0.8742	2.30

Note: All model parameters are optimized based on the minimization of BIC values

Figure 4 shows the decomposition of the series using the resultant ETS (MAM) model into the level, slope, and the seasonal component

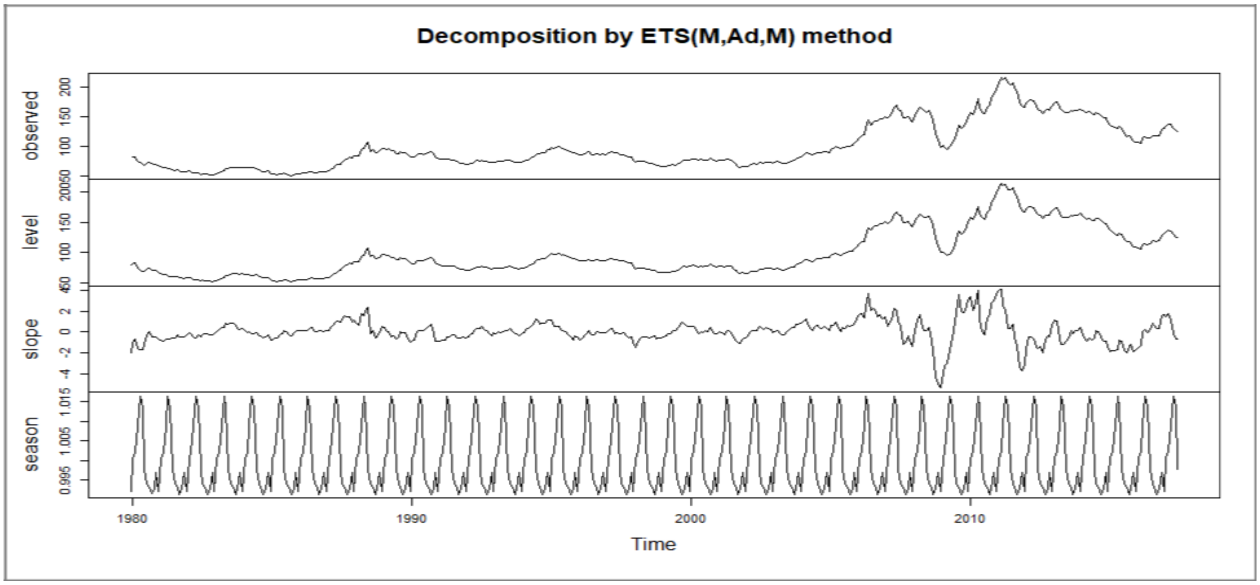

Figure 30: Decomposition of the Series by ETS (MAM)

Model diagnostics

Use of time series modelling techniques relies on the satisfaction of the assumption that, the prediction errors are white noise in nature (Köppelová & Jindrová, 2019) usually an uncorrelated stochastic quantity with zero mean and constant variance (Zhang & Karniadakis, 2017). The residual plot in figure 4.4 depicts that the assumption of constant variance over time was met. That is the residuals seems to have a constant mean and variance over time with minor fluctuations. Secondly, the forecast errors are normally distributed as indicated by the histogram. Lastly, there is no significant autocorrelation at lags 1-24 as depicted by the Autocorrelation Function (ACF) plot.

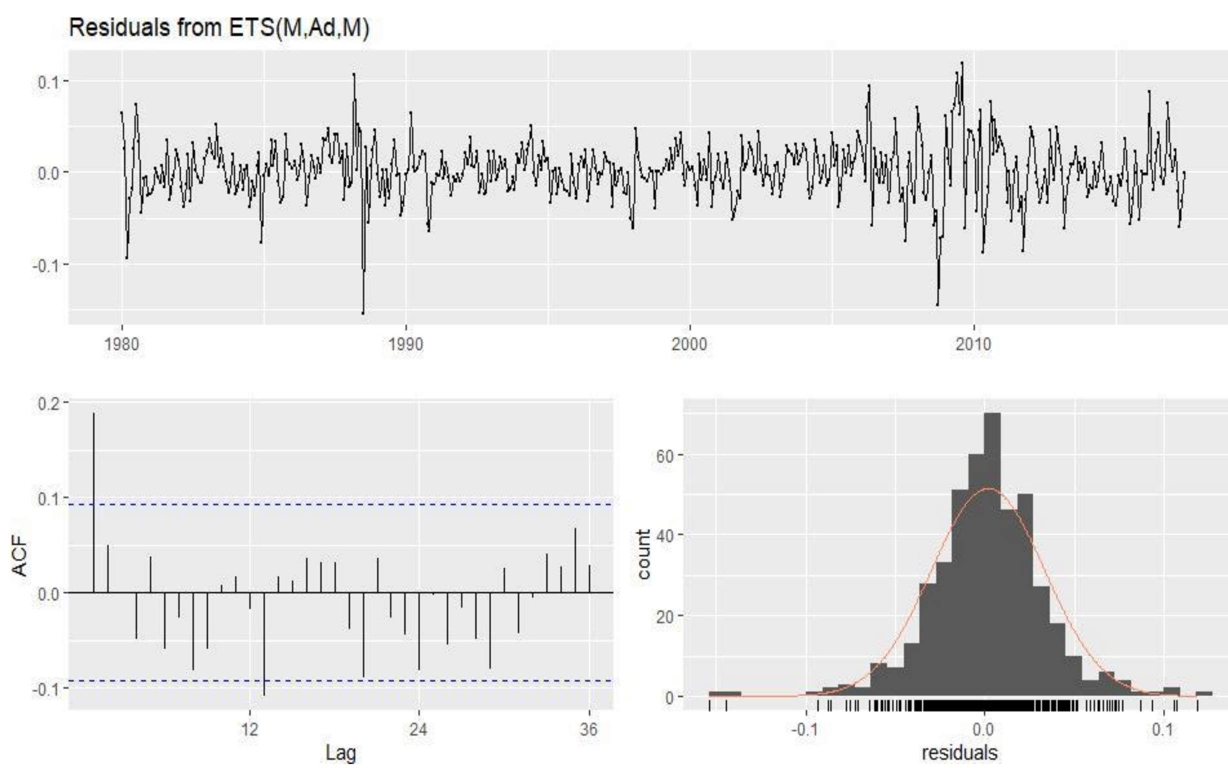

Figure 31: Residuals Diagnostics

Forecasting

Given the MAM model minimized the MAPE and that the assumption of heteroscedasticity, normality, and no autocorrelation of the forecast errors was met, this HWES technique is an adequate predictive model of the industrial inputs price index. The 24 months step-ahead forecasts from the model are shown as a blue line, with the 80% prediction intervals as a dark grey shaded area, and the 95% prediction intervals as a grey shaded area (Figure 4.5).

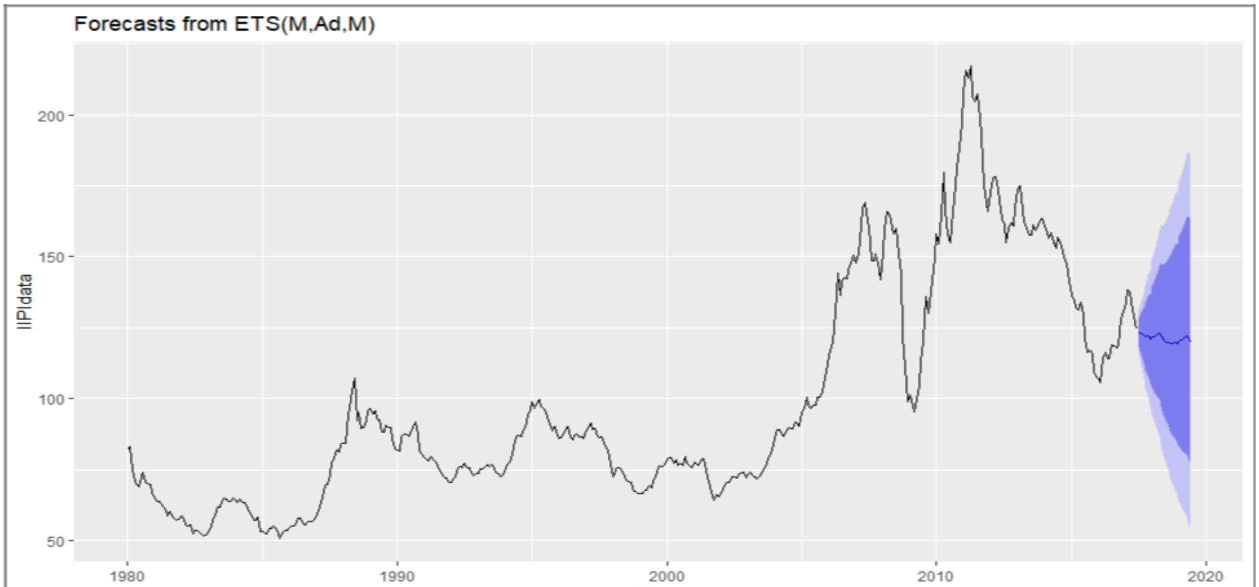

Figure 32: Forecasts from MAM HW model

CONCLUSION

The exponential smoothing technique was applied to the industrial inputs price index series to allow for an examination of its underlying component and in making short period time forecasting. The best forecasting model was a hybrid of both additive and multiplicative model. The specification of the model was a multiplicative error, additive trend, and multiplicative seasonality ("MAM") with a performance accuracy of 2.3% in terms Mean Absolute Percentage Error (MAPE) in making 24 months step-ahead forecasts. The estimated smoothing of alpha, beta and gamma were; 0.9647, 0.1378, and 0.0004, respectively. The low value of the seasonal parameter ( ) suggests that the industrial inputs price index series is not highly affected by seasonal fluctuations. The high value of the smoothing parameter α points out that the variation of the series is large. The results highlight that the prices index series is higher variability in the short run. Thus, there is a need to ensure that prices are stable and sustainable. Nonetheless, the 24-period forecast indicates a falling trend in the price index. Owing to its simplicity and accuracy, the HWES technique can be of practicable importance for monthly time series forecasting

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Declaration of Competing Interests

The author declares no competing interests.

Authors' contributions

All authors have read and agreed to the final paper.

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