

FORECASTING THE CONSUMER PRICE INDEX OF GHANA USING EXPONENTIAL SMOOTHING METHODS

Boniface Aabeyir
SDA Senior High School
Post Office Box 45
Ashanti Region-Ghana

Abstract

Consumer price index is a social and economic indicator that measures changes over time in the general level of prices of consumer goods and services that households acquire, use or pay for consumption. Rising CPI also often leads to the central bank to raise interest rates, tightening money supply, reduce the money supply and other measures to tighten monetary policy, which flow into reduction of capital stock funds for greater returns, often accompanied by high inflation. The study seeks to determine a time series exponential smoothing method which fit the CPI and use it forecast the future values of CPI. Minitab software is used to analyze the CPI from March 2013 to November 2018. Out three exponential smoothing methods, it is realized that the method which best fit the series is the Winters' additive method with exponential smoothing constants for the level, trend and seasonal variation as $\alpha = 0.7$, $\gamma = 0.2$ and $\delta = 0.2$ respectively. This method is chosen on the basis that it has the lowest MAPE, MAD and MSD. The validity of the model is further checked by comparing the fitted values with the actual values. The errors in prediction were very minimal. The model is therefore recommended for forecasting CPI of Ghana in the next twelve months.

Key words: Consumer price index, exponential smoothing, ARIMA

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1.0 Introduction

The consumer price index (CPI) in Ghana measures changes in the prices paid by consumer for a basket of goods and services. In another words, CPI is a social and economic indicator that measures changes over time in the general level of prices of consumer goods and services that households acquire, use or pay for consumption. If the CPI rises faster than wages, the purchasing power which is the amount we can buy with our cedi decreases and therefore affects our cost of living.

The CPI is a key economic indicator since a rising CPI is an early warning signal of imminent economic challenges since it triggers a rise in inflation. A rising inflation affects the policy rate of the central bank (Bank of Ghana) and results increase in interest rates of loans. The CPI actually controls the policy direction of the central bank. Apart from its role as a guide for future central bank policies, the CPI release can be useful in predicting the course of national politics, due to the tendency of voters to punish governments which cannot help them at times of rising food prices or prices of petroleum products (Forexfraud.com, 2019).

The CPI has more macroeconomic consequences also which include pension benefits and large-scale spending plans. Since pension obligations and other large-scale spending plans are often pegged to the CPI, even very minor changes in the CPI can alter the prices of financial portfolios by millions of pounds (Powell et. al., 2016).

In trying to build a formidable and resilient economy, it is imperative to know the long run behavior of the CPI and it is in the light of this that the study is being conducted to find the appropriate time series model for forecasting the CPI of Ghana using data from March 2013 to December 2018. A lot of

methods have been used to analysis and forecast time series data, such as autoregressive model autoregressive moving average (ARIMA) model and exponential smoothing models (Jie et al., 2015) but this study seeks to find the suitable exponential smoothing model for CPI and use it to forecasts for the next ten (10) months.

1.1 Literature Review

A lot of intensive works have been done using times series modeling. One of the most popular and frequently used stochastic time series models is the autoregressive integrated moving average (ARIMA) and the popularity of the ARIMA model is mainly due to its flexibility to represent several varieties of time series with simplicity as well as the associated Box-Jenkins methodology (Zhang, 2003, Hipel and McLeod, 2003).

Adams et al., modeled Nigeria's consumer price index using ARIMA model. The Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) models were estimated and the best fitting ARIMA model was used to obtain the post-sample forecasts. It was discovered that the best fitted model was ARIMA (1, 2, 1). The model was validated by Ljung-Box test ($Q = 19.105$ and $p > .01$) with no significant autocorrelation between residuals at different lag times. Finally, the five years forecast was made, which showed an average increment of about 2.4% between 2011 and 2015 with the highest CPI being estimated as 279.90 in the 4th quarter of the year 2015.

Papalaskaris et al., 2016, employed seasonal autoregressive integrated moving average (SARIMA) $(0, 0, 0)(0, 1, 1)_{12}$ model to perform short term of monthly rainfall in parts Greece and North-Eastern Mediterranean basin. In fitting of a SARIMA model to monthly Naira-Euro exchange rates, Etuk (2013), proposed and fitted SARIMA $(0, 1, 1)(1, 1, 1)_{12}$. This model was shown to adequately explain the variation in the monthly Naira-Euro exchange rates.

Exponential smoothing method has established itself as one of the leading forecasting strategies (Nur et al., 2013). Siregar et al., 2016, conducted to determine the performance of the system in forecasting realization palm oil production using exponential smoothing method. The study compared several methods based on exponential smoothing (ES) technique such as single ES, double exponential smoothing holt, triple exponential smoothing, triple exponential smoothing additive and multiplicative to predict the palm oil production. The result showed that triple ES additives had lowest error rate compared to the other models with RMSE of 0.10 with a combination of parameters $\alpha = 0.6$, $\beta = 0.02$, and $\gamma = 0.02$. According to Tirkeş et al., 2017, several statistical models have been used in demand forecasting in food and beverage (F&B) industry and the choice of the most suitable forecasting model remains a central concern. Their main goal was to propose an optimization model based on demand forecasting approach depending on a comparative study using trend analysis, Holt-Winters' exponential smoothing and decomposition method of time series forecasting for estimating a realistic future demand.

Karmaker et al., 2017, in their study of time series model for predicting jute yarn demand, performed by statistical analysis using Minitab 17 software to determine the appropriate exponential forecasting techniques. Performance of all methods was evaluated on the basis of forecasting accuracy and the analysis showed that Winter's additive model gave the best performance in terms of lowest error determinants.

2.0 Methodology

The purpose of the study is to identify the appropriate exponential smoothing method which fits the data based on the forecasting errors and use it to forecast the next nine months CPI of Ghana. Three exponential smoothing methods will be looked at especially, the simple exponential smoothing method, double exponential smoothing or Holt's method and the Winters' method using Minitab 16.

Exponential smoothing models (Gardner, 1985) are classified as either seasonal or nonseasonal. Holt exponential smoothing method is the most popular double exponential smoothing method proposed by Holt (1957) as an extension of the simple exponential smoothing method to allow forecasting of data with a trend (Jie et al., 2015).

2.1 Simple Exponential Smoothing

The simple exponential smoothing (SES) model is best suited for a short-term forecasting, and usually this model is used for the prediction a future when the series has no trend and no seasonal variation. The forecasting equation is

$$F_t = \alpha y_t + (1 - \alpha)F_{t-1},$$

where F_t is a forecast for the time series at t , F_{t-1} represents the value of forecasting for the previous period at $t-1$ and y_t is the actual value at t and $0 \leq \alpha \leq 1$.

2.2 Holt's Method

Double exponential smoothing or Holt's method by Holt (1957), an extension of the simple exponential method, is used to forecast data having linear trend. It consists of a forecasting equation, level and trend equations.

$$\text{Forecast equation: } \hat{y}_t = l_{t-1} + b_{t-1}$$

$$\text{Level equation: } l_t = \alpha y_t + (1 - \alpha)(l_{t-1} + b_{t-1})$$

$$\text{Trend equation: } b_t = \gamma(l_t - l_{t-1}) + (1 - \gamma)b_{t-1}$$

where \hat{y}_t is the fitted value, or one-step-ahead forecast, at time t , l_t is level estimate at time t , b_t is trend (slope) estimate at time t , α is smoothing constant for level $0 \leq \alpha \leq 1$ and γ is smoothing constant for trend $0 \leq \gamma \leq 1$.

Winters' Method

Holt (1957) and Winters (1960) extended Holt's method to capture seasonality and the method is called Hot-Winters' method or simply Winters' method. The method comprises the forecast equation and three smoothing equations namely, the level equation, the trend equation and the seasonal equation. There are two types of Winters' method. These are two types of the additive and multiplicative methods. When the magnitude of seasonal pattern appears constant the additive model is used and when it varies with the size of the sample, the multiplicative method is used.

Forecasting equation for additive model

$$\text{Forecasting equation: } \hat{y}_t = l_{t-1} + b_{t-1} + s_{t-p}$$

$$\text{Level equation: } l_t = \alpha(y_t - s_{t-p}) + (1 - \alpha)(l_{t-1} + b_{t-1})$$

$$\text{Trend equation: } b_t = \gamma(l_t - l_{t-1}) + (1 - \gamma)b_{t-1}$$

$$\text{Seasonal component: } s_t = \delta(y_t - l_{t-1}) + (1 - \delta)s_{t-p}$$

Forecasting equation for multiplicative model

$$\text{Forecasting equation: } \hat{y}_t = (l_{t-1} + b_{t-1})s_{t-p}$$

$$\text{Level equation: } l_t = \alpha \left(\frac{y_t}{s_{t-p}} \right) + (1 - \alpha)(l_{t-1} + b_{t-1})$$

$$\text{Trend equation: } b_t = \gamma(l_t - l_{t-1}) + (1 - \gamma)b_{t-1}$$

$$\text{Seasonal component: } s_t = \delta \left(\frac{y_t}{l_t} \right) + (1 - \delta)s_{t-p}$$

where l_t is the level at time t , α is the weight for the level, b_t is the trend at time t , γ is the weight for the trend, s_t is the seasonal component at time t , δ is the weight for the seasonal component, p is the seasonal period, y_t is the data value at time t and \hat{y}_t is the fitted value, or one-period-ahead forecast, at time t .

2.3 Measures of Accuracy

Three measures of accuracy of the fitted model are considered. These are mean absolute percentage error (MAPE), mean absolute deviation (MAD), and mean squared deviation (MSD) for each of the smoothing methods. For the three measures, the smaller the value, the better the fit of the model.

2.3.1 MAPE

The mean absolute percentage error measures the accuracy of fitted time series values. It expresses accuracy as a percentage.

$$\text{MAPE} = \frac{\sum \left| \frac{(y_t - \hat{y}_t)}{y_t} \right|}{n} \times 100$$

2.3.2 MAD

Mean absolute deviation measures the accuracy of fitted time series values. It expresses accuracy in the same units as the data, which helps conceptualize the amount of error.

$$\text{MAD} = \frac{\sum |y_t - \hat{y}_t|}{n} \times 100$$

2.3.3 MSD

The mean squared deviation is always computed using the same denominator, n , regardless of the model, so you can compare MSD values across models. MSD is a more sensitive measure of an unusually large forecast error than MAD.

$$\text{MSD} = \frac{\sum |y_t - \hat{y}_t|^2}{n} \times 100$$

3.0 Analysis of Results

3.1 Descriptive Statistics of the CPI

The descriptive statistics considered here include measures of central tendency, measure of dispersion and quartiles. They are displayed in table 1 below.

Table 1: Descriptive Statistics: CPI

Variable	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
CPI	69	165.30	37.24	108.00	130.60	168.00	200.85	224.20

From table 1 above, the average (mean) of the CPI is 165.30. The minimum CPI recorded during the period is 108.00 and the greatest is 224.20. The standard deviation is 37.24. the table further reveals that 25% of the CPI are below 130.60, half are above and below 168.00 and 75% of the CPI are below 200.85.

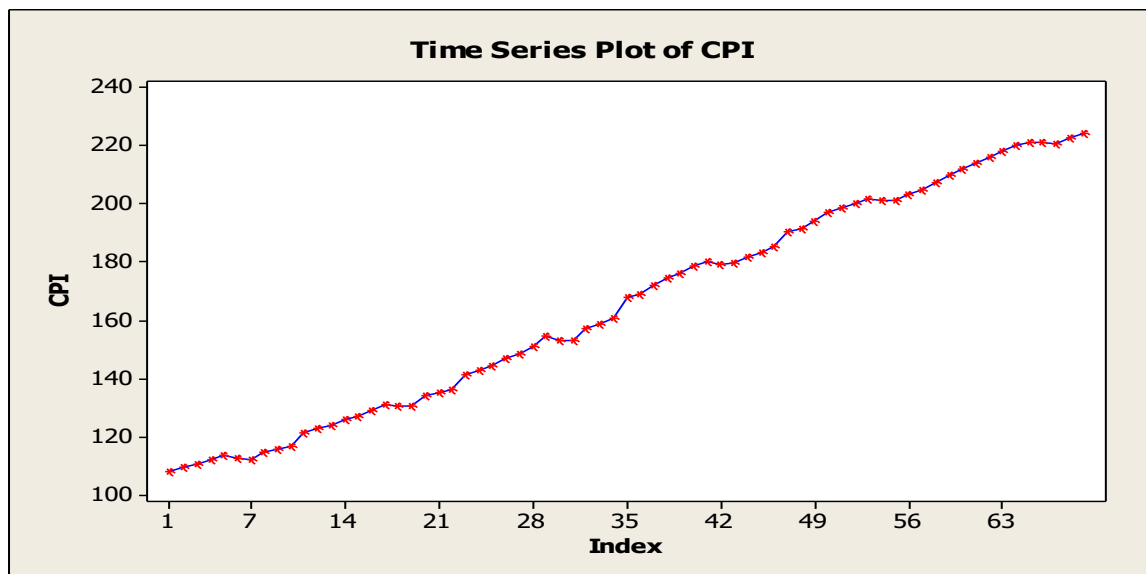


Figure 1: Plot of the CPI

From figure 1 above is the plot of the 69-month CPI of Ghana from March 2013 to November 2018. Clearly from the plot in figure 1 above, the CPI has an increasing trend suggesting that the simple exponential method must be ruled out as a possible method of forecasting the CPI of Ghana. It is now left with two possible methods (Holt’s and Winters’ methods).

Table 2: Smoothing constants and forecasting errors under SES method

Smoothing constant (alpha)	MAPE	MAD	MSD
0.5	2.07	3.45	14.23
0.6	1.76	2.82	10.52
0.7	1.55	2.47	8.26
0.8	1.40	2.22	6.79
0.9	1.29	2.03	5.80

From table 2 above, it is realized that as the smoothing constant increases, the mean absolute percentage error (MAPE) decreases but as the smoothing constant is inversely proportional to the mean absolute deviation (MAD) and the mean squared deviation (MSD). The least of three measures of accuracy values are 1.29, 2.03 and 5.80 for the MAPE, MAD and MSD respectively. Among the three, the MAPE value of 1.29 with a smoothing constant of 0.9 is the minimum.

Table 3: Forecasting errors under Holt’s method

Alpha (level)	Gamma (Trend)	MAPE	MAD	MSD
0.1	0.1	1.58	2.44	8.60
0.2	0.1	1.27	1.94	5.88
0.2	0.2	1.26	1.92	6.02
0.2	0.3	1.35	2.06	6.36
0.2	0.4	1.44	2.21	6.99

From table 3 above, the alpha values chosen were 0.1 and 0.2. The gamma values varied between 0.1 and 0.4. The lowest accuracy measures of the five trials are 1.26, 1.92, and 5.88 for MAPE, MAD, and MSD, respectively. The optimal exponential smoothing constant for each level (alpha) and trend (gamma) is 0.2 because they have the lowest MAPE and MAD.

Table 4: Smoothing constants and forecasting errors under Winters' additive method

Alpha (α)	Gamma (γ)	Delta (δ)	MAPE	MAD	MSD
0.4	0.2	0.2	0.4014	0.6203	0.6231
0.5	0.2	0.2	0.3583	0.5555	0.5311
0.6	0.2	0.2	0.3376	0.5262	0.4849
0.7	0.2	0.1	0.3293	0.5161	0.4666
0.7	0.2	0.2	0.3281	0.5159	0.4662
0.7	0.2	0.3	0.3285	0.5182	0.4682
0.7	0.3	0.3	0.3334	0.5294	0.4711
0.8	0.2	0.2	0.3287	0.5203	0.4664
0.9	0.2	0.2	0.3352	0.5326	0.4807

From table 4 above, the smoothing constant, alpha is varied between 0.4 and 0.9 while the gamma was between 0.2 and 0.3. The other constant, delta, was also varied between 0.1 and 0.3. of the nine trials, the minimum measures of accuracy was 0.3281 with smoothing constants $\alpha = 0.7$, $\gamma = 0.2$ and $\delta = 0.2$.

Table 5: Smoothing constants and forecasting errors under Winters' multiplicative method

Alpha (α)	Gamma (γ)	Delta (δ)	MAPE	MAD	MSD
0.1	0.1	0.1	1.8703	3.0165	13.6638
0.2	0.1	0.1	1.6152	2.5947	9.3010
0.2	0.2	0.1	1.6235	2.5955	9.1894
0.2	0.1	0.2	1.3976	2.1812	6.7910
0.2	0.1	0.3	1.2448	1.8976	5.3683
0.2	0.1	0.4	1.1469	1.7247	4.5529
0.2	0.1	0.5	1.0935	1.6344	4.0658
0.2	0.1	0.6	1.0631	1.5816	3.7524
0.2	0.1	0.7	1.0466	1.5550	3.5333
0.2	0.1	0.8	1.0304	1.5281	3.3730
0.2	0.1	0.9	1.0148	1.4995	3.2613
0.2	0.2	0.2	1.4046	2.1852	6.5152
0.2	0.2	0.3	1.2420	1.8903	5.0566

In table 5 above, there were 13 trials in all and α values varied between 0.1 and 0.2. The gamma, γ , varied between 0.1 and 0.2 and delta, δ , varied between 0.1 and 0.9. The optimal smoothing constants are $\alpha = 0.2$, $\gamma = 0.1$ and $\delta = 0.9$ and the least value of the MAPE is 0.0148.

The simple exponential smoothing method has been ruled out earlier as the plot of the CPI is characterized by upward movement. Clearly, there is a trend in the series and as indicated earlier, the exponential smoothing method is used when the series has no trend and seasonal variation. The measures of accuracy in table 2 affirms this point as the MAPE, MAD and MSD values of the SES are the largest among the other methods. After ruling out the SES method, the choice of the appropriate method for forecasting the CPI is limited to the Holt's and the two Winters' methods. The Winters' additive method is considered appropriate for forecasting the CPI since it has the lowest value measures of accuracy. The exponential constants for the chosen Winters; additive model are $\alpha = 0.7$, $\gamma = 0.2$ and $\delta = 0.2$ and the measures of accuracy are MAPE=0.3281, MAD=0.5159 and MSD=0.4662.

3.2 In-sample and Post-sample Forecast

To judge the forecasting ability of the selected exponential smoothing method, the sample period forecasts are computed. The sample period forecasts are obtained by simply plugging the actual values of the explanatory variable in the Minitab using the Winters' additive method. For the in-sample forecast, the forecast values are compared with the actual values of the CPI to validate the exponential

smoothing method or procedure chosen. The post-sample forecast is done to obtain the future values of the CPI. The results of the in-sample and post-sample forecasts are shown in table 6.

Table 6: Forecast values and their 95% confidence limits

<i>Month</i>	<i>Actual value</i>	<i>Forecast</i>	<i>LCL</i>	<i>UCL</i>
18-Mar	214.1	214.482	213.161	215.803
18-Apr	216.0	216.912	215.324	218.500
18-May	218.1	218.134	216.220	220.047
18-Jun	220.4	220.036	217.764	222.309
18-Jul	221.1	221.728	219.076	224.379
18-Aug	221.1	220.713	217.671	223.756
18-Sep	221.0	220.274	216.831	223.716
18-Oct	222.6	222.889	219.041	226.736
18-Nov	224.2	224.061	219.805	228.318
18-Dec		225.416	220.747	230.085
19-Jan		230.071	224.988	235.155
19-Feb		231.294	225.794	236.793
19Mar		233.908	227.991	239.825
19-Apr		236.338	230.003	242.674
19-May		237.560	230.805	244.315
19-Jun		239.463	232.287	246.638
19-Jul		241.154	233.558	248.750
19-Aug		240.140	232.122	248.157

Table 6 indicates that the differences between the actual and the predicted values (errors) are not great and this also confirms the validity of the Winters' additive method and is used to forecast the next nine months CPI of Ghana provided there is no intervention.

Conclusion

The objective of the study is to determine the appropriate time series exponential smoothing method for forecasting the CPI of Ghana for the next nine months. The results show that the Winters' additive method with smoothing constants $\alpha = 0.7$, $\gamma = 0.2$ and $\delta = 0.2$ is most appropriate for the series based on the least measures of accuracy. The minimum values of its MAPE, MAD and MSD are 0.3281, 0.5159 and 0.4662 respectively. It is therefore recommended for forecasting the next 12-month CPI of Ghana provided no interventions will be put in place during the period.

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Data used in the Analysis

13-Mar	108
13-Apr	109.7
13-May	110.5
13-Jun	112.2
13-Jul	113.6
13-Aug	112.8
13-Sep	112
13-Oct	114.5
13-Nov	115.4
13-Dec	116.6
14-Jan	121.2
14-Feb	122.6
14-Mar	123.7
14-Apr	125.8
14-May	126.9
14-Jun	129
14-Jul	131

14-Aug	130.7
14-Sep	130.5
14-Oct	133.9
14-Nov	135.1
14-Dec	136.4
15-Jan	141.1
15-Feb	142.8
15-Mar	144.3
15-Apr	146.9
15-May	148.4
15-Jun	151
15-Jul	154.5
15-Aug	153.3
15-Sep	153.1
15-Oct	157.2
15-Nov	158.9
15-Dec	160.6
16-Jan	168
16-Feb	169.2
16-Mar	172
16-Apr	174.4
16-May	176.4
16-Jun	178.8
16-Jul	180.3
16-Aug	179.2
16-Sep	179.5
16-Oct	182
16-Nov	183.5
16-Dec	185.3
17-Jan	190.4
17-Feb	191.6
17-Mar	194
17-Apr	197.2
17-May	198.6
17-Jun	200.4
17-Jul	201.7
17-Aug	201.3
17-Sep	201.3
17-Oct	203.3
17-Nov	205.1
17-Dec	207.2
18-Jan	210.1
18-Feb	211.9

18-Mar	214.1
18-Apr	216
18-May	218.1
18-Jun	220.4
18-Jul	221.1
18-Aug	221.1
18-Sep	221
18-Oct	222.6
18-Nov	224.2