Time series analyses of Egyptian CPI rates during the Ukraine -Russa war - SARIMA and Holt-Winters Models

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Abstract

Decision makers always have big challenge in analyze time series data. It is how to Find the best forecasting model. Time series models seasonal autoregressive integrated moving average (SARIMA), and Holt-Winters method) are methods that predict future values by analyzing past values. It plays an important role in many practical fields that depending on seasonal time series data.

This study is amid to build a good fit time series model of monthly Egyptian Consumer Price index (CPI) during the Ukraine -Russa war and forecasting the future values, using (CPI) data from Jan 2018 until June-2022. Applied on Autoregressive Integrated Moving Average (SARIMA) model and Holt-Winters method tool available in SPSS-26. The result reveal that the proposed models is shown to be adequate and with the original observations its forecasting is shown to agree closely. Also, according to the statical indicators, a Winters additive is better forecasting than ARIMA ((0,1,0) $(0,0,1)_{12}$) Model) for the monthly Egyptian CPI data.

Keywords: **"**forecasting, SARIMA model, seasonal time series, Egyptian CPI, Holt-Winters' additive method."

1. Introduction

Six months ago, Ukraine -Russa war was started. It has generated a humanitarian disaster with political, socioeconomic, and economic consequences. As a fast result, fuel and food prices have risen significantly. So, it slows down the global economy and elevate inflation all over the world. In Egypt most goods and services prices have risen significantly According to https://www.capmas.gov.eg. The CPI in May 2022 was 130.2 as an indicator for a fast inflation. So, it is important to get a good model to forecast of the as a helpful tool to the governments to prepare the socioeconomic policies.

Consumer Price index (CPI) is a statistical index used to calculate the average change price in a month from a collection of goods and services, which consumed by households and residents within a certain month. It is intended to determine the changes in a fixed group of goods/services price that are generally consumed by local people. (Farouk, Rashwan (2022))

Forecasting using Time series Models Holt-Winters Trend and Seasonality method and Autoregressive Integrated Moving Average (SARIMA) as a method for analyzing past values to predict future values to develop appropriate models that describe the inherent structure for univariate time series data. (ARIMA)supports both an autoregressive and moving average elements and time series data trend. the seasonal Autoregressive Integrated Moving Average model (SARIMA) models are account for the seasonal property (a time series with a repeating cycle). Seasonal variations -in the time series- are a time series fluctuation that are regular repeated at short intervals (e.g., daily, weekly, monthly, quarterly) usually within a year. many studies have been investigated SARIMA model and Holt-Winters Trend and Seasonality method forecasting advantage to other time series model such as Suhartono, (2011), used seasonal autoregressive integrated moving average get a time series forecasting: subset, multiplicative or additive model about the number of tourist arrivals to Bali, Indonesia., Chen, et al, (2018) had a time series forecasting of temperatures using SARIMA: an example from Nanjing, Siregar,(2020) Using SARIMA Model ,he made a Nigeria Inflation Rates December 2017 – May 2018 Forecasting, Nadeem, et al, (2022) are using SARIMA method to forecast office supplier demand, Sunengsih,and Jaya, (2022)study two years after the pandemic, forecasting the number of new covid-19 cases in the United States of America, a comparative analysis of gated recurrent units (GRU), long short-term memory (LSTM) cells, autoregressive Integrated moving average (ARIMA), (SARIMA) for forecasting COVID-19 trends was done by ArunKumar, et al, (2022), Morales, and Anguiano (2022), got data science - time series analysis of oil & gas production in Mexican fields. Also, Molla, et al, (2016) got Performance Assessment of SARIMA Model with Holt– Winter's Trend and Additive Seasonality Smoothing Method on forecasting Electricity Production of Australia an Empirical Study, Ponziani (2021) had a forecasting of Jakarta Islamic index (JII) returns using Holt-Winters family model, and Hansun S. et al, (2022) had a revisiting of the Holt-Winters' additive method for better forecasting.

2. Holt-Winters Trend and Seasonality method

Among the forecasting algorithms, the Holt–Winters models are one of the most popular methods. To model the three aspects of the time series; the average, the trend over time, and a cyclical repeating pattern (seasonality), Holt-Winters method is a good way for that. It depends on an exponentially weighted moving average (EWMA) to "smooth" a time series for predicting typical values or average for the present and future using lots of values from the past. Exponential smoothing means that older observations are given relatively less weights in forecasting than the recent observations. There are two different Holt-Winters' methods equations Depending on the seasonality model whether, it is in an additive or multiplicative way. The model equations are given as (Mgale, et al, (2022)):

$$Z_t = (\beta_0 + t\beta_1) + SN_t + IR_t \qquad \text{additive}$$

$$Z_t = (\beta_0 + t\beta_1) \times SN_t \times IR_t \qquad \text{Multiplicative}$$

Where I is number of seasons in a year, SN_t is a seasonal pattern and IR_t refers to irregular components.

Using The Holt-Winters' method with trend and additive seasonality, if one has some time series x_t, he can define a new time series s_t that's a smoothed version of x_t. The basic equations for the Holt-Winters' method with trend and additive seasonality is based on the three following smoothing equations and a forecasting equation is shown as: (Szmit, et al, (2012))

2.1 Level equation

The level is a smoothed estimate of the value of the data at the end of each period. The Holt-Winters' method's Level equation can be formed as

Level: $L_t = \alpha(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1})$

where:

L_t is Level, Y_t is real (measured) value of variable in moment t, s is time series period, α is data smoothing factor, b is trend component and S is seasonal component.

2.2. Trend Equation

Trend is a smoothed estimate of average growth at the end of each period. The Holt-Winters' method's trend equation can be formed as

Trend: $b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}$

, β is trend smoothing factor

2.3. Seasonality equation

The Holt-Winters' method 's seasonality equation can be formed as

$$\text{seasonality: } S_t = \gamma(Y_t - L_t) + (1 - \gamma)S_{t-s}$$

,γ is the seasonal change smoothing factor

2.4. *Forecast* equation

Finally, to obtain the predictions F_{t+m} ahead, the information from the observed values (X_t) is projected through the next forecasting Equation k steps. the Holt-Winters' method's *Forecast* equation can be formed as

$$Forecast\text{: } F_{t+m} = L_t + mb_t + S_{t-s+m}$$

Where, F_{t+m} is the forecast for m period ahead, and t time and α, γ, β are the smoothing parameters that bounded in the interval (0, 1). when the closer to 1 means the more weight of the new values against the older ones.

3. Seasonal Autoregressive integrated moving Average (SARIMA)

To implement time series model ARIMA to analyze non-seasonal time series data, we assume that the time series is linear and follows a normal distribution or any statistical distribution. SARIMA model has the same assumptions, and it is an extension of it used to analyze data which contain seasonal and non-seasonal data. It is an extension of the ordinary ARIMA model to analyze time series data that contain seasonal and non-seasonal behaviors. For the seasonal parts of the model, So, A SARIMA model is a new form of the ARIMA model by including additional three new hyperparameters as seasonal terms. It can be written as ARIMA (p, d, q) (P, D, Q)$_S$. (Chen P., et al, (2018)) We use uppercase notation (P, D, Q) , for the seasonal parts of the model and lowercase notation (p, d, q) for the non-seasonal parts of the model. The general form of the SARIMA (p, d, q) (P, D, Q) model is given as (Suhartono, (2011))

$$\varphi_p(\mathrm{B})\Phi_P B^s(1-\mathrm{B})^d\,(1\text{-}B^s)^D Y_t = \theta_q(B)\Theta_Q(B^s)e_t$$

Where the seasonal components and the non- seasonal components are shown in table (1) and table (2) (Msofe, and Mbago (2019).

Table (1): the seasonal components

terms	seasonal components
	AR terms
P	the number of seasonal AR terms (lags of the stationary series)
AR(P)	$AR(P) = \Phi_P B^S = 1 - \Phi_1 B^S - \Phi_2 B^{2S} - \ldots \Phi_P B^{PS}$
	MA **terms**
Φ_P	seasonal moving average parameter
MA($\boldsymbol{Q}$) Q	$MA(\boldsymbol{Q}) = \Theta_Q B^S = 1 - \Theta_1 B^S - \Theta_2 B^{2S} - \ldots \Theta_Q B^{QS}$ the order of MA terms (lags of the forecast errors)
Θ_Q	seasonal moving average parameter
	another terms
D	degree (order) of seasonal differencing, $\Delta^D{}_s = (1 - B^s)^D$
s	the number of seasons per year

Table (2): the non- seasonal components

terms	The non- seasonal components
	AR terms
p	non-seasonal AR order
AR(p)	$AR(p) = \varphi_p B = 1 - \varphi_1 B - \varphi_2 B^2 - \ldots \varphi_p B^p$
	MA **terms**
φ_p	non-seasonal moving average parameter
MA(q)	$MA(q) = \theta_q B = 1 - \theta_1 B - \theta_2 B^2 - \ldots \theta_q B^q$
q	non-seasonal order of MA terms
θ_q	non-seasonal moving average parameter
	another terms
d	degree (order) of non-seasonal differencing
Δ^d	non-seasonal moving average parameter, $\Delta^d = (1 - B)^d$
B	the back-shift operator, $B^j x_t = x_{t-j}$, $B^j e_t = e_{t-j}$,j=0,1,2,….
e_t	a white noise (i.e., normal with zero mean, and constant variance)
μ	a constant.

Values p, d, and q are determined depending on utilization of an estimator AIC (Akaike's Information Criterion).

The seasonal ARIMA (SARIMA) model has a main advantage that, it can analyze the seasonal behavior of time series either it is stationary or non-stationary. (Falatouri, et al (2022))

For forecasting we can use HEGY test as a seasonal unit root test to find the value of d and D of the SARIMA model. In a time, series, the seasonality has two types:

1.if it is considered as a deterministic component, to account seasonal variations it is sufficient to inter seasonal dummies into the models.

2.if it is considered as a stochastic component, it requires seasonally differencing as a test for seasonal unit roots, we can use HEGY test as a seasonal unit root test.

4. Application

This study is using SPSS (26) to analyze the monthly Egyptian CPI data from Jan 2018 until May-2022.From the data and statistics publications of https://www.capmas.gov.eg/Pages/IndicatorsPage.aspx?Ind

To describes the proposed SARIMA, and Holt-Winters Additive models for Egyptian CPI data and comparing its results to choose the best forecasting of them for forecasting of the Egyptian CPI during the Ukraine -Russa war

4.1. Stationarity Checking

To make forecasts of a time series historical values, the first step is to Check the temporal pattern for monthly Egyptian CPI data time series Stationarity by plotting it as shown in figure (1) to identify any unusual values.

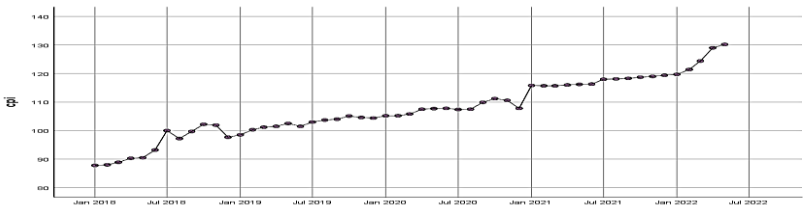


Figure 1: Original series graph

From figure (1), we can see that there are no unusual values. A stationary series is the series that has constant mean and variance over time. By having the second difference of the original values So, we have a stationary series as shown in figure (2).

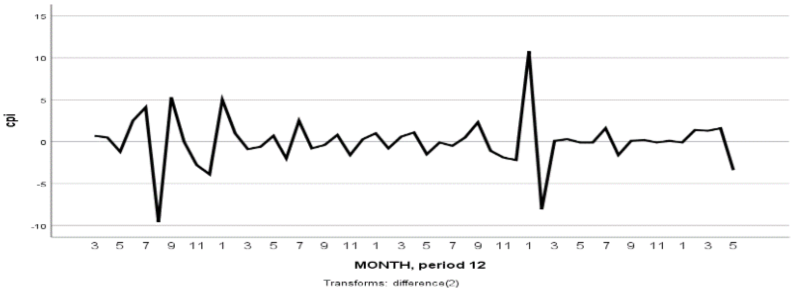


Figure (2): A stationary series of Egyptian CPI data time series

Also, the time-series data is being stationary if the ACF graph cuts off rapidly, but if the ACF graph dies down too slow, the series is considered nonstationary. Figure (3) shows the Egyptian CPI data time series ACF graph

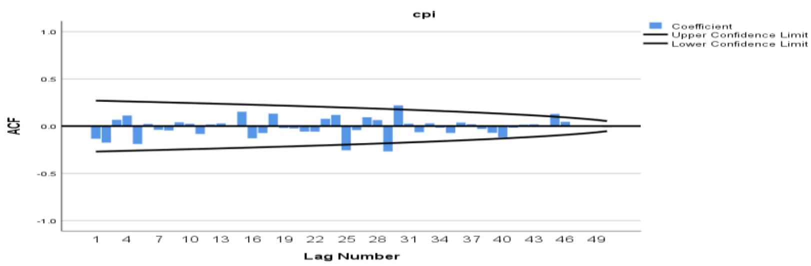


Figure (3): the Egyptian CPI data time series ACF graph

From figure 2, figure 3 we confirm the Egyptian CPI data time series

data is Stationarity.

4.2 namely model identification

After we confirm the data is Stationarity, for the model identification, formulate a class of models and assume certain hypotheses. We select the order of the successive seasonal differencing that required to make the series stationary and specific the order of stationary or regular (SARIMA) polynomial required to represent sufficient time series model.

Using The autocorrelation function (ACF) and the partial autocorrelation function (PACF) are the most important tools for forecasting and time series analysis. To quantify if there are lag k linear dependence between time series observations, we used the ACF. Using SPSS statistical package, we create model as ARIMA (0,1,0) (٠,0,1)$_{12}$.

4.3. Estimation of model parameters

For the Egyptian CPI data time series, table (3) shows the estimation of ARIMA (0,1,0) $(0,0,1)_{12}$ and Holt-Winters Additive models parameters Using SPSS (26)

Table (3): the estimated model parameters

Model Parameters	ARIMA (0,1,0) $(٠,0,١)_{12}$	Sig.	Model Parameters	Winters' Additive	Sig.
Constant	1.978	.000	Alpha (Level)	.918	.000
Difference	1		Gamma (Trend)	.0٠3	0.932
MA, Seasonal Lag 1	.098	.516	Delta (Season)	0.001	0.999
Numerator Lag 0	-.187	0.009			

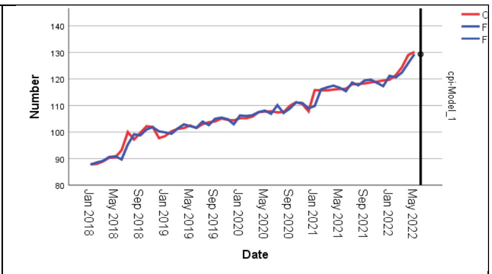
4.4. Forecasting

This involved predicting future number of the Egyptian CPI data time-series data using the fitted model selected. The new monthly CPI in Egypt values of forecast over period Feb. 2022 to June 2022 Are presented in Table (4).

Table (4): The new forecasting monthly CPI in Egypt

Month	2	3	4	5	6
Winters' Additive	121	122	126	129	130
ARIMA (0,1,0) $(٠,0,1)_{12}$	121	123	126	130	131

Also, figure (4) Shows the forecasting values of the two proposed models over period 52 month.

Winters' Additive	

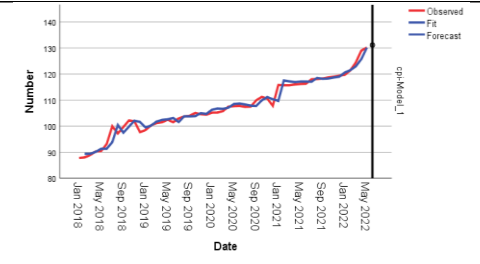
ARIMA (0,1,0) $(\cdot,0,1)_{12}$	

Figure (4): the forecasting values over period from Jan.2018 to June2022

4.5. diagnostic checking for the identified model

The next stage is to examine the residuals from the fitted model.

We have a good forecasting method if the residuals are uncorrelated and have zero mean. Using the Ljung-Box test, the null hypothesis tests that residuals are white noise with test statistic as given: (Msofe &Mbago (2019))

$$Q = n(n+2)\sum_{k=1}^{n}\frac{r_k^2}{h-m} \qquad \sim {\chi^2}_{h-m}$$

Where

r_k is the sample autocorrelation at lag k

h is the maximum lag being considered

n is the sample size after any differencing

m is the number of the fitted parameters in the model

As shown in table (5), for monthly CPI in Egypt time-series data, the two models Winters' Additive Ljung-Box Q (18) values.

Table (5)- Ljung-Box Q (18) for monthly CPI in Egypt time-series data

	Ljung-Box Q (18)	Sig.	DF
Winters' Additive	17.931	.266	15
ARIMA (0,1,0) $(\cdot,0,1)_{12}$	14.339	.643	17

So, we can't reject null hypothesis that the residuals are white noise, that means the two models Winters' Additive and ARIMA ((0,1,0) $(\cdot,0,1)_{12}$ are adequate for data.

4.6. Forecasting accuracy measures

Now, to test if model forecasts is well or not, we depend on some important tests. to insure how forecasted values are close to the observed values in the validation period, and to measure the performance of forecast, the flowing statistics (AIC, MAPE (Mean Absolute Percentage Error), RSME (The Root Mean Square Error), (MSE)the mean-square error , MAE (mean absolute error) which using minimizing forecast errors were used to make Shure that the proposed model has an accurate Forecasting. As small RMSE and MAPE value near to zero a model quality is high. Table (6) showed the formula used to compute every indictor of them and its value.

Table (6): Forecasting accuracy measures

indictor	formula	ARIMA (0,1,0) $(٠,0,١)_{12}$	Winters' Additive
RMSE	RSME= $\sqrt{\sum_{i=}^{n}(y_i - \hat{y}_i)^2/n}$	1.866	1.648
MAPE	$MAPE = \sqrt{\sum e_t^2 /n}$	1.179	1.044
AIC	AIC=−2log(L)+2k	0.162	0.147
MAE	$MAE = \sum_{t=1}^{n} \lvert e_t \rvert /n$	1.252	1.126
BIC	BIC =n*ln (SSR/n)+ n*ln(n)	1.475	1.224
R^2	SSR/SST	.966	.975

where

$SSR = \sum_{i=1}^{n}(y_i - \bar{y})^2 - \sum_{i=1}^{n}(y_i - \hat{y}_i)^2,$

$$SSE = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

L is the maximum value of the likelihood function for the model, n = the sample size, and k = the number of parameters (including $\boldsymbol{\sigma^2}$) = p+q+c+1 where c = 1 if there is a constant term and c = 0 otherwise. (Abonazel and Abd-Elftah (2019)). Also, we can calculate AIC for ARIMA as formula

$$\text{AIC (p, q)} = \ln\left(\frac{\sum e_i^2}{n}\right)+\frac{2}{n}(p+q).$$

A smaller value of AIC, BIC, RMSE, and MAE and a bigger value of R^2 criteria indicate that the two models are preferable models. the best forecasting model will be the model with the minimum AIC According to Table 6, Winters' Additive model shows the lowest AIC value. Thus, this model should be considered as the best forecasting model.

4.7. application of the model and Residual Check

By analyzing correlation in ACF plots. If the residuals are not correlated the correlations, are Gaussian white noise, then the model is adequate to represent the time series. Otherwise, the model will need to be revisited. Also, to verify the validity of the model fit, once we have a fitted model to the data, it is necessary to check the residual plots. If the residuals have a mean except zero, then the forecasts are biased. If correlations between residuals have a value except zero, then the forecasting is not optimization. We may determine appropriate parameters of an ARIMA model by analyzing (ACF) and (PACF) plots as in figure (5) that shows the residuals (ACF) and (PACF) plots of the two proposed models.

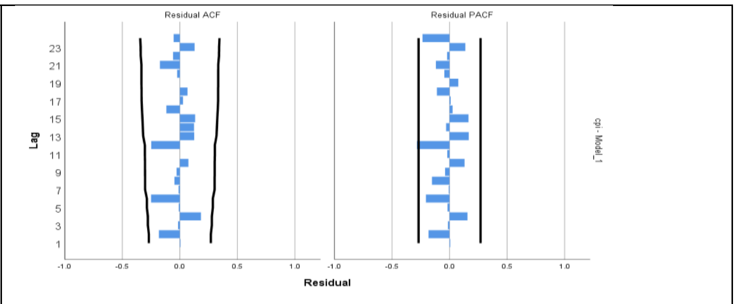
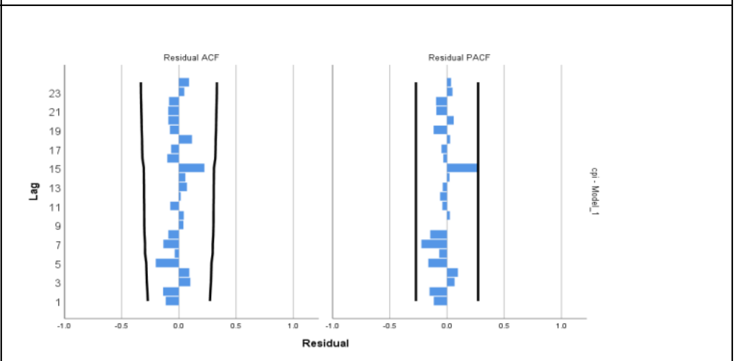
Winters' Additive	
ARIMA (0,1,0) (٠,0,١)$_{12}$	

Figure (5): the residuals (ACF) and (PACF) plots

From figure (5), we can say that the two models Winters' Additive and ARIMA ((0,1,0) (٠,0,1)$_{12}$ are adequate for monthly CPI in Egypt time-series data.

5.Conclusion

After five months of the Ukraine -Russa war and increasing of CPI in Egypt and all over the world, Egyptian CPI time-series data remains extremely high. We forecasted the value of monthly Egyptian CPI between Feb.2022 and June 2022 in this study using SARIMA Model and Holt-Winters method to have a good time series forecasting of monthly Egyptian CPI. According to the previous statistical indictor, time series forecasting models are preferable models. Also, as the time series forecasting Models of the Egyptian CPI during the Ukraine -Russa war the Winters' Additive model has more accurate forecasting than ARIMA (0,1,0) (٠,0,1)$_{12}$ model.

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تحليل السلاسل الزمنية لمؤشر أسعار المستهلكين المصري خلال الحرب الأوكرانية والروسية - نموذجا SARIMA و Holt-Winters

د. مها فاروق توفيق إبراهيم

الملخص

يواجه صانعو القرار دائمًا تحديًا كبيرًا في تحليل بيانات السلاسل الزمنية وهو محاولة العثور على أفضل نموذج للتنبؤ بالقيم المستقبلية. نماذج السلاسل الزمنية للمتوسط المتحرك الموسمي المتكامل الانحدار الذاتي (SARIMA) ، وطريقة هولت وينترز (Holt-Winters method) هي اساليب احصائية تتنبأ بالقيم المستقبلية من خلال تحليل القيم السابقة. ويعد لكلاهما دورًا مهمًا في العديد من المجالات العملية التي تعتمد على بيانات السلاسل الزمنية الموسمية.

تأتي هذه الدراسة لبناء نموذج سلسلة زمنية مناسبة لمؤشر أسعار المستهلك المصري الشهري (CPI) خلال حرب أوكرانيا وروسيا والتنبؤباستخدام بيانات (CPI) من يناير ٢٠١٨ حتى يونيو ٢٠٢٢ باستخدام ادوات نموذج المتوسط المتحرك المتكامل للانحدار الذاتي الموسمي (SARIMA) وأداة طريقة Holt-Winters المتوفرة في SPSS-26. اوضحت نتائج الدراسة أن النماذج المقترحة أظهرت أنها كافية بالنسبة للمشاهدات الأصلية كما يظهر أن تنبؤاتها تتفق بشكل وثيق. أيضًا، وفقًا للمؤشرات الإحصائية، واكدت ان Winters additive اعطت تنبوًا أفضل من ARIMA ((0,1,0) $(0,0,1)_{12}$) لبيانات مؤشر أسعار المستهلكين المصري الشهرية.

الكلمات المفتاحية

التنبؤ، نموذج SARIMA، السلاسل الزمنية الموسمية، الرقم القياسي لأسعار المستهلك المصري، طريقة Holt-Winters additive