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Modeling Palestinian COVID-19 Cumulative Confirmed Cases: A Comparative Study

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ABSTRACT

COVID-19 is still a major pandemic threatening all the world. In Palestine, there were 26,764 COVID-19 cumulative confirmed cases as of 27th August 2020. In this paper, two statistical approaches, autoregressive integrated moving average (ARIMA) and k-th moving averages - ARIMA models are used for modeling the COVID-19 cumulative confirmed cases in Palestine. The data was taken from World Health Organization (WHO) website for one hundred seventy-six (176) days, from March 5, 2020 through August 27, 2020. We identified the best models for the above mentioned approaches that are ARIMA (1,2,4) and 5-th Exponential Weighted Moving Average – ARIMA (2,2,3). Consequently, we recommended to use the 5-th Exponential Weighted Moving Average – ARIMA (2,2,3) model in order to forecast new values of the daily cumulative confirmed cases in Palestine. The forecast values are alarming, and giving the Palestinian government a good picture about the next number of COVID-19 cumulative confirmed cases to review her activities and interventions and to provide some robust structures and measures to avoid these challenges.

1. Introduction

The SARS-CoV-2 (COVID-19) is a new pandemic which spreads rapidly from person to person and to many countries (Ceylan, 2020). In most countries, the health systems are tenuous and especially in war regions. Now, This pandemic is the world crisis. According to studies, COVID-19 originated from Wuhan, China, in the end of 2019 and has caused an economic crisis whose impact will be felt for the next years (WHO, 2020). On January 30, 2020, the World Health Organization (WHO) declared the outbreak as a Public Health Emergency of International concern (International Health Regulations, 2020 30 January 2020; WHO, 2020). According to the ministry of health in Palestine, the first case was detected on March 5, 2020.152 deaths are reported on August 27, 2020 with more than 26,764 total number of infected cases. The phase of COVID-19 epidemics can be decomposed as an exponential growth. Since forecasting is an important issue nowadays, there are many different methods have been proposed and developed to get accurate forecasts. The well-known used method is called the Box and Jenkins method using autoregressive integrated moving average (ARIMA) models. Also, many studies in different fields discussed using different forecasting models as ARIMA models and k-th moving averages (k-th simple moving average (k-th SMA), k-th weighted moving average (k-th WMA) and k-th exponential weighted moving average (k-th EWMA)) with ARIMA models in order to find the best accurate forecasting models under some conditions, for example, Crane and Crotty

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(1967), Shami and Snyder (1998), Billah, King, Snyder, & Koehler (2006), Burman and Shumway (2006), Shih and Tsokos (2008), Tsokos (2010), Safi and Dawoud (2013) and Dawoud and Kaciranlar (2017a, 2017b, 2017c)). Recently, there are many studies about building models for forecasting the ongoing trend with data-driven analysis and estimating the COVID-19, to mention a few, Li et al. (2020), Fanelli and Piazza (2020), Roda et al. (2020), Wei et al. (2016), Al-qaness et al. (2020), Anastassopoulou et al. (2020), Wang et al. (2020), Ayinde et al. (2020), Ghosal et al. (2020), Ceylan (2020) and Ogundokun et al. (2020). The main purpose of this article is modeling COVID-19 cumulative confirmed cases in Palestine using different existing methods as ARIMA and k-th moving averages − ARIMA models for giving accurate forecast values. This article is organized as follows, in section 2 we present some fundamental definitions. In section 3 we give and describe measures of forecast accuracy. In section 4 we present data description, forecasting techniques and the fitting models for COVID-19 data. Finally, in section 5 some conclusions are given.

2. Fundamental definitions

In this section, we present the definitions of ARIMA, the *k*-th SMA, *k*-th WMA and *k*-th EWMA models.

Definition 1. (Box et al., 1994) (ARIMA Model)

The classicalARIMA(p, d, q) *model is defined as*

$$\varphi_p(B)\ (1-B)^d\ T_t = \theta_q(B)\ \varepsilon_t, \tag{2.1}$$

where $B^j T_t = T_{t-j}$, $(1-B)^d$ is the difference filter, d is the degree of differencing of the series, $\varphi_p(B) = (1-\varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p)$ and $\theta_q(B) = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$.

Stationarity and invertibility requires the roots of $\varphi_p(B)$ and $\theta_q(B)$ to lie outside the unit circle, respectively.

Definition 2. (Shih & Tsokos, 2008) (The *k*-th SMA method)
The *k*-th SMA method of a time series $\{T_t\}$ is defined as

$$S_t = \frac{1}{k}\sum_{j=0}^{k-1} T_{t-k+1+j}, \tag{2.2}$$

where $t = k, k+1, \ldots, n$.

Definition 3. (Shih & Tsokos, 2008) (The *k*-th SMA Back-Shift)
The *k*-th SMA Back-Shift operator in order to obtain the estimates of the original time series data $\{T_t\}$, that is.
$\widehat{T}_t = k\,\widehat{S}_t - T_{t-1} - T_{t-2} - \cdots - T_{t-k+1}$. (2.3).

Definition 4. (Tsokos, 2010) **(**The *k*-th WMA Method)
The *k*-th WMA method of a time series $\{T_t\}$ is defined as:

$$W_t = \frac{\sum_{j=0}^{k-1}(j+1)\ T_{t-k+1+j}}{(1+k)\ k/2}, \tag{2.4}$$

where $t = k, k+1, \ldots, n$.

Definition 5. (Tsokos, 2010) (The *k*-th WMA Back-Shift**)**
The *k*-th WMA Back-Shift operator in order to obtain the estimates of the original time series data $\{T_t\}$, that is.
$\widehat{T}_t = \frac{[(1+k)\ k/2]\ \widehat{W}_t - (k-1)\ T_{t-1} - (k-2)\ T_{t-2} - \cdots - T_{t-k+1}}{k}$. (2.5).

Definition 6. (Tsokos, 2010) (The *k*-th EWMA Method)
The *k*-th EWMA method of a time series $\{T_t\}$is defined as:

$$E_t = \frac{\sum_{j=0}^{k-1} (1-\alpha)^{k-j-1}\, T_{t-k+1+j}}{\sum_{j=0}^{k-1} (1-\alpha)^{j}}, \tag{2.6}$$

where $t = k,\ k+1,\ \dots,\ n$ and the smoothing factor $\alpha = \frac{2}{k+1}$.

Definition 7. (Tsokos, 2010) (The *k*-th EWMA Back-Shift)

The *k*-th EWMA Back-Shift operator in order to obtain the estimates of the original time series data $\{T_t\}$, that is,

$$\widehat{T}_t = \sum_{j=0}^{k-1} (1-\alpha)^j\, \widehat{E}_t - (1-\alpha)\, T_{t-1} - (1-\alpha)^2 T_{t-2} - \cdots - (1-\alpha)^{k-1} T_{t-k-1}. \tag{2.7}$$

3. Measures of forecast accuracy

Several measures of forecast accuracy have been introduced by many authors. These measures are recommended to use in comparing the forecast methods accuracy which are applied to univariate time series data. For example, Hyndman and Koehler (2006) introduced the Mean Square Error (MSE) as the most used measure of deviation between the actual and the predicted value.

Definition 9. The MSE measure is defined as:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \left(Y_i - \widehat{Y}_i\right)^2 \tag{3.1}$$

where Y_i is the actual value and, $\widehat{Y}_i$ is the predicted value. MSE is one of the most commonly used measures of forecast accuracy and the $RMSE = \sqrt{MSE}$.

4. Fitting forecasting models for COVID-19 data

This section presents data description, forecasting techniques and the fitting models for COVID-19 data by using the two different approaches, ARIMA (*p*,*d*,*q*) and k-th moving averages-ARIMA (*p*,*d*,*q*) models. Consider the daily COVID-19 cumulative confirmed cases in Palestine, from 5-3–2020 through 27-8-2020, the forecasting results are presented in the following sub-sections.

4.1. Data description

We use a daily COVID-19 cumulative confirmed cases dataset of Palestine from 5-3–2020 through 27-8-2020 (data source: WHO website., 2020). The time-series plot of the daily COVID-19 cumulative confirmed cases is in Fig. 1.

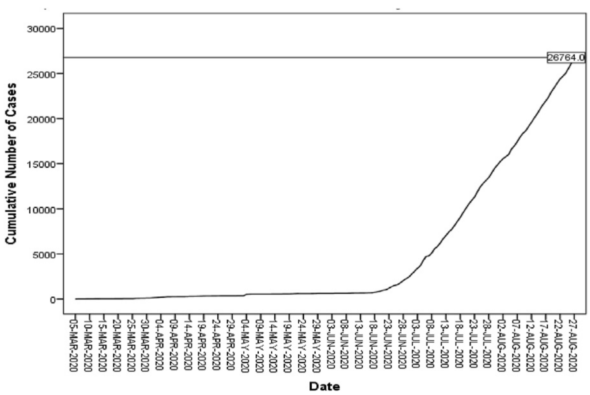

Fig. 1. Daily COVID-19 cumulative confirmed cases over time.

Fig. 1 shows that the Daily COVID-19 cumulative confirmed cases over time is exponentially increasing which the cumulative number of confirmed cases reaches 26,764 cases as of 27, August 2020.

4.2. Forecasting technique

In this study, we are fitting the classical ARIMA, a *k*-th SMA, a *k*-th WMA and *k*-th EWMA with ARIMA models for 90% (approximately 158 observations) of the available data which is called the in-sample forecast or the training data and the remaining 10% (approximately 18 observations) is used for the out-of-sample forecast or testing the models. The forecast accuracy measures to these forecasting models are given for the in-sample and the out-of-sample. R-statistical software is used for fitting the above mentioned models.

4.3. Fitting the classical ARIMA model for COVID-19 data

After taking the second difference of the original data in order to make it stationarity, different combinations of ARIMA models with $p+q \leq 5$ and their corresponding RMSE values are shown in Table 1.

Table 1 shows that the lowest RMSE value among all models is for ARIMA (1,2,4) which is equal to 60.66346 for in-sample forecasts. This result indicates that ARIMA (1,2,4) model is more efficient than other mentioned ARIMA models with $p+ q \leq$ 5for in-sample forecasts.

We use maximum likelihood estimation and show the results obtained from the R statistical software in Table 2. Here we see that $\varphi_1 = -0.7880$, $\theta_1 = 0.2011$, $\theta_2 = -0.9299$, $\theta_3 = -0.0099$ and $\theta_4 = 0.4589$. We also see that the estimated noise variance is $\hat{\sigma}_e^{\ 2} = 3680$.

4.4. Fitting the k-th moving averages - ARIMA models for COVID-19 data

Different combinations of k-th moving averages-ARIMA models with $k \leq 5$ and their corresponding RMSE values are shown in Table 3.

Table 3 shows that the lowest RMSE value among all models is for 5-th EWMA-ARIMA (2,2,3) which is equal to 59.9422 for in-sample forecasts. This result indicates that 5-th EWMA-ARIMA (2,2,3) model is more efficient than other k-th moving averages-ARIMA models with $k \leq 5$ for in-sample forecasts.

We use maximum likelihood estimation and show the results obtained from the R statistical software in Table 4. Here we see that $\varphi_1 = -0.0086$, $\varphi_2 = -0.8788$, $\theta_1 = 0.1584$, $\theta_2 = 0.9112$ and $\theta_3 = 0.3873$. We also see that the estimated noise variance is $\hat{\sigma}_e^{\ 2} = 3593$. Noting the *P*-values, the estimates of all autoregressive and moving average coefficients are significantly different from zero statistically.

Table 5 shows the actual and forecasting results for COVID-19 cumulative confirmed cases from August 14, 2020 to August 31, 2020 based on the classical ARIMA (1,2,4) and 5th EWMA-ARIMA (2,2,3) models.

Table 5 shows that the 5-th EWMA-ARIMA forecasts are so near to the actual values of the COVID-19 cumulative confirmed cases than that of the classical ARIMA. Also, the RMSE for ARIMA and 5-th EWMA-ARIMA equal 158.1097 and 138.3910, respectively for the out-of sample forecasts. This result shows that RMSE of 5-th EWMA-ARIMA is 87.53% of RMSE for ARIMA. In other words, the RMSE of ARIMA model is 1.14 times RMSE of the 5-th EWMA-ARIMA model. This means 5-th EWMA-ARIMA model for forecasting is much more accurate and efficient than the ARIMA forecasting model.

Table 6 shows the forecasting results for COVID-19 cumulative confirmed cases from 28 to 08–2020 to 30-10-2020 (62 values) based on the classical ARIMA (1,2,4) and 5th EWMA-ARIMA (2,2,3) models.

Table 1
The RMSE of forecast accuracy for the different-ARIMA models for in-sample.

Model Order	(1,2,0)	(2,2,0)	(3,2,0)	(4,2,0)	(5,2,0)	(0,2,1)
RMSE	74.70927	63.61521	63.19098	62.1342	61.83542	66.02938
Continued						
Model Order	**(0,2,2)**	**(0,2,3)**	**(0,2,4)**	**(0,2,5)**	**(1,2,1)**	**(1,2,2)**
RMSE	65.71853	61.43936	61.19928	61.18612	65.94331	63.84385
Continued						
Model Order	**(1,2,3)**	**(1,2,4)**	**(2,2,1)**	**(2,2,2)**	**(2,2,3)**	**(3,2,1)**
RMSE	61.14791	**60.66346**	62.44582	61.96617	61.11008	62.21753
Continued						
Model Order	**(3,2,2)**	**(4,2,1)**	**(0,2,0)**			
RMSE	61.95796	61.74251	78.79781			

Table 2
Maximum Likelihood Estimates from R Software: COVID-19 series. The estimated model would be written.

$$T_t = 1.212\ T_{t-1} + 0.576\ T_{t-2} - 0.7880\ T_{t-3}\ + \varepsilon_t - 0.2011\ \varepsilon_{t-1} + 0.9299\ \varepsilon_{t-2} + 0.0099\ \varepsilon_{t-3} - 0.4589\ \varepsilon_{t-4}. \quad (4.1)$$

	AR (1)	MA (1)	MA (2)	MA (3)	MA (1)
Coefficients	−0.7880	0.2011	−0.9299	−0.0099	0.4589
Standard Error	0.1156	0.1299	0.0984	0.0995	0.1121

Table 3
The RMSE of forecast accuracy for the k-th moving averages-ARIMA models for in-sample.

Models	2nd SMA-ARIMA	2nd WMA-ARIMA	2nd EWMA-ARIMA	3rd SMA-ARIMA	3rd WMA-ARIMA	3rd EWMA-ARIMA
RMSE	62.14366	61.44077	61.35545	62.14131	61.14754	61.32235
Continued						
Models	**4th SMA-ARIMA**	**4th WMA-ARIMA**	**4th EWMA-ARIMA**	**5th SMA-ARIMA**	**5th WMA-ARIMA**	**5th EWMA-ARIMA**
RMSE	74.34683	62.87605	62.88568	68.77919	62.0709	**59.9422**

Table 4
Maximum Likelihood Estimates from R Software: COVID-19 series.

$$\begin{aligned} E_t &= 1.9914\ E_{t-1} - 1.8616\ E_{t-2} + 1.749\ E_{t-3} - 0.8788\ E_{t-4} \\ &+\varepsilon_t - 0.1584\ \varepsilon_{t-1} - 0.9112\ \varepsilon_{t-2} - 0.3873\ \varepsilon_{t-3} \end{aligned} \quad (4.2)$$

	AR (1)	AR (2)	MA (1)	MA (2)	MA (3)
Coefficients	−0.0086	−0.8788	0.1584	0.9112	0.3873
Standard Error	0.0437	0.0392	0.1028	0.1000	0.1107

Table 5
Actual and Forecasting results of ARIMA (1,2,4) and 5-th EWMA-ARIMA (2,2,3) models daily COVID 19 cumulative confirmed cases from August 10, 2020 to August 27, 2020.

Date	Actual data	Forecast	
		ARIMA	5th EWMA-ARIMA
10–08–2020	18,651	18,766	18,787
11–08–2020	19,121	19,254	19,296
12–08–2020	19,594	19,702	19,776
13–08–2020	20,093	20,196	20,267
14–08–2020	20,525	20,653	20,704
15–08–2020	21,056	21,140	21,151
16–08–2020	21,554	21,604	21,575
17–08–2020	21,935	22,086	22,007
18–08–2020	22,391	22,553	22,459
19–08–2020	23,003	23,032	22,912
20–08–2020	23,427	23,501	23,321
21–08–2020	23,939	23,978	23,763
22–08–2020	24,396	24,450	24,177
23–08–2020	24,707	24,925	24,603
24–08–2020	25,024	25,398	25,101
25–08–2020	25,577	25,872	25,630
26–08–2020	26,162	26,345	26,100
27–08–2020	26,764	26,820	26,521

5. Conclusion

In previous studies, many statistical methods and time series models were used to forecast epidemic cases. In this article, we have applied the ARIMA and the k-th moving averages-ARIMA models on the data of the cumulative confirmed cases of COVID-19 in Palestine. We have examined the model selection sensitivity based on forecast accuracy criterion, RMSE, for the above mentioned models. The main finding in general is that some of k-th moving averages ARIMA models give better results for in-sample and out-of-sample forecasts than the classical ARIMA models. In particular, the best model is 5-th EWMA-

Table 6
Forecast values for daily COVID 19 cumulative confirmed cases from 01 to 09–2020 to 30-10-2020 (64 values) based on ARIMA (1,2,4), 5th EWMA-ARIMA (2,2,3).

Date	ARIMA	5th EWMA-ARIMA	Date	ARIMA	5th EWMA-ARIMA
28–08–2020	27,293	26,897	**29–09–2020**	42,453	41,797
29–08–2020	27,767	27,531	**30–09–2020**	42,927	42,258
30–08–2020	28,240	27,994	**01–10–2020**	43,401	42,718
31–08–2020	28,715	28,463	**02–10–2020**	43,874	43,177
01–09–2020	29,188	28,937	**03–10–2020**	44,348	43,638
02–09–2020	29,662	29,351	**04–10–2020**	44,822	44,098
03–09–2020	30,136	29,831	**05–10–2020**	45,296	44,558
04–09–2020	30,609	30,291	**06–10–2020**	45,769	45,018
05–09–2020	31,083	30,755	**07–10–2020**	46,243	45,479
06–09–2020	31,557	31,218	**08–10–2020**	46,717	45,939
07–09–2020	32,031	31,669	**09–10–2020**	47,191	46,399
08–09–2020	32,504	32,131	**10–10–2020**	47,664	46,859
09–09–2020	32,978	32,594	**11–10–2020**	48,138	47,320
10–09–2020	33,452	33,055	**12–10–2020**	48,612	47,780
11–09–2020	33,926	33,514	**13–10–2020**	49,085	48,240
12–09–2020	34,399	33,972	**14–10–2020**	49,559	48,700
13–09–2020	34,873	34,434	**15–10–2020**	50,033	49,160
14–09–2020	35,347	34,895	**16–10–2020**	50,507	49,621
15–09–2020	35,821	35,354	**17–10–2020**	50,980	50,080
16–09–2020	36,294	35,814	**18–10–2020**	51,454	50,541
17–09–2020	36,768	36,275	**19–10–2020**	51,928	51,001
18–09–2020	37,242	36,736	**20–10–2020**	52,402	51,461
19–09–2020	37,716	37,195	**21–10–2020**	52,875	51,921
20–09–2020	38,189	37,655	**22–10–2020**	53,349	52,381
21–09–2020	38,663	38,116	**23–10–2020**	53,823	52,842
22–09–2020	39,137	38,576	**24–10–2020**	54,297	53,302
23–09–2020	39,611	39,036	**25–10–2020**	54,770	53,762
24–09–2020	40,084	39,496	**26–10–2020**	55,244	54,222
25–09–2020	40,558	39,957	**27–10–2020**	55,718	54,683
26–09–2020	41,032	40,417	**28–10–2020**	56,192	55,143
27–09–2020	41,506	40,877	**29–10–2020**	56,665	55,603
28–09–2020	41,979	41,336	**30–10–2020**	57,139	56,063

ARIMA (2,2,3) among all models. It is recommended for practitioners to use the k-th moving averages – ARIMA models for modeling any phenomenon and getting accurate forecast values.

Declaration of competing interest

The author declares that he has no conflict of interest.

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