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Short research communication

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ABSTRACT

Background: COVID-19 has become a threat worldwide, affecting every country.

Aims: This study aimed to identify COVID-19 cases in Algeria using times series models for forecasting the disease.

Methods: Confirmed COVID-19 daily cases data were obtained from 21 March 2020 to 26 November 2020 from the Algerian Ministry of Health. Forecasting was done using the Autoregressive Integrated Moving Average (ARIMA) models (0,1,1) with Minitab 17 software.

Results: Observed cases during the forecast period were accurately predicted and placed within prediction intervals generated by ARIMA. Forecasted values of COVID-19 positive cases, recoveries and deaths showed an accurate trend, which corresponded to actual cases reported

during 252, 253 and 254 days. Results were strengthened by variations of less than 5% between forecast and observed cases in 100% of forecasted data.

Conclusion: ARIMA models with optimally selected covariates are useful tools for predicting COVID-19 cases in Algeria.

Keywords: COVID-19, time series, double exponential smoothing, ARIMA, forecast, Algeria

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Introduction

On 11 March 2020, the World Health Organization (WHO) declared COVID-19 as a pandemic. The pandemic had spread from mainland China to other countries and territories, disrupting socioeconomic activities. As of 26 November 2020, COVID-19 had infected more than 60 776 978 people globally, killed more than 1 428 228, and resulted in a lockdown that forced people to stay in their homes (1).

Algeria reported its first COVID-19 case on 25 February 2020. By 26 November, it had reported 79 110 confirmed cases, 51 334 recoveries and 2352 deaths (2).

SARS-CoV-2, the COVID-19 virus is very infectious, and many people were not following the non-pharmaceutical public health prevention measures recommended by the Algerian

government and other governments to control the pandemic, thus increasing the risks of transmission (2,3).

Accurate forecasting of COVID-19 case trends was essential for preparedness by health authorities to manage the pandemic and resource planning. Time series models such as ARIMA have been widely used to statistically model and forecast infectious disease trends (4). ARIMA models are preferred in this context because they are suitable for investigating short-term effects of acute infectious diseases and are flexible and appropriate for several trajectories (4,5). ARIMA models have been used in several studies to forecast COVID-19 outbreak trends (6-9).

In this study, we developed ARIMA models using daily COVID-19 confirmed and active cases in Algeria to identify the best fitting model of COVID-19 cases from 21 March 2020 to 26 November 2020.

Materials and methods

Data source

Data for this study included confirmed COVID-19 daily cases data obtained from 21 March 2020 to 26 November 2020 from the Algerian Ministry of Health (10).

Methods

The following equation highlights the exponential smoothing method and the ARIMA processes (11):

Determine the first smoothing value and the parameter α

$$St' = \alpha X + (1-\alpha) St-1' \quad (1)$$

Determine the second smoothing value

$$St'' = \alpha St' + (1 - \alpha)St-1'' \quad (2)$$

ARIMA model for time series sata ARIMA model is stated as follows:

$$\Phi(B)(1 - B)dXt = \theta(B)Zt \quad (3)$$

Where:

Φ(B) is an autoregressive operator

O(B) is a moving average operator

(1 − B)d is a differencing operator. It is the expression of dth consecutive differencing so as to make the series stationary

Zt is a Gaussian white noise series with mean zero and variance (σ2z).

ARIMA forecast is based on previous values and portrayed by 3 terms – p, d, q. Where p is the order for the auto regressive expression (AR), q is the order for the moving average expression (MA) and d is the number of differencing required making the time arrangement fixed.

The experiment was carried out using Minitab 17 programming software (12). In general, the equation can be approached using a regression model:

$$Yt = \alpha + \beta 1Yt-1 + ... + \beta pyt-p + \Phi 1\ et\ -1 + ... + \Phi qet-q + \varepsilon t \quad (4)$$

εt = errors from the accompanying conditions.

Results

Using the time-series model approach, the pattern of COVID-19 data distribution in Algeria showed an exponential distribution pattern, where the addition of positive cases increased significantly everyday of the pandemic. The distribution pattern was the same for the number of people who recovered and died (Figure 1). For the positive COVID-19 cases, the mean absolute percentage error (MAPE) value was smaller than the error rate at 10% (Table 1). The increase in the number of people who were positive for COVID-19 directly affected the prediction model for patients who recovered and died (
Figure 1
). For recovered cases, MAPE value was smaller than the error value set at 10% error rate (
Table 1
). The recovery rate for COVID-19 patients increased simultaneously with the number of positive cases because of the non-pharmaceutical public health measures taken by the government from 21 March 2020. For deaths due to COVID- 19, the MAPE value was greater than the error value set at 10% (
Table 1
). The increase in mortality was possibly due to the extent of infection and the medical history of the patients.

In the time series model with 5% error probability (α), the graph followed the ARIMA process (0,1,1), with the P value MA 1 (0.0%) smaller than α.

Estimated results of parameters model for COVID-19 positive data using ARIMA models

Referring to equation (4), mathematically, the ARIMA model (0,1,1) can be stated using the following coefficients: Yt = 317.65 – 0.879et–1

Same as COVID-19 positive data, in the time series model with 5% error probability (α), the graph followed the ARIMA process (0,1,1) with the P value MA 1 (0,0%) smaller than α.

Estimated parameters for COVID-19 Recovery data results using ARIMA model

Referring to equation (4), mathematically the ARIMA model (0,1,1) can be stated as follows: Yt = 205.53 – 0.30et–1

After the positive and recovery data were analysed in time series model with the 5% error probability (α), the graph followed the ARIMA process (0,1,1) with the P value MA 1 (0.00%) smaller than α.

All estimated parameter results of the ARIMA model

Referring to equation (4), mathematically, the ARIMA model (0,1,1) can be stated.

The results of predictions of COVID-19 cases in Algeria (positive, recovered and deaths) showed a gap in the resulting distribution patterns, where the increase in the number of positive cases was not offset by an increase in the number of patients who recovered and a decrease in the number of patients who died. This indicates that public behaviour did not comply with the rules set by the government (physical distancing, large-scale social restrictions, washing of hands, and mask use).

Discussion

From the time WHO declared COVID-19 a pandemic on 11 March 2020, several countries experienced an exponential increase in COVID-19 cases (3), which put a lot of pressure on most healthcare systems worldwide. In response, health authorities attempted to forecast the trend of the pandemic, but this proved difficult because COVID-19 is a novel disease with limited data and knowledge about its trends and dynamics (2). Our forecast showed an accurate trend, which corresponded to the number of positive cases observed and reported by the Ministry of Health in Algeria during 3 days (252,253 and 254). The same situation was observed for forecasted recoveries and deaths.

This finding was strengthened by variations of less than 5% between the forecast and observed cases in 100% of the forecasted data points (Table 2). Similar studies conducted in South Korea, Iran and Italy predicted similar case trends using ARIMA models (6-8).

The strengths of this study include: firstly, this is the first paper to report the use of ARIMA models to forecast COVID-19 cases and trends in Algeria. Secondly, this was the first attempt to use smoothen case data to improve accuracy as compared to similar studies on ARIMA models for COVID-19 conducted in other countries (6-7). Thirdly, we used several independent covariates, which provided more accurate signals to develop short-term model predictions for immediate outbreak response. Finally, we optimized the model training and validation period to

provide the highest number of data points to generate the best fit model.

Conclusion

This study demonstrates the effectiveness of ARIMA models as an early warning strategy that can provide accurate COVID-19 forecasts on larger data points (251 days). Forecasted values of COVID-19 positives, recoveries and deaths showed an accurate trend which corresponded to the actual cases observed and reported by the Ministry of Health in Algeria during 3 days (252, 253 and 254). We are confident that the ARIMA model can be used to generate accurate and reliable forecasts of daily COVID-19 cases and similar pandemics, with the addition of new data points and independent covariates.

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Competing interests: None declared.

Prévision des cas de COVID-19 confirmés quotidiennement en Algérie à l'aide des modèles ARIMA

Résumé

Contexte : La COVID-19 est devenue une menace à l'échelle mondiale, touchant tous les pays.

Objectif : La présente étude visait à identifier les cas de COVID-19 en Algérie à l'aide de modèles de séries chronologiques pour la prévision de la maladie.

Méthodes : Les données sur les cas de COVID-19 confirmés quotidiennement ont été obtenues du 21 mars au 26 novembre 2020 auprès du ministère algérien de la Santé. Les prévisions ont été effectuées à l'aide de modèles autorégressifs à moyennes mobiles intégrées

(Autoregressive Integrated Moving Average, ARIMA) (0,1,1) en recourant au logiciel Minitab 17.

Résultats : Les cas observés pendant la période de prévision ont été prédits avec précision et se situaient dans les intervalles de prédiction générés par les modèles ARIMA. Les valeurs de prévision pour les cas positifs de COVID-19, les guérisons et les décès liés à la maladie ont montré une tendance précise, qui correspondait aux cas réels signalés pendant 252, 253 et 254 jours. Les résultats ont été renforcés par des variations de moins de 5 % entre les cas prédits et ceux observés dans 100 % des données de prévision.

Conclusion : Les modèles ARIMA dotés de covariables sélectionnées de manière optimale sont des outils utiles pour prédire les cas de COVID-19 en Algérie.

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WHO EMRO | Forecasting daily confirmed COVID-19 cases in Algeria using ARIMA models

الحالات الفعلية المُبلغ بها خلال 252 ، و 253 ، و 254 يومًا . وعُززت النتائج باختلافات
تقل عن 5% بين التنبؤ والحالات المرصودة في 100% من البيانات المتوقعة .

: تُعدُّ نماذج متوسط الانحدار الذاتي المتكامل (أريما) مع المتغيراتالاستنتاجات
المشاركة المختارة على النحو الأمثل أدوات مفيدة للتنبؤ بحالات كوفيد -19 في الجزائر .

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