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Predictive models for COVID-19 cases, deaths and recoveries in Algeria

M. Lounis a, O. Torrealba-Rodriguez b,*, R.A. Conde-Gutiérrez c,*

a Department of Agro-veterinary Science, Faculty of Natural and Life Sciences, University of Ziane Achour, BP 3117, Road of Moundbara, Djelfa 17000, Algeria
b Universidad Politécnica del Estado de Morelos (Upemor), Boulevard Cuauhnahuac #506, Col. Lomas del Tecom, Iztapalapa, Morelos CP 62250, México
c Centro de Investigación en Recursos Energéticos y Sustentables, Universidad Veracruzana, Av. Universidad Km 7.5, Col. Santa Isabel, Coatzaocolcos, Veracruz CP 96535, México

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ABSTRACT

This study was conducted to predict the number of COVID-19 cases, deaths and recoveries using reported data by the Algerian Ministry of Health from February 25, 2020 to January 10, 2021. Four models were compared including Gompertz model, logistic model, Bertalanffy model and inverse artificial neural network (ANNi). Results showed that all the models showed a good fit between the predicted and the real data ($R^2 > 0.97$). In this study, we demonstrate that obtaining a good fit of real data is not directly related to a good prediction efficiency with future data. In predicting cases, the logistic model obtained the best precision with an error of 0.92% compared to the rest of the models studied. In deaths, the Gompertz model stood out with a minimum error of 1.14%. Finally, the ANNi model reached an error of 1.16% in the prediction of recovered cases in Algeria.

Introduction

The Coronavirus disease 2019 (COVID-19) is certainly the worst worldwide crisis in the 21st century which has provoked a real disaster [1]. This disease which was reported in December 2019 in the city of Wuhan in China has been reported in almost all countries. The current count shows a total of >100 million cases and >2.1 million deaths [2]. Despite the applied preventive measures to control the disease, the number still increase [2]. Thus, understanding the diffusion feature of this disease is of great importance for the national authorities to adopt and adapt the best preventive measures [3].

In this way, since the first days of its emergence, multiple studies were carried out to understand the epidemic spreading and estimate the epidemiological parameters of this disease. These studies used various categories of models including Agent-based models, Machine Learning and Artificial Intelligence (AI) approaches, Bayesian models, Compartmen tal models, Network models, Statistical models, and Hybrid models [4]. Also, researchers applied and developed different approaches that give the best performance according to the countries’ data [4].

Related works

Different researchers applied different models to forecast the COVID-19 epidemic curve. Below we will present some studies that attempted to forecast COVID-19 using Gompertz model, logistic model, Bertalanffy model and inverse Artificial Neural Networks (ANNi). Catala et al, 2020 [5] employed the Gompertz model to analyze the spreading of COVID-19 and predict the new cases in 28 European countries. Results showed that the model gave a success of 90% in short-term prediction of daily new cases especially in countries that are in the initial stages of the COVID-19 outbreak. Valencia et al, 2020 [6] assessed the early mitigation measures against COVID-19 in Puerto Rico using the Gompertz model. The authors suggested that these measures averted a number of 6155 COVID-19 cases (7466 estimated/1311 observed) and 211 deaths (354 estimated/143 observed) during the observation period. The authors suggested that the wide predictive intervals were due to the relatively small number of observations.

Areeponga and Sunthornwit, 2020 [7] made a comparison of forecasting between logistic and Gompertz models in Southeast Asian countries. Their findings showed that Gompertz model is suitable in forecasting COVID-19 in Indonesia, Philippines, and Malaysia and logistic model was better for the other countries in South Asia. Reddy et al, 2020 [8] applied different phenomenological models (Richards, 3 and 4 parameters logistic, Weibull and Gompertz models) for a short term forecasting of COVID-19 cases and deaths at the national and provincial level in South Africa and compared their predictions to the observed values in the studied

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period. The authors concluded that all the applied models provided reliable and accurate forecasts for a maximum period of 10 days. Jia et al, 2020 [9] applied three mathematical models including Bertalanffy, Gompertz and logistic models to estimate the progression of COVID-19 in Wuhan. The applied models predicted that the turning point will be on February 9, 2020 and the COVID-19 will end probably in late-April 2020. They also reported that the logistic model gave the best fitting in Wuhan than Bertalanffy and Gompertz models, while the Gompertz model was better in fitting the data outside Wuhan. Before they tested the three models for SARS and they found that logistic and Gompertz were more accurate than Bertalanffy model. Ahmadi et al, 2020 [10] forecasted the COVID-19 epidemic evolution in Iran using Gompertz, von Bertalanffy, and least squared error (LSE) models with 95% confidence interval basing on severely sick patients needing hospitalization. After the estimation of the predicted number of COVID-19 cases and deaths for April 3, 2020 by each model, they predicted that the COVID-19 epidemic curve will be flat from May 13 until July 2020 in Iran if the prevention measures continue with the same trend. Martelloni and Martelloni, 2020 [11] studied the evolution of the COVID-19 in Italy with the Logistic model, Gompertz model and the interpolating model (for cases and deaths). They reported that the logistic model is the best candidate to describe the situation in Italy. In the study of Yue et al, 2020 [12], the logistic and the Gompertz models were applied to evaluate possible peaks of the COVID-19 pandemic in the different states of the USA. The result showed that if it was possible to identify the first peak in the states of Montana and Hawaii, it was unclear when the other states will reach theirs peaks. it was also predicted that 75% of regions will probably not reach the first peak of before August 2, 2020. Atta-nayake et al, 2020 [13] used four phenomenal models: Gompertz, logistic, Weibull, and exponential growth models to evaluate overall growth rate, final size, and short-term forecasts in Sri Lanka, Italy, the United States, and Hebei province of China. The authors showed that logistic and Gompertz models are the most appropriate in the cited countries. Findings of the research demonstrated that if the outbreak seems to be extinct in Hebei, China and in a decreasing phase in Italy and Sri Lanka further transmissions are possible in the United States. Bartolomeo et al, 2020 [14] compared the exponential decay model applied to WR and the Gompertz model for a short-term forecasting of the COVID-19 epidemic, and for the estimation for the final epidemic size. The obtained results showed that predictions provided by the EDM applied to WR are better than the Gompertz model. Torrealla-Rodriguez et al, 2020 [15] applied Gompertz, Logistic, Artificial Neural Networks and inverse Artificial Neural Networks (ANNi) models to predict the endpoint, the inflexion point and the final number of COVID-19 cases in Mexico. Results of the study showed that the used models gave a good fit between the estimated and the observed data on total confirmed cases expressed by a coefficient of determination $R^2 > 0.99$.

Other prediction studies using ANN were also performed:

- In the study of Ahmed and Asad, 2020 [16], an ANN model was used to make a short-time prediction of COVID-19 confirmed cases, deaths and recoveries in Pakistan using previous data of 137 days. The authors reported that the model was well fitted and could be helpful for a prediction of 7 future days.
- Farooq and Bazaz, 2020 [17] employed deep learning to propose an Artificial Neural Network (ANN) based real-time online incremental learning technique to study the transmission dynamics and prevention measures against COVID-19. The authors proposed an effective method to significantly reduce the number of deaths based on the development of natural immunity in the low risk group of the population and isolation of the high risk group.
- Niazkar and Niazkar, 2020 [18] used fourteen ANN-based models to estimate the confirmed cases of COVID-19 in China, Japan, Singapore, Iran, Italy, South Africa and United States of America. Their study indicated that implementation of a 14-days incubation period of COVID-19 in the ANN-based model ameliorate the prediction accuracy especially in countries that have experienced the first peak of the COVID-19 outbreak.
- Mallalo et al, 2020 [19] examined the applicability of multi-layer perceptron artificial neural networks in modeling cumulative incidence of COVID-19 at the county-level across the continental United States. The authors reported that even the model indicated a reasonable prediction, demographic, socioeconomic and environmental factors were influential in predicting COVID-19 new cases.

The aim of this work is to compare the projections of predictive models with different approaches, such as mathematical and computational. These models were used to visualize the evolution of COVID-19 cases, deaths, and recoveries in Algeria by estimating the total number and the endpoint.

In summary, the main contributions of this paper are:

1. Comparison of four models with different mathematical approaches for modeling and predicting the dynamics of cases, deaths, and recoveries caused by COVID-19 in Algeria.
2. Demonstrate that the prediction efficiency of the models proposed in this work is not directly related to achieving the best fit with the real data during the modeling process.
3. Demonstrate that developing and contrasting more than one predictive model can allow the generation of reliable data in a certain period of time in order to support decision-making.
Material and methods

COVID-19 dataset

The dataset used in this study includes the Algeria total and daily COVID-19 confirmed cases, deaths and recoveries, collected from the Algerian official website of the Ministry of health \[20\]. Data were obtained over the period from February 25, 2020, to January 10, 2021. It is to mention that the confirmed cases are only based on RT-PCR test results and the number of real cases is higher. The number of cases recorded on January 10th, 2021 (after 307 from the first case) was 102,144 and the number of deaths was 2807 persons while 69,212 persons recovered from the disease.

The number of total confirmed and recovered cases are presented in Fig. 1A, the number of deaths is presented in Fig. 1B

COVID-19 modeling:

Mathematical and computational prediction models based on data growth have been useful in various research areas, such as: engineering \[21\], agronomy \[22\] and medicine \[23\]. These models allow visualizing through the projections obtained, a series of possible results that can support the study of a specific dynamic behavior. Mathematical models are applied from differential equations to simulate and predict the dynamics of non-linear behaviors. In contrast, computational models are based on learning processes to represent non-linear outputs.

In this work, we used four models to forecast COVID-19 cases, deaths and recoveries in Algeria: Gompertz model, logistic model, Bertalanffy model and inverse artificial neural network (ANNi).

Gompertz model

The Gompertz model that we use for the simulation of COVID-19 in Algeria is based on a differential equation that belongs to the modeling of sigmoid curves, which have been shown to obtain satisfactory forecasts with respect to the observed data \[24\]. In the literature, different variants of the Gompertz model have been applied due to the number of parameters used, but they generally coincide in using a double exponential. We carry out the modeling and forecasting through the following equation:

\[
y_i = ae^{-be^{-cx}}
\]

Considering that: \(y_i\) is the forecasted cumulative number, \(a\) is the maximum forecasted number during the pandemic, \(b\) and \(c\) are coefficients obtained during the fitting of the data real and \(x\) is time based on the number of days since the first case.

Logistic model

The Logistic model that we have applied in this work for the modeling and forecasting of COVID-19 (like the Gompertz model), has shown to obtain a good agreement with the available data \[25\]. The Logistic model is developed from an ordinary differential equation, which represents an initial phase of exponential growth and decreasing growth as it approaches a forecast maximum. In general, the model uses three parameters, which are adjusted from the real data. The logistic model can be expressed as:

\[
y_i = \frac{a}{1 + e^{-bx}}
\]

Considering that \(y_i\) is the forecasted cumulative number, \(a\) is the maximum forecasted number during the pandemic, \(b\) and \(c\) are coefficients obtained during the fitting of the data real and \(x\) is time based on the number of days since the first case.

Bertalanffy model

The Bertalanffy model, compared to the models described above, has stood out for its good performance in modeling COVID-19 \[26\]. This model is proposed from a differential equation, which represents a growth curve as a sigmoid function. To determine the maximum growth value, it is necessary to fit the model parameters. The Bertalanffy model that we used for modeling and forecasting is described in the following equation:

\[
y_i = a(1 - e^{-bx})^c
\]

Considering that: \(y_i\) is the forecasted cumulative number, \(a\) is the maximum forecasted number during the pandemic, \(b\) and \(c\) are coefficients obtained during the fitting of the data real and \(x\) is time based on the number of days since the first case.

Inverse artificial neural network model

The inverse artificial neural network model is a computational methodology that has been applied to forecast values based on the coefficients obtained during the learning process, demonstrating a good extrapolation capacity \[15,27\].

For the development of the ANNi model, it is necessary to train an artificial neural network (ANN). Before starting the learning process, the output to simulate is divided by 1000 (to avoid large coefficients) and the input variable is normalized \((x)\) in an interval of \([0.1–0.9]\).
Considering that: \( x_{\text{real}} \) is the real value, \( x_{\text{min}} \) is the minimum value of the real data and \( x_{\text{max}} \) is the maximum value of the real data.

Once the best neural network architecture to simulate the output is found, the ANN model is inverted to obtain an objective function. The following equation shows in a general way the approach of the ANNI model (applying a tangent sigmoid transfer function in the hidden layer and a linear transfer function in the output).

\[
\min(f_{(i)}) = -y_i + \sum_{i=1}^{n} \left[ W_{0(i)} \left( \frac{2}{1 + \exp\{-2(W_{1(i)} \times I_{n(i)} + b_{1(i)})\} - 1 \right) \right] + b_{2}
\]  

(5)

Considering \( x \) is the number of days since the first case. \( W_{i}, W_{0}, b_{1}, b_{2} \) are fitting coefficients. \( y_{i} \) is the forecasted cumulative number, \( n \) is the number of neuron in the hidden layer. To guarantee the correct execution of Eq. (5), the forecasted cumulative number must be divided by 1000 (as mentioned previously) according to the extrapolated days of number (normalized using the Eq. 4).

In this work, the objective function was minimized through a genetic algorithm chosen for its efficiency and stability in the search for global optimal solutions [28]. Finally, coupling the genetic algorithm to the ANNI model allows solving the objective function in the shortest possible time, providing the approximate day on which a certain number of accumulated cases will occur.

**Estimation of the parameters and coefficients in data fit**

To carry out the estimation of parameters in the mathematical models, it is necessary to apply an optimization algorithm to fit the data. The Nelder-Mead simplex algorithm was chosen, due to its ability to search and its design to solve non-linear optimization problems without restrictions, generating a rapid initial decrease in the values of a function [29]. The optimization algorithm fitted the parameters using the least squares method in order to minimize the sum of the squared of the differences between the data obtained from the mathematical models and the real data, as represented by the following equation:

\[
\min_{W_{i}, b_{1}, b_{2}} \left\{ SSE = \sum_{i=1}^{n} (y_{i}^{\text{real}} - y_{i}^{\text{model}})^2 \right\}
\]  

(6)

To fit the coefficients in the ANN model, a learning process is executed in order to minimize the difference between the desired output and the result obtained by the model through a Backpropagation algorithm. In this work, the Levenberg-Marquardt algorithm was chosen, because it is designed to approach second-order training fast without having to compute the Hessian matrix obtaining better convergence when training neural networks [30].

All the calculations necessary to develop the mathematical and computational models and the application of the optimization algorithms were carried out with Matlab R2014a mathematical software.

**Models performance**

To estimate the accuracy of each model, the coefficient of determination \( R^2 \) was calculated by the following equation:

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (X_{\text{real}}(i) - X_{\text{out model}}(i))^2}{\sum_{i=1}^{n} (X_{\text{real}}(i) - X_{\text{mean real}})^2}
\]  

(7)

To evaluate the fit of the models, the mean absolute percentage error (MAPE) was applied, because it measures the size of the absolute error in percentage terms. This criterion is calculated through the following equation:

\[
\text{MAPE} = \frac{\sum_{i=1}^{n} \left| \frac{X_{\text{real}}(i) - X_{\text{model}}(i)}{X_{\text{model}}(i)} \right|}{n} \times 100\%  
\]  

(8)

Where: \( X = \frac{1}{n} \sum_{i=1}^{n} X_i \) is the average of the value; \( x_{\text{model}} \) is the output value obtained by the model and \( x_{\text{real}} \) is the real value.

To determine the good fit of each of the predictive models, the test of the paired t-test was used in order to compare the means of two dependent variables of a single group (contemplating two-tails). The paired t-test arises with the following assumptions:

The null hypothesis \( H_0 \) is that the sample mean of the differences is zero. Therefore, there is no statistically significant difference between the real data and those obtained by the predictive models.

The alternative hypothesis \( H_i \) is that the sample mean of the differences is nonzero. Therefore, there is a statistically significant difference between the real data and those obtained by the predictive models.

For the null hypothesis accepted, the value obtained by Eq. (9) must be less than the critical value obtained from tables [31].

\[
t = \frac{\bar{d}}{s_d/\sqrt{n}}
\]  

(9)

Where \( s_d = \sqrt{\frac{s^2}{n}} \) and \( s^2 \) is the variance of the difference between the real data and those obtained by the models and \( \bar{d} \) is the average of difference between each pair of data.

**Results and discussion**

Once the parameters of the mathematical models and the coefficients of the computational model have been adjusted, these models can be applied for modeling and forecasting COVID-19 in Algeria. The models are defined for COVID-19 cases, deaths and recoveries by the following equations:

**For COVID-19 Cases:**

- **Gompertz model**

  \[
y = 232448.5e^{-5.8586t - 0.006576t^2}
\]  

(10)

- **Logistic model**

  \[
y = \frac{136853.2}{1 + e^{39030 - 0.0133997t}}
\]  

(11)

- **Bertalanffy model**

  \[
y = 1189229.6(1 - e^{-0.00122357t})^{2.1728}
\]  

(12)

- **ANNi model**

  \[
  \min(f_{(i)}) = -y + \left[ -32.6576\left(\frac{2}{1 + e^{-2(-3.4698x + 3.5712)}} - 1\right) \right] + \left[ -18.6804\left(\frac{2}{1 + e^{-2(-12.1152x + 5.5604)}} - 1\right) \right] + \left[ -4.0238\left(\frac{2}{1 + e^{-2(-13.5004x + 14.6211)}} - 1\right) \right] + \left[ 13.7906\left(\frac{2}{1 + e^{-2(-23.1132x - 10.5517)}} - 1\right) \right] + 68.9604
  
\]  

(13)

**For deaths:**

- **Gompertz model**
\[ y = 4594.5e^{-3.3046\times 10^{-0.0010948x}} \] (14)

- **Logistic model**

\[ y = \frac{3378.4}{1 + e^{-2.82444x}} \] (15)

- **Bertalanffy model**

\[ y = 12879 \left(1 - e^{-0.0010948x}\right)^{1.2223} \] (16)

- **ANNi model**

\[

\min(f_{(x)}) = -y + \left[ \frac{2}{1 + e^{-\left(2(12.7634x) - 1.4039)\right)}} - 1 \right] \\
+ 0.3241 \left[ \frac{2}{1 + e^{-\left(2(-14.3208x) + 13.3225)\right)}} - 1 \right] \\
+ -1.0062 \left[ \frac{2}{1 + e^{-\left(2(-3.8497x) + 1.64437)\right)}} - 1 \right] \\
+ 0.139 \left[ \frac{2}{1 + e^{-\left(2(-3.7152x) - 3.6636\right)}} - 1 \right] + 3.6636

\]

(17)

For recovered cases:

- **Gompertz model**

\[ y = 118736.5e^{-5.1906e^{-0.0010948x}} \] (18)

- **Logistic model**

\[ y = \frac{82444.4}{1 + e^{-3.6756-0.0165328x}} \] (19)

- **Bertalanffy model**

\[ y = 339460.5(1 - e^{-0.0020464x})^{1.1042} \] (20)

- **ANNi model**

\[

\min(f_{(x)}) = -y + \left[ \frac{2}{1 + e^{-\left(2(10.9758x) - 8.8099)\right)}} - 1 \right] \\
+ 2.4742 \left[ \frac{2}{1 + e^{-\left(2(-41.4496x) + 32.0732)\right)}} - 1 \right] \\
+ 2.8240 \left[ \frac{2}{1 + e^{-\left(2(14.0950x) - 13.8417)\right)}} - 1 \right] \\
+ 15.6501 \left[ \frac{2}{1 + e^{-\left(2(9.0490x) - 4.7581)\right)}} - 1 \right] + 36.4267

\]

(21)

We first calculated the R² and MAPE for each model from the month of May 2020 to January 10, 2021 (this period was chosen as adequate to cover the homogeneous stability of all models). Table 1 shows the results obtained from the application of the R² and MAPE criteria for COVID-19 cases, deaths and recoveries.

Based on Table 1, we can conclude that the ANNi model presents the best fit. To determine the good fit of each of the models, in addition to the previous criteria, it is feasible to apply the paired t-test (using the same period of time as in the previous criteria). The results in Table 2 indicate that all the predictive models pass the paired t-test for the cases and recovered by COVID-19, which justifies their good fit with respect to the real data using a confidence level of 95%.

In deaths from COVID-19, the Gompertz, Logistics, and ANNi models fail the test. However, later it will be analyzed that a model with a good fit reflected through the previous criteria is not related to the prediction efficiency for a certain period of time.

**COVID-19 cases**

Results of the Gompertz model showed that the inflection point has been attempted on January 10, 2021 and the endpoint will be reached after 2362 days (13 August 2026) with a total number of 232,448 cases (Fig. 2).

According the logistic model, the inflection point was attempted on December 14, 2020 and the endpoint will be reached on January 04, 2023 (after 1045 days). The total number at the end point is estimated at 136,853 cases (Fig. 3).

For the inverse ANN model, Fig. 4 shows that the inflection point has been attempted on January 22, 2020 which in accordance with observed data where the maximum number of daily cases was reported on November 23, 2020 (1133 cases). According to this model, the
epidemic will end on August 22, 2022 with a final number of 138,112 cases.

At last, the Bertalanffy model results showed that the decline phase will begin after 632 days (17 November 2021) and the final number will be about 1,183,604 cases after about 5000 days from the first case detected (Fig. 5).

COVID-19 deaths

Results of our models showed that the number of deaths will reach: 4594 cases for the Gompertz model (23 June 2024) (Fig. 6), 3378 cases for the logistic model (August 06, 2022) (Fig. 7), 7461 cases for the ANNi (September 09, 2021) (Fig. 8) and a number of 12,813 cases on Fig. 2. Confirmed and predicted COVID-19 cases in Algeria by the Gompertz model.

Fig. 3. Confirmed and predicted COVID-19 cases in Algeria by the Logistic model.

Fig. 4. Confirmed and predicted COVID-19 cases in Algeria by the ANNi model.
COVID-19 recovered cases

According to the applied models, the total numbers of recovered persons are shown in Figs. 10-13.

Results showed that 72,957 persons will recover from COVID-19 at the end of the epidemic by the ANNi model (June 09, 2021) (Fig. 10). This number is estimated at 82,444 persons by the logistic model (September 18, 2022) (Fig. 11). For the Gompertz model the number of recovered cases will be 11,8736 persons (April 15, 2025) (Fig. 12) while the estimated number for the Bertalanffy model is estimated at 33,9434
cases on November 16, 2033 (Fig. 13).

Comparison between the observed data and those predicted by the models was done in an out of sample prediction consisting of the next 26 days in order to evaluate the accuracy of this prediction by calculating the mean absolute percentage error (MAPE). Results show that in average Logistic (0.92%) and ANNi (1.24%) models have the lowest errors for confirmed cases (Table 2) while Gompertz (1.14%) logistic (1.29%) and Bertalanffy (1.39%) models gave the lowest errors for deaths (Table 3).

For recoveries, the lowest errors were obtained by the ANNi and the Bertalanffy models with values of 1.16 % and 1.42 % respectively (Table 4).
Comparison between the observed data and those predicted by the models was performed in an out of sample prediction consisting of the next 26 days, and in order to evaluate the accuracy of this prediction, the mean absolute percentage error (MAPE) was used. Results show that in average the prediction efficiency of Logistic model (0.92%) had the lowest error for confirmed cases (Table 3). While Gompertz model (1.14%) reached the lowest error for deaths (Table 4). For recoveries, the lowest error was obtained by the ANNi model with values of 1.16% (Table 5).

With these results, it is feasible to deduce that developing a predictive model with a good fit will not be a guarantee to obtain high efficiency in the forecast of cases, deaths and recoveries from COVID-19. For this reason, to generate a reliable prediction it is necessary to apply more than one predictive model and analyze which of them
approximates the dynamics due to virus contagion. Finally, the prediction efficiencies of the models applied in this study are satisfactory, despite the fact that the models can be categorized as simple because they are based on elementary mathematical equations that describe growth curves and a computational model based on artificial intelligence. However, the results obtained can be compared in efficiency with complex mathematical models, such as: Fractional Multi-Order Model [32,33], SQIR epidemic model [34], non-linear epidemic model [35], among others. Therefore, we recommend the application of both simple and complex models to compare the prediction efficiency and to provide accurate information on the dynamics of the disease.

**Conclusion**

In this paper we compared four models with different approaches in order to estimate COVID-19 cases, deaths and recoveries in Algeria. The ANNi model obtained the best fit of real data in the modeling process with respect to the total of confirmed cases, deaths, and recovered traduced with $R^2 = 0.9999$ and MAPE $= 1.04\%$, due to the learning process during the fit of its coefficients.
We evaluate the daily prediction of the models in a period of 26 days. The results indicate that the Gompertz, Logistic and ANNi models predict with an acceptable percentage error, obtaining a MAPE <1.16% applied in the cases, deaths and recoveries, respectively. It is important to conclude that to obtain a reliable prediction it is necessary to develop and compare more than one predictive model. Having this information can be useful to contemplate the different scenarios in which the dynamics of viruses can proceed.

It is to mention that these results are based only on PCR positive reported cases and the real number is higher. Also these models were applied taking into account the evolution of cases in Algeria according to the applied preventive measures. A probable hardening or relaxing in these measures or a probable vaccination could eventually have an effect on the epidemic curve. These models could be a helpful tool for the national authorities to truck the disease status especially if they could increase their testing capacities which could increase the accuracy of the forecasting of COVID-19 cases, deaths and recoveries.

CRediT authorship contribution statement

**M. Lounis:** Conceptualization, Formal analysis, Resources, Visualization. **O. Torrealba-Rodríguez:** Methodology, Formal analysis, Data curation, Writing - review & editing, Project administration, Funding acquisition. **R.A. Conde-Gutiérrez:** Methodology, Software, Validation, Investigation, Writing - original draft, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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