Asia Mathematika
Volume: 4 Issue: 2 , (2020) Pages: 150 – 160
Available online at **www.asiamath.org**

Forecasting the prevalence of COVID-19 outbreak in world using the ARIMA and exponential smoothing model

Manigandan P[1], Alagirisamy K[2*], Lokesh K[3], Pachiyappan D[4] and Hajira Banu G[5]
[1]Ph.D - Research Scholar, Department of Statistics, Periyar University, Salem-11, Tamil Nadu, India. Orchid iD: 0000-0001-8262-8421
[2]Assistant Professor, Department of Statistics, Periyar University, Salem-11, Tamil Nadu, India. Orchid iD: 0000-0003-1665-9769
[3]Ph.D - Research Scholar, Department of Statistics, Periyar University, Salem-11, Tamil Nadu, India. Orchid iD: 0000-0001-8933-3896
[4]Ph.D - Research Scholar, Department of Statistics, Periyar University, Salem-11, Tamil Nadu, India. Orchid iD: 0000-0001-7393-4726
[5]Assistant Professor,Department of statistics, Muthayammal Memorial College of arts and science, Periyar University, Salem-11, Tamil Nadu, India.

Received: 19 July 2020 • **Accepted:** 03 Aug 2020 • **Published Online:** 20 Aug 2020

Abstract: The novel pandemic of coronavirus (COVID-19) becomes a global threat. As of mid-Jun 2020, 7759691 COVID-19 cases in the world were total confirmed cases, including 430127 death cases, which illustrate how badly the pandemic affected the world. To examine the Confirmed and death case of the Corona Virus, We constructed ARIMA and Exponential Smoothing model models to prediction its trend in incidence in World. Methods; The novel epidemic of COVID-19 patient dataset has extracted from the World health origination (WHO) website includes confirmed and death cases from start-February to mid-Jun were used to establish. Estimate the ARIMA and Exponential Smoothing model to forecasting the prevalence of COVID-19 over the subsequent 60 days. Results; The better accuracy of ARIMA model with the lowest RMSE (root mean squared error), MAE (mean absolute error), MAP (mean absolute percentage) and MAPE was finally model selected for in sample simulation. The prediction of COVID-19 patients could obtain the value of total confirmed cases of 15853652, which could be a total death cases of 692639 at the mid of August. Conclusions; This study suggested that the most accurate prediction of COVID-19 prevalence in World using the ARIMA model was proposed as a useful tool for monitoring pandemic. This analytical tool offers a great contribution for researchers and healthcare managers in the evaluation of healthcare interventions in specific populations.

Key words: prediction, COVID-19 outbreak, ARIMA, ETS model, Time series

1. Introduction

The current epidemic of the novel coronavirus (SARS-CoV-2) affects primarily China's mainland and a cluster of severe pneumonia cases identified in Wuhan, China in December 2019 [17, 28]. Although the initial spreading potential of this novel coronavirus appears to be similar to that of the acute respiratory syndrome (SARS) [22], the current number of infections is already higher than the total number of cases reported for SARS outbreaks in 2002-2003 [28, 29, 35]. The timing and location of the outbreak have enabled the virus to spread rapidly among more mobile populations. The initial report of the observed events occurred during the traditional Chinese New Year when the largest population movement occurred each year [2]. Further, Wuhan is a city of more than 11

*Correspondence: alagiriperiyaruniversity1978@gmail.com

million people and is connected to many cities in China by public transport such as buses, trains, and airplanes [16, 21]. In the absence of pharmaceutical interventions, rapid action was needed by the Chinese government to prevent the spread of Wuhan inside and out.

To anticipate further evidence of combating the epidemic, mathematical and statistical modeling tools can be useful in making timely short-term predictions of reported events. These projections include estimates of expected disease burden, which will help public health officials prepare for medical care and other resources needed to combat the epidemic. Short-term projections lead to the intensity and type of interventions needed to mitigate an infection [10, 25]. In the absence of vaccines or antiviral agents for 2019-nCoV, effective non-pharmaceutical interventions such as personal protection and social exclusion may be important in controlling the infection. Statistical prediction models can be helpful in predicting and controlling this global epidemic threat. Here during this study, the ARIMA model is beneficial for predicting the confirmed prevalence of COVID-2019. We performed Auto Regressive Integrated Moving Average (ARIMA) model on the European Centre for Disease Prevention and Control COVID-19 data to predict the number of cases and deaths in COVID-19 [4, 26, 19]. To evaluate and compare the performances of time series models are two decomposition methods (regression and exponential smoothing), ARIMA, Wavelength Neural Network (WNN) and SVM methods in most cases [36, 15].

Therefore, this research aims at forecasting the COVID -19 disease trend using the ARIMA and exponential smoothing (ETS) model by taking total confirmed cases and total death cases into consideration. In this model will contribute to the arrangement of a scientific reference of risk estimate for COVID-19 control and prevention.

2. Material and Methods

2.1. Source of data

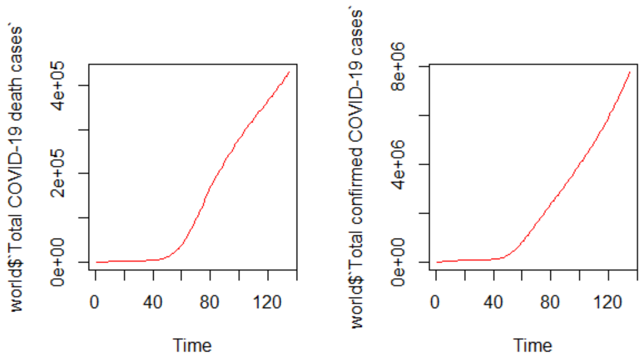
Patient data were obtained from the official website of the world health organization that records the most recent information of the coronavirus (COVID-19) infectious disease in World. The data model upgrade was done based on the mid-Jun 2020 update. The patient database comprised of 3 groups, especially infected case, death, and recovered cases. In this study, we excluded the COVID-19 information and prediction probable number of confirmed cases and death cases in the next 60 days. Rather than looking at the whole data, we only considered the observations from February 1, 2020. Fig. 1 is the plot of the total number of confirmed and death cases trend varied on a total basis. From these, data from mid-March 2020 to mid-Jun 2020 were used to construct the ARIMA and ETS models. Data from mid-Jun 2020 to mid-August 2020 were used to estimate the prediction performances of these models.

2.2. Autoregressive integrated moving average model development in R

Relying on the antecedent data to forecast confirmed and death case, the Autoregressive integrated moving average model structure a simplistic, yet distinguished approach applied for time series forecasting. Autoregressive integrated moving average was popularized by the work of [24, 9, 3]. To develop the ARIMA model, 2 types of linear regressions are integrated: the AR and the MA [3]. The Autoregressive model and Moving Average model is written as [3].

$$y_t = c + d_1 y_{t-1} + ... + d_p y_{t-p} + e_t \tag{1}$$

Figure 1. Total COVID-19 incidence during the period from start-February 2020 to mid-Jun 2020.



Likewise, the 'Moving Average model' can be written as [3]:

$$y_t = \alpha + \beta_1 + m_1\beta_{t-1} + ... + m_q\beta_{t-q} \tag{2}$$

By integrating these models with the same training data, the ARIMA (p, q) model becomes [3]:

$$y_t = c + d_1 y_{t-1} + ... + d_p y_{t-p} + \beta_1 + m_1\beta_{t-1} + ... + m_q\beta_{t-q} \tag{3}$$

where p and q are the AR and MA terms, equation (3) respectively.Three main steps involved ARMA modeling, identification, evaluation and diagnosis. Before analyze the situation must be based on the time series average and variance. The 'Augmented Dickey-Fuller' is used [6] in recognizing stationary in the Box-Cox test and mean in identifying whether the time series is stationary based on variance or not. The basic premise of this model is that time series data include statistical stationarity, which indicates that measured statistical properties of such as variance, mean, ACF, and PACF are constant over time [7, 20]. Though, if the training data shows non-stationarity, as is the case with real-life forecaster signals (e.g., death case and confirmed), the Autoregressive integrated moving average model requires differenced data to stationarity. This is denoted as ARIMA (p,d,q) where d is the degree of differencing [31].

All the models that passed the residual test were compared using the "Akaike information criterion" (AIC). The model which has the lowest values AIC was selected as the best fit model. The ACF and PACF of residuals, as well as the test of white noise, were determined to evaluate the goodness of fit. The methodology of the current study was based on a previous study as the reference [27]. Finally, the fitted Autoregressive integrated moving average model was used for short-term predicting of corona virus (COVID-19) incidence for 60 days. Two ARIMA models of COVID-19 daily confirmed and death cases were designed. The possible residuals for these two models to understand the case variance were plotted and statistical analysis was performed using 'R' version 3.6.3. A perform statistical analysis on the prevalence and incidence datasets, and the statistical significance level was set at 0.05.

2.2.1. Exponential Smoothing (ETS) model

The Exponential Smoothing model technique is based on the methods as described by Hyndman et al. and is made available through the forecast package in the R software environment [11]. It has three major parameters are the seasonal components, trend, error and which can be additive (A), multiplicative (M), or none (N) [12].

We employed the automatic selection of the Exponential Smoothing models to best fit exponential models that had multiplicative components and estimated possible alterative models prior to selecting the best performance model to simulate the data [14]. The optimum model was chosen based on either the lowest of AIC, AICc and BIC [37]. Results of Box-Ljung test Q- test suggest that the diagnosis whether the residual time series sequence was a white-noise sequence.

2.2.2. Performance of time series forecasting

To estimate the forecast performances of the models, four indices: the root mean squared error (RMSE), mean absolute error (MAE) and mean absolute percentage (MAP), MAPE were using to the prediction capabilities of the ARIMA and ETS models. The evaluate according to the equations as follows(4, 5, 6, 7);

$$RootMeanSquareError = \sqrt{mean(e_(^2t)} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t(1)| \tag{5}$$

$$MAP = \frac{1}{n}\sum_{t=1}^{n}re_t(1) \tag{6}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}|re_t(1)| \tag{7}$$

3. Results

3.1. Testing the Stationary

Initially, stationary of the time series should be examined. If the mean and variance of a time series are constants over time, then the time series may be considered as stationary. Plotting of such data against time will be horizontal along the time axis. Stationary means that there is no growth or decline in the data. The following graphical and analytical procedures may be followed to examine the stationary of a time series. (Figure 2), given below represents the stock exchange time series data that we analyzed and it specifies that the time series data are nonstationary. The series will be varied randomly over a period and there is no seasonal or global trend reference: Time series Graph (Plots the observations against time series), Autocorrelation function plots values against time, Partial autocorrelation function plots values against time.

3.2. Augmented Dickey-Fuller Test

To estimate whether a series has a unit root, the Augmented Dickey-Fuller unit root test, which has been used extensively in time series analysis, was implemented to determine the integrated order of variables. The results of the test are given in Table 1.

3.3. ARIMA Model diagnosis and recognition

As shown in Figure 2, the second order differences show that the COVID-19 virus times series require differencing methods (d = 2). To evaluate the main parameters of the ARIMA model, we drew the plots of ACF and PACF

Table 1. Results of Augmented Dickey-Fuller tests.

ADF test	Test statistics	Lag order	p-value
Total Confirmed cases (nonstationary)	- 1.5188	5	0.7767
Total Confirmed cases	-6.9908	5	0.01
Total Death cases (nonstationary)	-2.8024	5	0.2427
Total Death cases	-8.6114	5	0.01

Table 2. Parameters of the estimate, standard error, t-Statistic and p-values of the ARIMA models

Coefficient	Estimate	S.E of coefficient	t	p-value
Total confirmed cases ARIMA model (2,2,2)				
AR (1)	1.222454	0.044500	27.471	<2.2e-16 ***
AR (2)	-0.883068	0.047977	-18.406	<2.2e-16 ***
MA (1)	-1.484771	0.071669	-20.717	<2.2e-16 ***
MA (2)	0.903053	0.046458	19.438	<2.2e-16 ***
Total death cases ARIMA model (5,2,0)				
AR (1)	-0.283405	0.075085	-3.7745	0.0001604 ***
AR (2)	-0.316369	0.074469	-4.2483	2.154e-05 ***
AR (3)	-0.422302	0.069358	-6.0887	1.138e-09 ***
AR (4)	-0.302297	0.073650	-4.1045	4.052e-05 ***
AR (5)	-0.481004	0.074558	-6.4514	1.108e-10 ***

based on the difference time series that have been shown in Figure 3 and 4. In the ARIMA time series modelling, the best fit model generated from the sample data set is ARIMA (2, 2, 2) confirmed cases are because it had the minimum values (AIC = 2705.47, BIC = 2719.92, AICc = 2705.94) across all models tested. Results of Box-Ljung test Q- test suggest that the residual time series encompass a white noise (Q^* = 8.4079, df = 6, p = 0.2097). Next the ARIMA (5, 2, 0) death cases are because it had the minimum values (AIC = 2147.73, BIC = 2165.07, AICc = 2148.4) across all models tested. Results of Box-Ljung test Q- test suggest that the residual time series encompass a white noise (Q^* = 35.991, df = 5, p = 9.536e-07).Evaluation of the ARIMA model parameters, their testing results were presented in Table 2. While running the ETS (A, A, N) confirmed cases are because it had the minimum values (AIC = 3075.053, BIC = 3089.579, AICc = 3075.518) across all models tested. Results of Box-Ljung test Q- test suggest that the residual time series encompass a white noise (Q^* = 61.696, df = 6, p = 2.035e-11). Next the ETS (M, A, N) death cases are because it had the minimum values (AIC = 2419.737, BIC = 2434.264, AICc = 2420.203) across all models tested. Results of Box-Ljung test Q- test suggest that the residual time series encompass a white noise (Q^* = 25.744, df = 6, p = 0.0002484).

The forecast results from mid-Jun 2020 to mid-August 2020 in World according to the ARIMA and ETS models are presented in Figure 4 to 8 as shown in the forecast trend in total confirmed cases and death cases by mid-August 2020. For the ARIMA and ETS models, the observed prevalence in mid-August 2020 was within the 95 percent CI (confidence interval) of the best fitted and prediction values.

Figure 2. Second-order differences of total confirmed cases and death cases of COVID-19 in World.

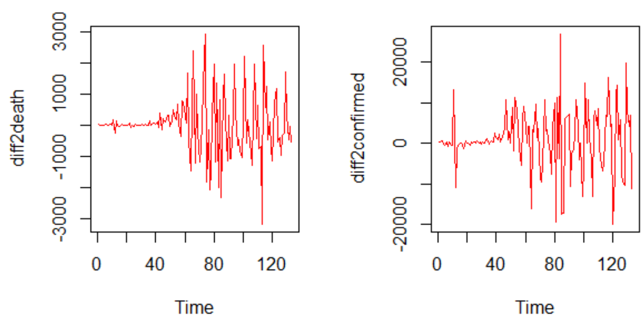


Figure 3. ACF and PACF plots for the total death cases of COVID-19 in World.

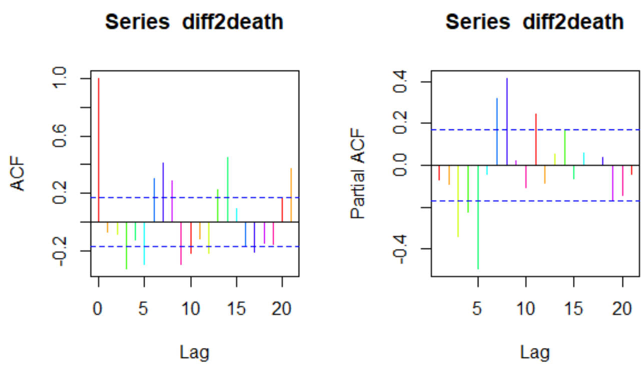
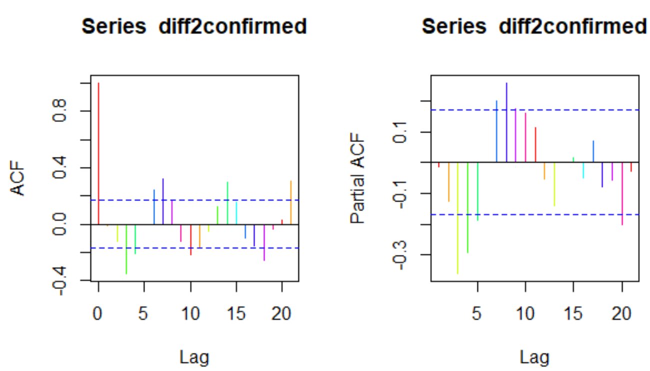


Figure 4. ACF and PACF plots for the total confirmed cases of COVID-19 in World.



3.4. Performance of accuracy models

The performance of forecast accuracy results for the ARIMA and ETS models is shown in Table 3. The performances of the best models from three aspects of simulation and prediction, the results showed that the ARIMA model had the lowest RMSE, MAE, MAP and MAPE than the model.

Figure 5. Forecast trend in total confirmed cases (COVID-19) ARIMA (2,2,2) incidence up to mid-Jun 2020 to mid-August 2020.

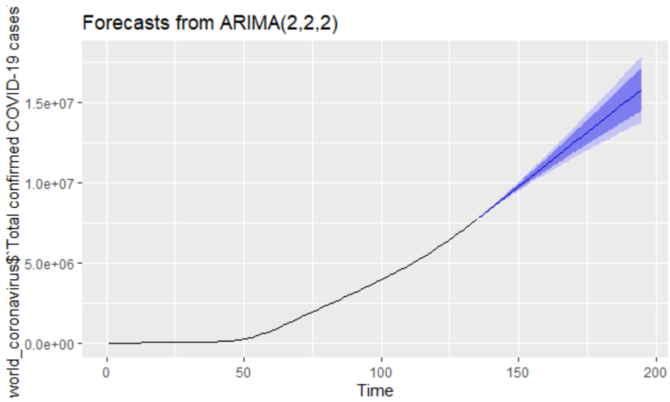


Figure 6. Forecast trend in death cases (COVID-19)ARIMA (5,2,0) incidence up to mid-Jun 2020 to mid-August 2020.

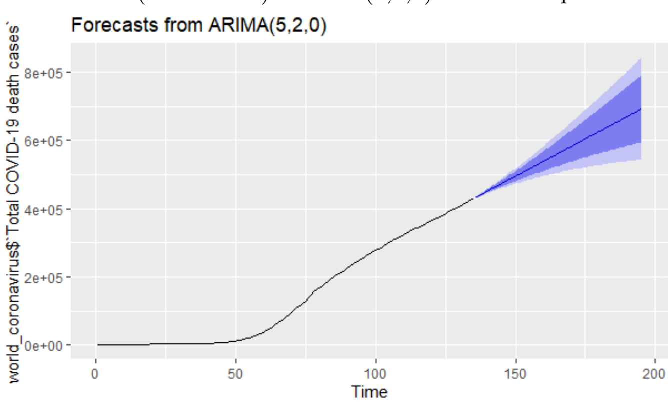
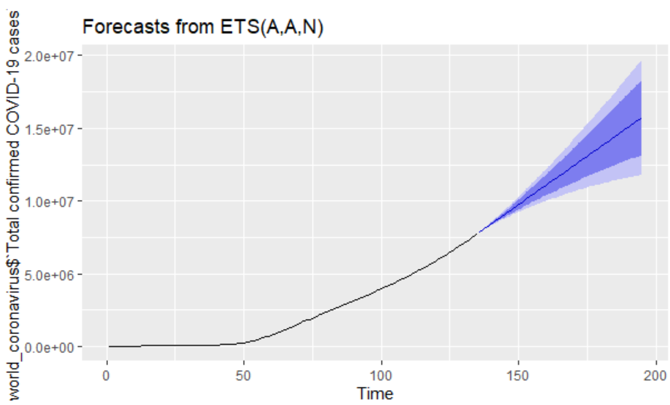


Figure 7. Forecast trend in total confirmed cases (COVID-19) ETS (A,A,N) incidence up to mid-Jun 2020 to mid-August 2020.



4. Discussion

The results of this study suggest that the ARIMA and ETS model was the best fit for simple mathematical models for short-term forecasting total COVID-19 prevalence based on the dataset from start-February 2020

Figure 8. Forecast trend in death cases (COVID-19)ETS (M,A,N) incidence up to mid-Jun 2020 to mid-August 2020.

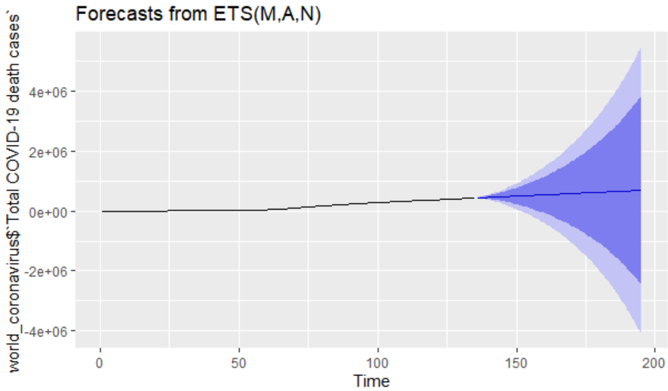


Table 3. Performance of observed and prediction COVID-19 virus from mid-Jun 2020 to mid-August 2020 using the ARIMA and ETS models.				
Models	Total confirmed cases ARIMA (2,2,2)	Total death cases ARIMA (5,2,0)	Total confirmed cases ETS model	Total death cases ETS model
RMSE	5983.536	731.8914	7327.649	1158.754
MAE	4159.244	475.8385	5034.601	744.356
MAP	0.3112535	0.7109892	0.1712846	0.4606057
MAPE	0.9166069	0.830018	0.8230958	0.861018

to mid-Jun 2020 in World. The prediction results determined that the COVID-19 prevalence was likely to increment only slightly over the successive 60 days. We have used the performance measure of the ARIMA and ETS models by calculating the RMSE, MAE, MAP and MAPE for the observed values and fitted values. We found that the ARIMA model had a higher forecasting performance model and was more appropriate for predicting the confirmed and death cases (COVID-19) prevalence in World. Therefore, it is most important for the health department to adopt in this model as the basis for an initial caution system that will allow the appropriate timely application of enhanced surveillance and reallocation of medical sources [34]. In particular, this measure will be conducive to the implementation of a high-performance prediction model for epidemic surveillance and as a treatment.

The ARIMA model has been applied in previous studies to historical HFRS incidence data are an important tool for HFRS surveillance in China and accurate forecasting of the HFRS incidence is possible using an ARIMA model [18]. Long-term observations [15, 8] and prediction [33, 32]. Moreover, evaluate and compare the performances of four time series models are two decomposition methods (regression and exponential smoothing), ARIMA and SVM. The present study indeed highlighted that the SVMs outperforms the ARIMA model and decomposition methods in most cases [3,15].The accuracy of ARIMA models in forecasting future epidemic of COVID-2019 proved the effectiveness in epidemiological surveillance [1,23,15,8]. Preceding studies on the accuracy of different methods for predictive epidemic behavior found that the ARIMA model has demonstrated better prediction performance measures than time-series nonlinear autoregressive model has been used for daily prediction of COVID-19 cases in India [13]. A previous study suggests that the prevalence of COVID-2019, we selected as the best ARIMA model for determining the incidence of COVID-2019 [5].

Moreover, it is most important to note that the travel in world contributed to the increasing in the prevalence of the coronavirus in May under the increased travel, around, and population mobility. Risks of

COVID-19 Increases in Current Markets. Although, people's awareness level of the infectious disease is rather inadequate. More even critical release is that they are still not effective vaccines and treatments. That, it is needful to further the research into vaccine generation and sufficient treatment methods. They are several limitations to be considered when interpreted the prediction results. Firstly, the natural social and environmental factors that influenced the prevalence of Covid-19; yet, due to dataset available, and the focus on time series forecasting, in this study these causes were not taken into the account. Secondly, we but obtained the COVID-19 prevalence dataset over 135 days and the short period of the COVID-19 time series may affect the model generated. Third, the ARIMA model applies only to short-term prediction, as the improvement of the pandemic is influenced and control by many factors [30]. Finally, future research should aim to improve the time series application to COVID-19 spread control.

5. Conclusion

In this study, based on the seasonal models of the coronavirus (COVID-19) prevalence in World, we suggest the ARIMA model as a used tool for monitoring the pandemic. The results of our study will be suggested that a serious public health problem particularly of strategies enforced for the control, prevention of COVID-19, development of coronavirus vaccines, and effectual treatment system. The ARIMA model showed better Confirmed case and death cases fitting and forecasting performance models. Combined with the predictive results, we found that Confirmed case and death cases (COVID-19) showed an increasing trend from mid-August 2020. Future research should aim to improve the time-series application to COVID-19 spread control.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://ourworldindata.org/coronavirus.

Acknowledgment

We are grateful to the study participants for their cooperation and participation. We thank D. Pachiyappan K. Lokesh and G. Hajira Banu for their help in data collection. We also thank Dr. K. Alagirisamy for the contributions for the preparation of the study.

Authors' contributions

Manigandan P and Alagirisamy K conceived and designed the study. Manigandan P, Lokesh K, Pachiyappan D and Hajira Banu G collected and organized the data. Manigandan P were in charge of statistical analysis and wrote the manuscript. Alagirisamy K revised and approved the final version of the manuscript. All authors read and approved the final submitted version.

References

[1] Allard, Rbc. Use of time-series analysis in infectious disease surveillance. Bulletin of the World Health Organization 1998; 76(4): 327.

[2] Ai, Siqi, Guanghu Zhu, Fei Tian, Huan Li, Yuan Gao, Yinglin Wu, Qiyong Liu, and Hualiang Lin. Population movement, city closure and spatial transmission of the 2019- nCoV infection in China. medRxiv, 2020.

[3] Box GE, Jenkins GM, Reinsel GC, Ljung GM. Time series analysis: forecasting and control John Wiley and Sons, Hoboken, NJ, 2008.

[4] Bayyurt, Lutfi, and Burcu Bayyurt. Forecasting of COVID-19 Cases and Deaths Using ARIMA Models. medRxiv, 2020.

[5] Benvenuto, Domenico, Marta Giovanetti, Lazzaro Vassallo, Silvia Angeletti, and Massimo Ciccozzi. Application of the ARIMA model on the COVID-2019 epidemic dataset. Data in brief, 2020, 105340.

[6] Cao, Shiyi, Feng Wang, Wilson Tam, Lap Ah Tse, Jean Hee Kim, Junan Liu, and Zuxun Lu. A hybrid seasonal prediction model for tuberculosis incidence in China.BMC medical informatics and decision making, Volume 13, Issue 1,(2013),56.

[7] Cheung, Yin-Wong, and Kon S. Lai. Lag order and critical values of the augmented Dickey–Fuller test. Journal of Business and Economic Statistics,Volume 13, Issue 3, 1995, 277-280.

[8] Feng, Huifen, Guangcai Duan, Rongguang Zhang, and Weidong Zhang. Time series analysis of hand-foot-mouth disease hospitalization in Zhengzhou: establishment of forecasting models using climate variables as predictors. PloS one, Volume 9, Issue 1,2014,e87916.

[9] Fattah, Jamal, Latifa Ezzine, Zineb Aman, Haj El Moussami, and Abdeslam Lachhab. Forecasting of demand using ARIMA model.International Journal of Engineering Business Management 10 (2018), 1847979018808673.

[10] Funk, Sebastian, Anton Camacho, Adam J. Kucharski, Rosalind M. Eggo, and W. John Edmunds. Real-time forecasting of infectious disease dynamics with a stochastic semi- mechanistic model.Epidemics 22 (2018), 56-61.

[11] Hyndman, Rob J., and Yeasmin Khandakar. Automatic time series for forecasting: the forecast package for R. No. 6/07. Clayton VIC, Australia: Monash University, Department of Econometrics and Business Statistics, 2007.

[12] Hyndman, Rob J., Anne B. Koehler, Ralph D. Snyder, and Simone Grose. A state space framework for automatic forecasting using exponential smoothing methods. International Journal of forecasting, Volume 18, Issue 3, (2002), 439-454.

[13] Khan, Farhan Mohammad, and Rajiv Gupta. "ARIMA and NAR based Prediction Model for Time Series Analysis of COVID-19 cases in India." Journal of Safety Science and Resilience, 2020.

[14] Kabacoff, R. R in Action: Data Analysis and Graphics with R, edn, 2015.

[15] Linthicum, Kenneth J., Assaf Anyamba, Compton J. Tucker, Patrick W. Kelley, Monica F. Myers, and Clarence J. Peters. Climate and satellite indicators to forecast Rift Valley fever epidemics in Kenya. Science, Volume 285, no. 5426 (1999), 397-400.

[16] Lai, Shengjie, Isaac I. Bogoch, Nick W. Ruktanonchai, Alexander Watts, Xin Lu, Weizhong Yang, Hongjie Yu, Kamran Khan, and Andrew J. Tatem. Assessing spread risk of Wuhan novel coronavirus within and beyond China, January-April 2020: a travel network-based modelling study. medRxiv, 2020.

[17] Li, Qun, Xuhua Guan, Peng Wu, Xiaoye Wang, Lei Zhou, Yeqing Tong, Ruiqi Ren et al. Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia. New England Journal of Medicine, 2020.

[18]] Liu, Qiyong, Xiaodong Liu, Baofa Jiang, and Weizhong Yang. Forecasting incidence of hemorrhagic fever with renal syndrome in China using ARIMA model. BMC infectious diseases, Volume 11,Issue 1, (2011), 218.

[19] Marbaniang, Strong P. Forecasting the Prevalence of COVID-19 in Maharashtra, Delhi, Kerala, and India using an ARIMA model. 2020.

[20] R Rosca, Elisabeta. Stationary and non-stationary time series. The USV Annals of Economics and Public Administration Volume 10, Issue 1, (2011), 177-186.

[21] Read, Jonathan M., Jessica RE Bridgen, Derek AT Cummings, Antonia Ho, and Chris P.Jewell. Novel coronavirus 2019-nCoV: early estimation of epidemiological parameters and epidemic predictions. MedRxiv, 2020.

[22] Riou, Julien, and Christian L. Althaus. Pattern of early human-to-human transmission of Wuhan 2019 novel coronavirus (2019-nCoV), December 2019 to January 2020. Eurosurveillance, Volume 25, Issue 4, (2020), 2000058.

[23] Roy, Santanu, Gouri Sankar Bhunia, and Pravat Kumar Shit. Spatial prediction of COVID-19 epidemic using ARIMA techniques in India. Modeling Earth Systems and Environment (2020), 1-7.

[24] Rojas, Ignacio, and Héctor Pomares, eds. Time series analysis and forecasting: selected contributions from the ITISE Conference. Springer, 2016.

[25] Shanafelt, David W., Glyn Jones, Mauricio Lima, Charles Perrings, and Gerardo Chowell. Forecasting the 2001 foot-and-mouth disease epidemic in the UK. EcoHealth, Volume 15, Issue 2, (2018), 338-347.

[26] Tandon, Hiteshi, Prabhat Ranjan, Tanmoy Chakraborty, and Vandana Suhag. Coronavirus (COVID-19): ARIMA based time-series analysis to forecast near future. arXiv preprint arXiv:2004.07859, (2020).

[27] Wang, Ya-wen, Zhong-zhou Shen, and Yu Jiang. Comparison of ARIMA and GM (1, 1) models for prediction of hepatitis B in China. PloS one, Volume 13, Issue 9,(2018), e0201987.

[28] World Health Organization.Coronavirus, Novel. situation report, 22. https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200211-sitrep-22-ncov. pdf, 2019.

[29] Wu, Joseph T., Kathy Leung, and Gabriel M. Leung. Nowcasting and forecasting the potential domestic and international spread of the 2019-nCoV outbreak originating in Wuhan, China: a modelling study. The Lancet,Volume 395, Issue 10225, (2020), 689-697.

[30] Xu, Qinqin, Runzi Li, Yafei Liu, Cheng Luo, Aiqiang Xu, Fuzhong Xue, Qing Xu, and Xiujun Li. Forecasting the incidence of mumps in Zibo City based on a SARIMA model. International journal of environmental research and public health,Volume 14, Issue 8 (2017), 925.

[31] Yuan, Chaoqing, Sifeng Liu, and Zhigeng Fang. Comparison of China's primary energy consumption forecasting by using ARIMA (the autoregressive integrated moving average) model and GM (1, 1) model. Energy 100 (2016), 384-390.

[32] Zhang, Li, M. I. Baibing, Xiaomei Xiang, Hui Song, Min Dong, Shuiping Zhang, Qi Zhang, Lingling Wang, Q. U. Pengfei, and Shaonong Dang. Application of multiple seasonal ARIMA model in predication of birth defect incidence in Xi'an area. Journal of Xi'an Jiaotong University (Medical Sciences), Volume 38, Issue 3 (2017), 371-374.

[33] Zheng, L., Liu, D. J., and Xian, X. U. Application of time series analysis in forecasting the incidence of pulmonary tuberculosis. Pract Prev Med,Volume 6, Issue 5, (2012), 375-83.

[34] Zhang, Guoliang, Shuqiong Huang, Qionghong Duan, Wen Shu, Yongchun Hou, Shiyu Zhu, Xiaoping Miao et al. Application of a hybrid model for predicting the incidence of tuberculosis in Hubei, China. PloS one, Volume 8, Issue 11, (2013), e80969.

[35] Zhang, Rongqiang, Hui Liu, Fengying Li, Bei Zhang, Qiling Liu, Xiangwen Li, and Limei Luo. Transmission and epidemiological characteristics of Novel Coronavirus (2019- nCoV)-Infected Pneumonia (NCIP): preliminary evidence obtained in comparison with 2003-SARS. MedRxiv, 2020.

[36] Zhang, Yuhu, Huirong Yang, Hengjian Cui, and Qiuhua Chen. Comparison of the ability of ARIMA, WNN and SVM models for drought forecasting in the Sanjiang Plain, China. Natural Resources Research, (2019), 1-18.

[37] Zeng, Qianglin, Dandan Li, Gui Huang, Jin Xia, Xiaoming Wang, Yamei Zhang, Wanping Tang, and Hui Zhou. Time series analysis of temporal trends in the pertussis incidence in Mainland China from 2005 to 2016. Scientific reports,Volume 6, Issue 1 (2016), 1-8.