International Journal of Applied Operational Research
Vol. 14, No. 1, pp. 11-23, Winter 2026

Journal homepage: ijorlu.liau.ac.ir

Modeling daily COVID-19 time series data using ARIMA models: A multi-country analysis

M. Maroufi, K. Zare*, M. R. Mahmoudi, D. Jamali, Z. Sajjadian

Received: 2 November 2025 **Accepted:** 14 December 2025

Abstract Modeling the temporal dynamics of COVID-19 is important for understanding the progression of the pandemic. This study fitted Autoregressive Integrated Moving Average (ARIMA) models to the daily numbers of confirmed COVID-19 cases and deaths in seven countries: the USA, Spain, the UK, Italy, Iran, Germany, and France. The dataset covered the period from February to April 2020. Model structures were identified using the autocorrelation function (ACF) and partial autocorrelation function (PACF), and the final models were selected based on the corrected Akaike Information Criterion (AICC) and Bayesian Information Criterion (BIC). Model adequacy was evaluated using residual diagnostics, including ACF/PACF plots and the Ljung–Box test, which showed no significant residual autocorrelation for the selected models. The results indicate that ARIMA models provide an adequate statistical framework for describing the temporal dependence structure of daily COVID-19 time series and offer a basis for further short-term analyses.

Keywords: COVID-19, Autoregressive Integrated Moving Average (ARIMA), Time Series Analysis.

1 Introduction

In December 2019, many news agencies reported the spread of a new type of coronavirus, COVID-19, in Wuhan [1]. This new virus affects the hepatic, gastrointestinal, respiratory and neurological systems. This pandemic covers the whole of the world and the number of cases and deaths due to

* **Corresponding Author.** (✉)
E-mail: karim.zare@iau.ac.ir (K. Zare)

M. Maroufi
Department of Statistics, Marv.C., Islamic Azad University, Marvdasht, Iran

K. Zare
Department of Statistics, Marv.C., Islamic Azad University, Marvdasht, Iran

M. R. Mahmoudi
Department of Statistics, Faculty of Science, Fasa University, Fasa, Iran
Research Institute of Statistics, Data Mining and Data Science, Fasa University, Fasa, Iran

D. Jamali
Department of Statistics, Marv.C., Islamic Azad University, Marvdasht, Iran

Z. Sajjadian
Bank Pasargad, Shiraz, Iran

[DOI: 10.71885/ijorlu-2026-1-744]

COVID-19 are increasing day by day [2-15]. Because of frequent economic, social and environmental impacts of COVID-19, modeling, estimating and forecasting the stochastic mechanisms of COVID-19 is a main problem for the experts in travel medicine and infectious diseases. To analyze different natural phenomena, many statistical and mathematical techniques can be used. Some popular techniques are machine learning, optimization, deep learning, clustering, numerical analysis, regression analysis, and time series modeling [16-49].

Based on the above considerations, this study aims to model the temporal patterns of the daily numbers of confirmed COVID-19 cases and deaths using ARIMA time-series models. In particular, we analyze daily records from seven countries—the USA, Spain, UK, Italy, Iran, Germany, and France—over the period from February to April 2020. Using the ACF and PACF for model identification and the AICc and BIC criteria for model selection, we assess whether ARIMA models can adequately capture the temporal dependence structure of these series.

The main contribution of this study is twofold. First, it provides a systematic, multi-country evaluation of the adequacy of ARIMA models for COVID-19 daily time-series data, which remains relatively limited in the existing literature. Second, the fitted models and the associated diagnostic results facilitate comparison of the temporal patterns of confirmed cases and deaths across different geographical regions, and they may serve as a basis for subsequent short-term forecasting studies.

2 Material and Method

This section is divided into two parts. In the first part, the datasets of this work are introduced and discussed. Second part considers the introduction of autoregressive integrated moving average time series.

2.1. Dataset

Datasets of this study, cover the numbers of daily confirmed and deaths due to COVID-19, from February to April 2020, in United States America (USA), Spain, United Kingdom (UK), Italy, Iran, Germany, and France. The daily COVID-19 data were obtained from the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU), an open-access database widely used in epidemiological research. The dataset records the daily cumulative numbers of confirmed cases and deaths reported by each country, from which the daily newly confirmed cases and deaths were derived as first differences of the cumulative series. The analysis covers the period from February 1, 2020, to April 30, 2020, yielding a maximum of 90 daily observations per country. However, the exact number of observations may vary slightly across countries due to the dates on which the first cases were officially reported. For example, the first confirmed cases were reported later in some countries (e.g., the USA, Spain, and the UK) than in others (e.g., Iran, Italy, and France), which affects the length of the available series for each country. The study period was selected for two main reasons. First, this interval captures the initial exponential growth phase of the pandemic, during which the temporal dynamics of the disease were most pronounced and relevant for time series modeling. Second, this period precedes the widespread implementation of large-scale vaccination programs and major policy shifts in several countries, thereby providing a relatively homogeneous

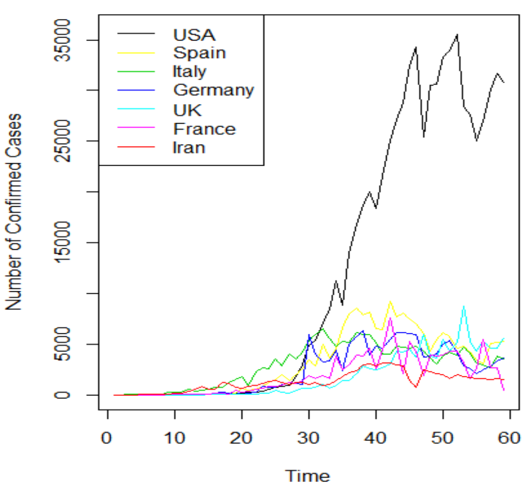
[DOI: 10.71885/ijorlu-2026-1-744]

observational window for comparative analysis across the seven countries. Finally, limiting the analysis to this period also ensures a balanced and comparable dataset across countries, avoiding the confounding effects of later waves and heterogeneous reporting practices.

The means and standard deviations of the daily confirmed and deaths due to COVID-19, in each country, are summarized in Table 1. The values of the means show that the minimum and maximum numbers of confirmed cases with COVID -19 are respectively corresponding to Iran and USA. Moreover, the minimum and the maximum numbers of deaths due to COVID -19 are respectively corresponding to Germany and USA. Figures 1 and 2 demonstrate the plots and the error-bar charts of the counts of the confirmed and deaths due to COVID -19, respectively.

Table 1 The mean and standard deviation for the number of confirmed and deaths due to COVID -19

	Country	**Mean ± Standard Deviation**
Cases	USA	11900.8 ± 13327.5
	Spain	3187.6 ± 3016.8
	Italy	2922.6 ± 2056.1
	Germany	2329.2 ± 2245.2
	France	1851.5 ± 1876.0
	UK	1842.1 ± 2207.7
	Iran	1294.5 ± 921.5
Deaths	USA	628.0 ± 1013.4
	Italy	385.5 ± 309.5
	Spain	330.1 ± 340.5
	France	316.6 ± 447.3
	UK	247.1 ± 342.0
	Iran	80.7 ± 55.6
	Germany	69.7 ± 94.9



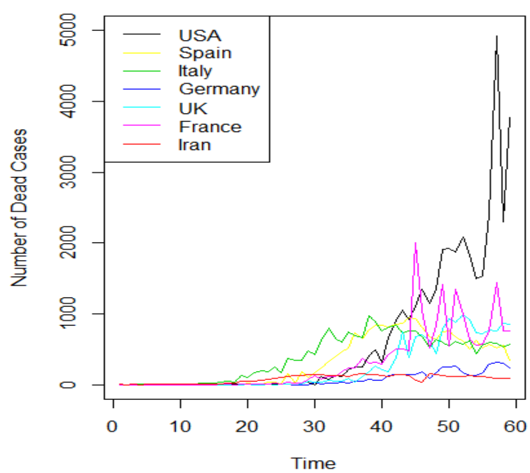


Fig. 1 Plots of the number of confirmed cases (Left), and the number of deaths (Right)

[DOI: 10.71885/ijorlu-2026-1-744]

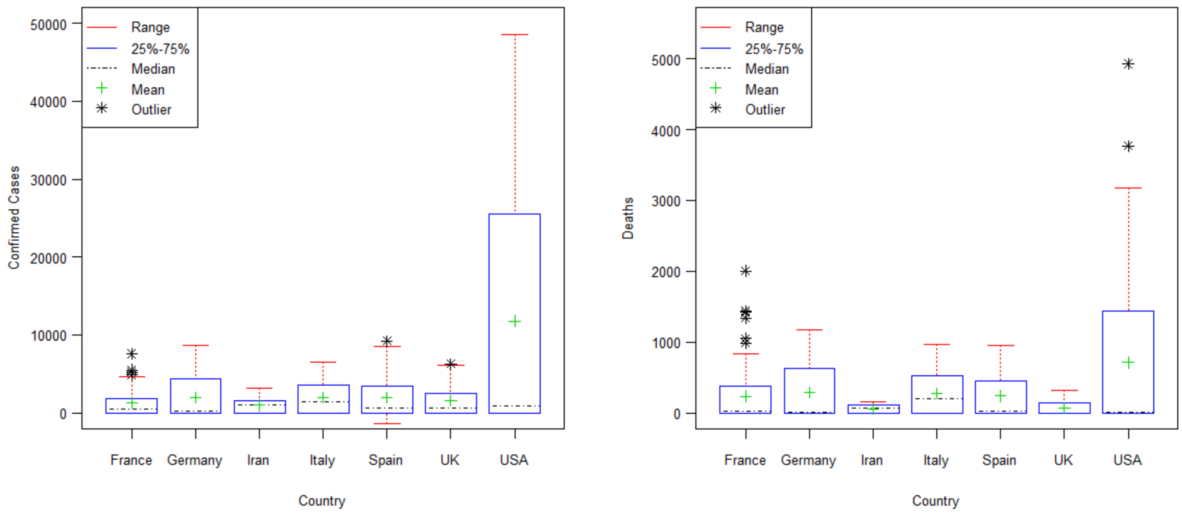


Fig. 2 Error-bar charts of the number of confirmed cases (Left), and the number of deaths (Right)

2.2. ARIMA Time Series

An autoregressive moving average (*ARMA*) process with orders *(p,q)*, *ARMA (p, q)*, is defined by

$$X_t - \emptyset_1 X_{t-1} - \cdots - \emptyset_p X_{t-p} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}, \tag{1}$$

where, $\emptyset_1, \dots, \emptyset_p$, and, $\theta_1, \dots, \theta_q$, are AR and MA parameters, respectively, and ε_t is a sequence of *white noise* sequence.

Remark 1 An ARMA model with orders *(p,q)*, and drift *c* is defined by

$$X_t - \emptyset_1 X_{t-1} - \cdots - \emptyset_p X_{t-p} = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}. \tag{2}$$

The integrated *ARMA* (*ARIMA*) model is a large class of time series that is achieved by differencing on *ARMA* models. Differencing, as an important data transformation method, is applied to remove the trend in time series and achieve a stationary process. The differencing of the first order is defined by

$$\nabla X_t = X_t - X_{t-1} = (1 - B) X_t, \tag{3}$$

where *B* is the one step backward shift operator. Consequently, the kth differencing is denoted by

$$\nabla^k X_t = (1 - B)^k X_t. \tag{4}$$

The first, second and third orders differencing are usually eliminated linear, quadratic and cubic trends.

[DOI: 10.71885/ijorlu-2026-1-744]

Remark 2 An ARMA model with orders *(p,q)*, and difference of order k is presented by *ARIMA(p,k,q)*.

Model identification and selection were conducted in a sequential manner. For each of the 14 analyzed time series (7 countries, each with daily cases and deaths), the model identification followed a two-step procedure. First, the order of differencing (d) was determined by examining the time-series behavior after successive differencing until a stationary pattern was obtained. Next, the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the differenced series were inspected to identify plausible values for the autoregressive (p) and moving-average (q) orders.

A set of candidate ARIMA(p, d, q) models was then fitted for each time series. The candidate models were compared using the corrected Akaike Information Criterion (AICC) and the Bayesian Information Criterion (BIC). Lower values of these criteria indicate a preferable balance between goodness of fit and model complexity. The final model was selected based on the lowest or jointly favorable AICC and BIC values, with preference given to the more parsimonious model when competing models showed similar performance. Finally, residual diagnostics, including residual ACF/PACF plots and the Ljung–Box test, were used to assess whether the residuals behaved as white noise.

3. Results

In this section the results of ARIMA time series to model the numbers of confirmed and deaths due to COVID -19, are reported. First, the orders of probable trends in datasets are estimated. Then, the sample ACF/PACF of dataset, and AICC and BIC are used to find and estimate the best orders of p and q for ARIMA model. Finally, the goodness of fitted models is evaluated.

3.1. Number of Confirmed Cases

The results of ARIMA time series to model the number of confirmed cases with COVID-19, are summarized in Table 2. The ARIMA modeling results presented in Table 2 reveal distinct temporal dynamics in the initial spread of COVID-19 across the seven countries. The diversity in the chosen model orders, ranging from simple random walk models to higher-order autoregressive-moving average processes, highlights the heterogeneity in early epidemiological reporting. Countries such as Italy and Iran were best fitted by the ARIMA(0,1,0) model (random walk with drift=0), suggesting that their daily case series followed a relatively consistent trend where the changes between successive days were primarily stochastic, without significant complex dependencies requiring AR or MA terms. In contrast, Germany, France, and Spain necessitated more complex models (e.g., ARIMA(2,1,4) for Germany and ARIMA(1,1,3) for France). The requirement for multiple AR and MA components in these countries likely reflects non-linear reporting patterns, such as significant fluctuations in testing capacity, administrative reporting lags, and shifts in public health policies during the February–April 2020 period. The ARIMA(0,1,1) models observed for the USA and the UK suggest that the reported case data contained transitory shocks—often associated with weekend reporting delays or sudden updates in cumulative counts—which were effectively smoothed by the first-order moving average term.

[DOI: 10.71885/ijorlu-2026-1-744]

Table 2 The results of ARIMA time series fitting on the number of confirmed cases with COVID-19

Country	Model ARIMA(p,d,q)	AR Coefficients	MA Coefficients	Drift	AICC	BIC	Ljung-Box P-value
USA	ARIMA(0,1,1)	-	$\theta_1 = -0.5815$	243.6654	2138.3	2146.2	0.734
Spain	ARIMA(2,1,1)	$\phi_1 = -1.1341$ $\phi_2 = -0.4859$	$\theta_1 = 0.7439$	0	1829.8	1840.2	0.654
Italy	ARIMA(0,1,0)	-	-	0	1660.2	1662.8	0.513
Germany	ARIMA(2,1,4)	$\phi_1 = -0.3969$ $\phi_2 = 0.3640$	$\theta_1 = -0.0272$ $\theta_2 = -1.2511$ $\theta_3 = 0.1455$ $\theta_4 = 0.7543$	38.2652	1724.9	1745.1	0.732
France	ARIMA(1,1,3)	$\phi_1 = 0.7432$	$\theta_1 = -1.4348$ $\theta_2 = 0.3386$ $\theta_3 = 0.2348$	0	1806.9	1819.9	0.498
UK	ARIMA(0,1,1)	-	$\theta_1 = -0.4225$	0	1780.8	1786.1	0.489
Iran	ARIMA(0,1,0)	-	-	0	1439.0	1441.6	0.629

Only non-zero parameters are reported.

According to Figures 3 and 4, up to 5% of residuals' *ACF/PACF* are out of zero range. The results verified that the fitted models are appropriate. Furthermore, the Ljung–Box test was not statistically significant ($p > 0.05$), indicating no evidence of remaining serial autocorrelation in the residuals. This result supports the adequacy of the fitted ARIMA model.

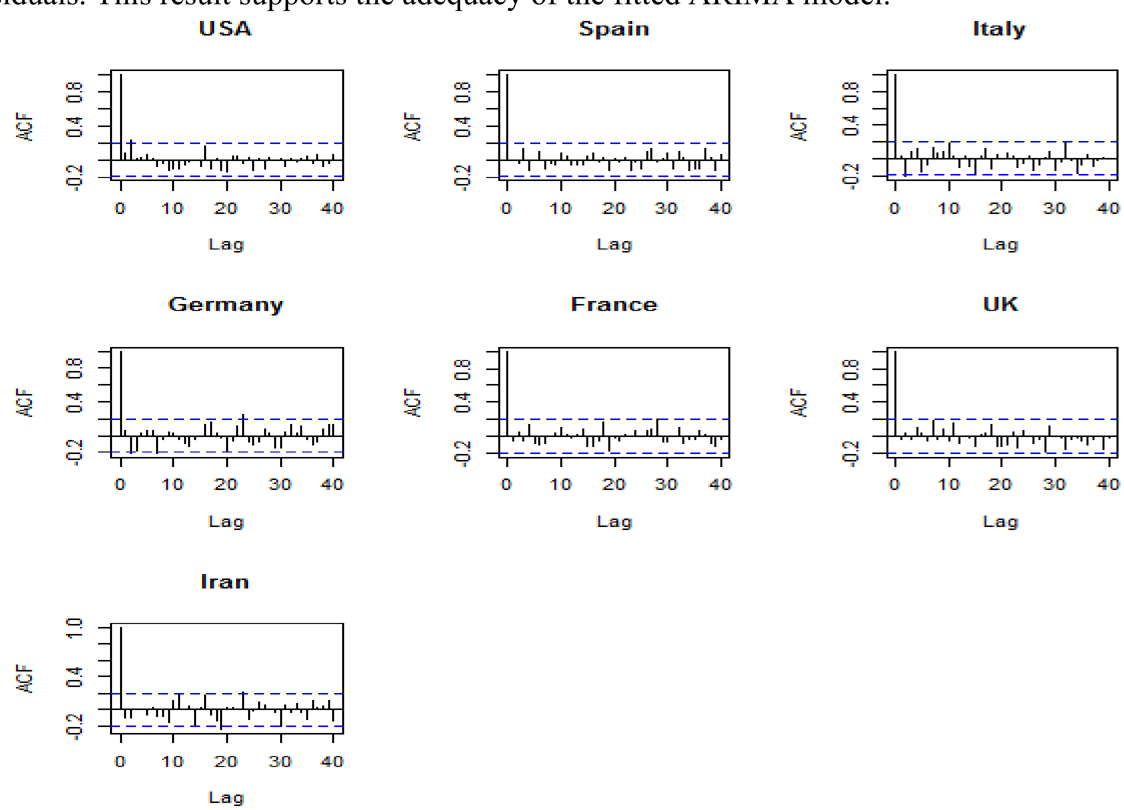


Fig. 3 ACF plot of the residuals for the fitted ARIMA model on daily confirmed COVID-19 cases

[DOI: 10.71885/ijorlu-2026-1-744]

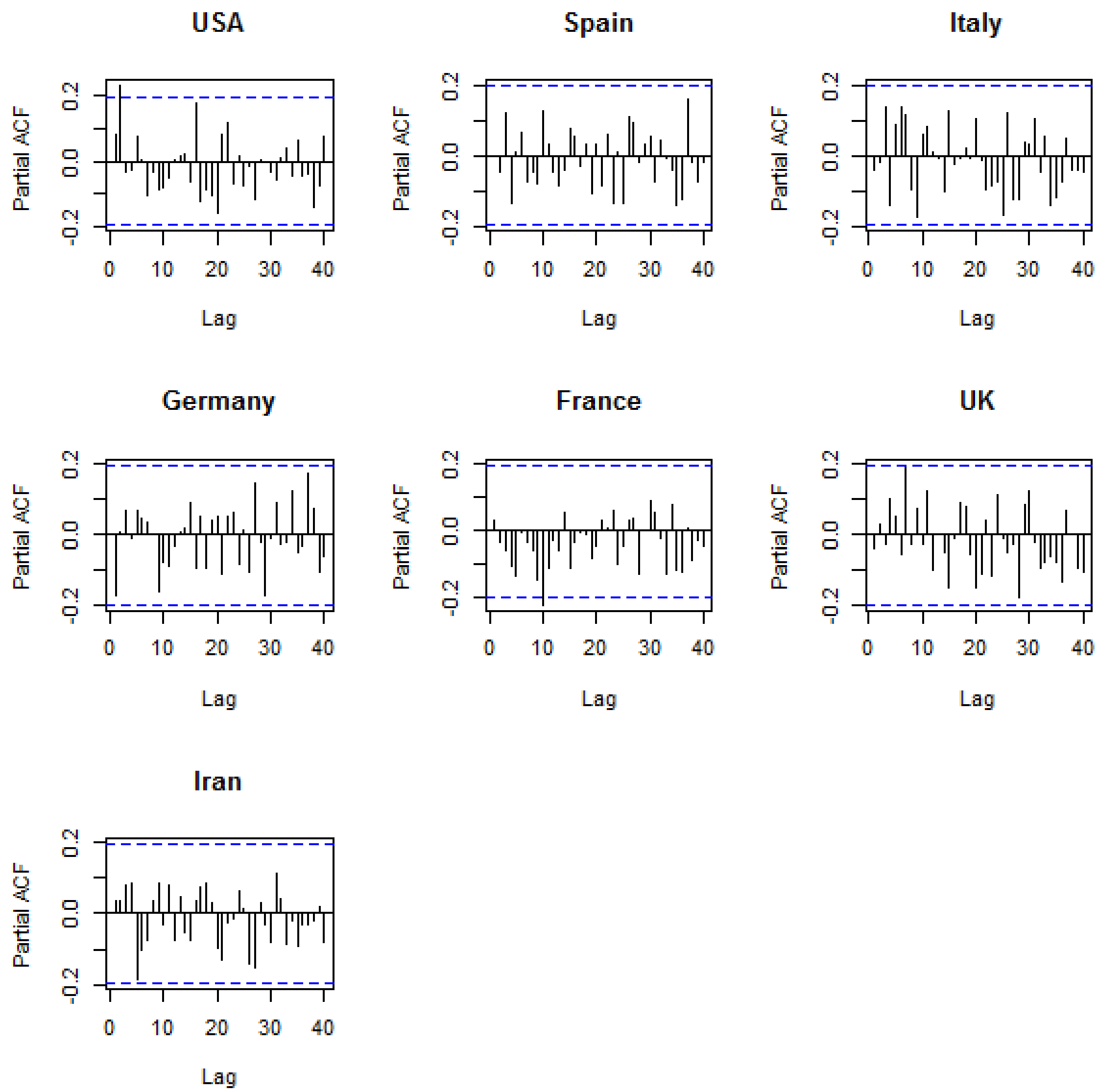


Fig. 4 PACF plot of the residuals for the fitted ARIMA model on daily confirmed COVID-19 cases

3.2. Number of Deaths due to COVID -19

The outputs of ARIMA time series to model the number of deaths due to COVID-19, are summarized in Table 3. Table 3 shows that the ARIMA models fitted to the daily COVID-19 death series exhibit greater structural diversity than those for confirmed cases, reflecting the delayed and more irregular nature of mortality reporting. Unlike the case series, where relatively simple models were adequate for some countries, the death series often required higher-order AR and MA terms, suggesting that mortality dynamics were influenced by both persistence over time and short-term reporting shocks. In Spain and the UK, the selected ARIMA(3,1,2) models indicate a relatively complex temporal structure, implying that daily deaths were shaped by multiple lagged effects. This may be related to delayed clinical progression from infection to death, as well as irregular

[DOI: 10.71885/ijorlu-2026-1-744]

reporting patterns during the early months of the pandemic. Italy and the USA also required MA terms of order 3, which suggests that sudden day-to-day fluctuations were important in explaining the variability in death counts. In these countries, mortality reporting may have been affected by administrative delays, weekend effects, or periodic batch reporting. Germany was best described by an ARIMA(2,1,0) model, indicating that autoregressive dependence played a more important role than moving-average shocks in the death series. By contrast, France was adequately fitted by ARIMA(0,1,1), suggesting that a simple short-term shock component was sufficient to model the observed fluctuations. Iran, with ARIMA(0,1,0), showed the simplest structure among all countries, which may reflect a more monotonic progression in the reported death series during the study period or a shorter effective dynamic range in the available data.

Table 3 The results of ARIMA time series fitting on the number of deaths due to COVID-19

Country	Model	AR Coefficients	MA Coefficients	Drift	AICC	BIC	Ljung-Box P-value
USA	ARIMA(0,1,3)	-	$\theta_1 = -0.6369$ $\theta_2 = 0.3396$ $\theta_3 = -0.3397$	0	1656.6	1667.0	0.621
Spain	ARIMA(3,1,2)	$\phi_1 = 1.0326$ $\phi_2 = -0.4279$ $\phi_3 = -0.1070$	$\theta_1 = -1.5332$ $\theta_2 = 0.9320$	2.3821	1299.5	1317.2	0.592
Italy	ARIMA(1,1,3)	$\phi_1 = 0.8146$	$\theta_1 = -1.3637$ $\theta_2 = 0.3259$ $\theta_3 = 0.2731$	0	1246.5	1259.4	0.853
Germany	ARIMA(2,1,0)	$\phi_1 = -0.2835$ $\phi_2 = -0.4391$	-	0	1399.6	1407.4	0.651
France	ARIMA(0,1,1)	-	$\theta_1 = -0.6490$	0	1494.6	1499.9	0.718
UK	ARIMA(3,1,2)	$\phi_1 = 0.9298$ $\phi_2 = -0.3761$ $\phi_3 = -0.2247$	$\theta_1 = -1.6651$ $\theta_2 = 0.9331$	0	1133.4	1148.9	0.438
Iran	ARIMA(0,1,0)	-	-	0	820.9	823.5	0.691

Only non-zero parameters are reported.

According to Figures 5 and 6, up to 5% of residuals' *ACF/PACF* are out of zero range. The results verified that the fitted models are appropriate. Furthermore, the Ljung–Box test was not statistically significant ($p > 0.05$), indicating no evidence of remaining serial autocorrelation in the residuals. This result supports the adequacy of the fitted ARIMA model.

[DOI: 10.71885/ijorlu-2026-1-744]

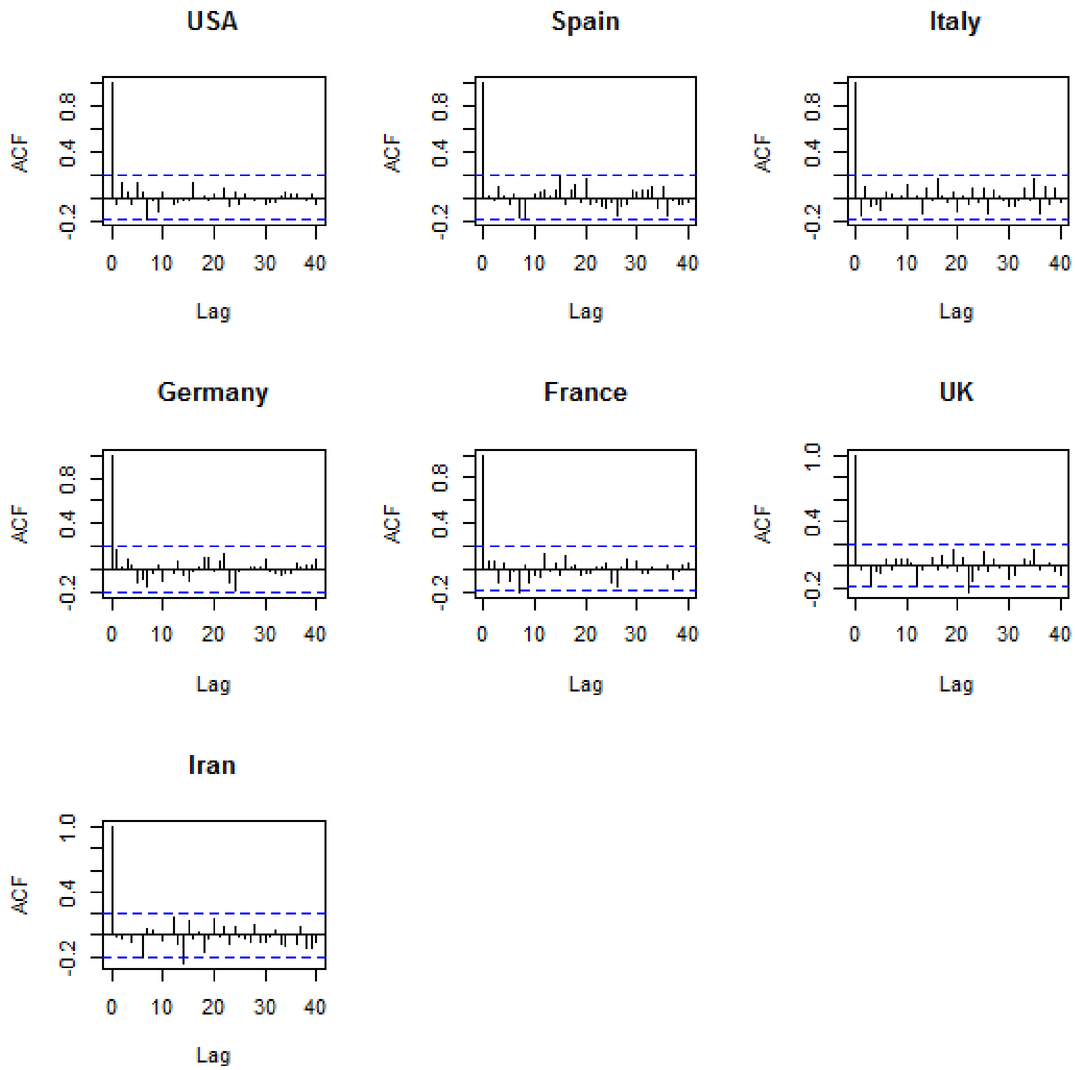


Fig. 5 ACF plot of the residuals for the fitted ARIMA model on deaths due to COVID-19

[DOI: 10.71885/ijorlu-2026-1-744]

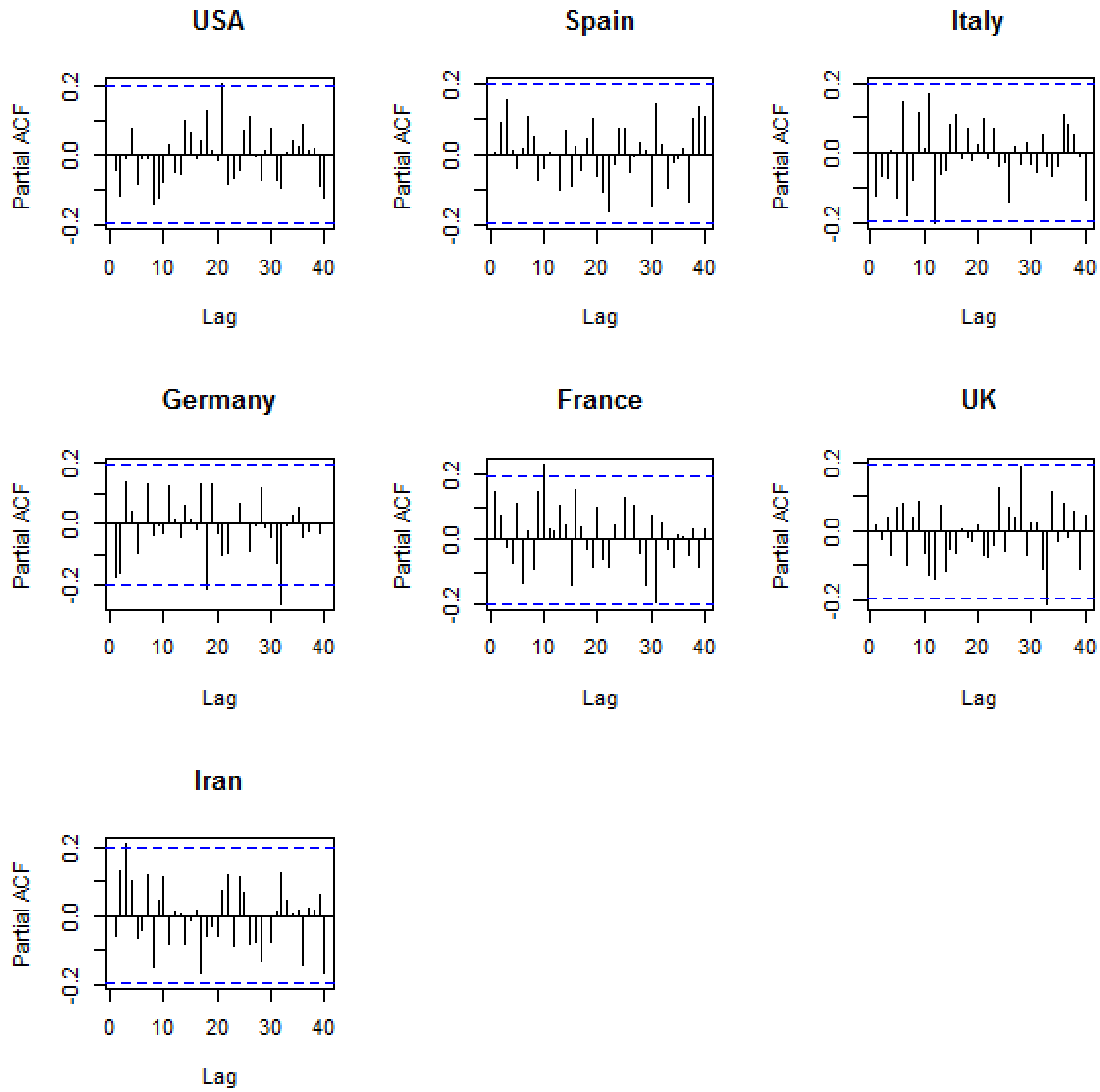


Fig. 6 PACF plot of the residuals for the fitted ARIMA model on daily confirmed COVID-19 cases

4. Conclusion

The purpose of this study was primarily model fitting and diagnostic assessment; however, the fitted models may serve as a basis for future short-term forecasting analyses. We tried to model the stochastic mechanisms of COVID-19 in several regions. ARIMA time series were employed to model the numbers of confirmed and deaths with COVID-19. The results indicate that the selected ARIMA models adequately represented the temporal dependence structure of the observed daily confirmed-case and death series for the selected countries. The results obtained in this paper can be used for the purpose of mathematical modelling as those discussed in [47-49]. This issue can be suggested as the future direction of this paper.

[DOI: 10.71885/ijorlu-2026-1-744]

Limitations: Although the ARIMA models provided a useful descriptive fit to the observed series, the analysis is limited by the relatively short study window and by possible cross-country differences in reporting practices, testing intensity, and case classification. These factors may introduce heterogeneity into the time series and should be considered when interpreting the results.

References

1. Lu, R., Zhao, X., Li, J., Niu, P., Yang, B., Wu, H., Wang, W., Song, H., Huang, B., Zhu, N., Bi, Y., Ma, X., Zhan, F., Wang, L., Hu, T., Zhou, H., Hu, Z., Zhou, W., Li, Z., … Tan, W. (2020). Genomic characterisation and epidemiology of 2019 novel coronavirus: Implications for virus origins and receptor binding. The Lancet, 395(10224), 565–574. https://doi.org/10.1016/S0140-6736(20)30251-8
2. Fanelli, D., & Piazza, F. (2020). Analysis and forecast of COVID-19 spreading in China, Italy and France. Chaos, Solitons & Fractals, 134, 109761. https://doi.org/10.1016/j.chaos.2020.109761
3. Gautret, P., Lagier, J. C., Parola, P., Hoang, V. T., Meddeb, L., Mailhe, M., Doudier, B., Courjon, J., Giordanengo, V., Vieira, V. E., Tissot-Dupont, H., Honoré, S., Colson, P., Chabrière, E., La Scola, B., Rolain, J. M., Brouqui, P., & Raoult, D. (2020). Hydroxychloroquine and azithromycin as a treatment of COVID-19: Results of an open-label non-randomized clinical trial. International Journal of Antimicrobial Agents, 56(1), 105949. https://doi.org/10.1016/j.ijantimicag.2020.105949
4. Stoecklin, S. B., Rolland, P., Silue, Y., Mailles, A., Campese, C., Simondon, A., Mechain, M., Meurice, L., Nguyen, M., Bassi, C., Yamani, E., Behillil, S., Ismael, S., Nguyen, D., Malvy, D., Lescure, F. X., Georges, S., Lazarus, C., Tabaï, A., … Levy-Bruhl, D. (2020). First cases of coronavirus disease 2019 (COVID-19) in France: Surveillance, investigations and control measures, January 2020. Eurosurveillance, 25(6), 2000094. https://doi.org/10.2807/1560-7917.ES.2020.25.6.2000094
5. Amrane, S., Tissot-Dupont, H., Doudier, B., Eldin, C., Hocquart, M., Mailhe, M., Dudouet, P., Ormières, E., Ailhaud, L., Parola, P., Lagier, J. C., Brouqui, P., Zandotti, C., Ninove, L., Luciani, L., Boschi, C., La Scola, B., Raoult, D., Million, M., Colson, P., & Gautret, P. (2020). Rapid viral diagnosis and ambulatory management of suspected COVID-19 cases presenting at the infectious diseases referral hospital in Marseille, France, January 31st to March 1st, 2020: A respiratory virus snapshot. Travel Medicine and Infectious Disease, 36, 101632. https://doi.org/10.1016/j.tmaid.2020.101632
6. Rothe, C., Schunk, M., Sothmann, P., Bretzel, G., Froeschl, G., Wallrauch, C., Zimmer, T., Thiel, V., Janke, C., Guggemos, W., Seilmaier, M., Drosten, C., Vollmar, P., Zwirglmaier, K., Zange, S., Wölfel, R., & Hoelscher, M. (2020). Transmission of 2019-nCoV infection from an asymptomatic contact in Germany. New England Journal of Medicine, 382(10), 970–971. https://doi.org/10.1056/NEJMc2001468
7. Takian, A., Raoofi, A., & Kazempour-Ardebili, S. (2020). COVID-19 battle during the toughest sanctions against Iran. The Lancet, 395(10229), 1035–1036. https://doi.org/10.1016/S0140-6736(20)30668-1
8. Remuzzi, A., & Remuzzi, G. (2020). COVID-19 and Italy: What next? The Lancet, 395(10231), 1225–1228. https://doi.org/10.1016/S0140-6736(20)30627-9
9. Onder, G., Rezza, G., & Brusaferro, S. (2020). Case-fatality rate and characteristics of patients dying in relation to COVID-19 in Italy. JAMA, 323(18), 1775–1776. https://doi.org/10.1001/jama.2020.4683
10. Lazzerini, M., & Putoto, G. (2020). COVID-19 in Italy: Momentous decisions and many uncertainties. The Lancet Global Health, 8(5), e641–e642. https://doi.org/10.1016/S2214-109X(20)30110-8
11. Legido-Quigley, H., Mateos-García, J. T., Campos, V. R., Gea-Sánchez, M., Muntaner, C., & McKee, M. (2020). The resilience of the Spanish health system against the COVID-19 pandemic. The Lancet Public Health, 5(5), e251–e252. https://doi.org/10.1016/S2468-2667(20)30060-8
12. Lillie, P. J., Samson, A., Li, A., Adams, K., Capstick, R., Barlow, G. D., Easom, N., Hamilton, E., Moss, P. J., Evans, A., Ivan, M., PHE Incident Team, Taha, Y., Duncan, C. J. A., Schmid, M. L., & The Airborne HCID

[DOI: 10.71885/ijorlu-2026-1-744]

Network. (2020). Novel coronavirus disease (COVID-19): The first two patients in the UK with person to person transmission. Journal of Infection, 80(5), 578–602. https://doi.org/10.1016/j.jinf.2020.02.020

13. Razai, M. S., Doerholt, K., Ladhani, S., & Oakeshott, P. (2020). Coronavirus disease 2019 (COVID-19): A guide for UK GPs. BMJ, 368, m800. https://doi.org/10.1136/bmj.m800
14. Hunter, D. J. (2020). COVID-19 and the stiff upper lip—the pandemic response in the United Kingdom. New England Journal of Medicine, 382(16), e31. https://doi.org/10.1056/NEJMp2005755
15. Burke, R. M., Midgley, C. M., Dratch, A., Fenstersheib, M., Haupt, T., Holshue, M., Ghinai, I., McPherson, T. D., Tressler, S., S. S., Tong, S., D. J., Patel, A., et al. (2020). Active monitoring of persons exposed to patients with confirmed COVID-19—United States, January–February 2020. MMWR Morbidity and Mortality Weekly Report, 69(9), 245–246. https://doi.org/10.15585/mmwr.mm6909e1
16. Haghbin, H., Mahmoudi, M. R., & Shishebor, Z. (2011). Large sample inference on the ratio of two independent binomial proportions. Journal of Mathematical Extension, 5(1), 87–95.
17. Mahmoudi, M. R., Behboodian, J., & Maleki, M. (2017). Inference on the ratio of means in two independent populations. Journal of Statistical Theory and Applications, 16(3), 366–374.
18. Mahmoudi, M. R., & Mahmoodi, M. (2014). Inference on the ratio of variances of two independent populations. Journal of Mathematical Extension, 7(2), 83–91.
19. Mahmoudi, M. R., & Mahmoodi, M. (2014). Inference on the ratio of correlations of two independent populations. Journal of Mathematical Extension, 7(4), 71–82.
20. Mahmoudi, M. R., Nasirzadeh, R., & Mohammadi, M. (2019). On the ratio of two independent skewnesses. Communications in Statistics - Theory and Methods, 48(7), 1721–1727.
21. Mahmoudi, M. R., Maleki, M., & Pak, A. (2017). Testing the difference between two independent time series models. Iranian Journal of Science and Technology, Transactions A: Science, 41, 665–669.
22. Mahmoudi, M. R., Heydari, M. H., & Roohi, R. (2019). A new method to compare the spectral densities of two independent periodically correlated time series. Mathematics and Computers in Simulation, 160, 103–110.
23. Mahmoudi, M. R., Heydari, M. H., & Avazzadeh, Z. (2019). Testing the difference between spectral densities of two independent periodically correlated (cyclostationary) time series models. Communications in Statistics - Theory and Methods, 48(9), 2320–2328.
24. Mahmoudi, M. R., Mahmoudi, M., & Nahavandi, E. (2016). Testing the difference between two independent regression models. Communications in Statistics - Theory and Methods, 45(21), 6284–6289.
25. Mahmoudi, M. R., Maleki, M., & Pak, A. (2018). Testing the equality of two independent regression models. Communications in Statistics - Theory and Methods, 47(12), 2919–2926.
26. Mahmoudi, M. R. (2019). On comparing two dependent linear and nonlinear regression models. Journal of Testing and Evaluation, 47(1), 20170461. https://doi.org/10.1520/JTE20170461
27. Pan, J. J., Mahmoudi, M. R., Baleanu, D., & Maleki, M. (2019). On comparing and classifying several independent linear and non-linear regression models with symmetric errors. Symmetry, 11(6), 820. https://doi.org/10.3390/sym11060820
28. Bahrami, M., Amiri, M. J., Mahmoudi, M. R., & Koochaki, S. (2017). Modeling caffeine adsorption by multi-walled carbon nanotubes using multiple polynomial regression with interaction effects. Journal of Water and Health, 15(4), 526–535.
29. Zarei, A. R., & Mahmoudi, M. R. (2017). Evaluation of changes in RDIst index effected by different potential evapotranspiration calculation methods. Water Resources Management, 31(15), 4981–4999. https://doi.org/10.1007/s11269-017-1790-7
30. Heydari, M. H., Avazzadeh, Z., & Mahmoudi, M. R. (2019). Chebyshev cardinal wavelets for nonlinear stochastic differential equations driven with variable-order fractional Brownian motion. Chaos, Solitons & Fractals, 124, 105–124.
31. Mahmoudi, M. R., & Maleki, M. (2017). A new method to detect periodically correlated structure. Computational Statistics, 32(4), 1569–1581.
32. Nematollahi, A. R., Soltani, A. R., & Mahmoudi, M. R. (2017). Periodically correlated modeling by means of the periodograms asymptotic distributions. Statistical Papers, 58(4), 1267–1278.

[DOI: 10.71885/ijorlu-2026-1-744]

33. Mahmoudi, M. R., Heydari, M. H., & Avazzadeh, Z. (2018). On the asymptotic distribution for the periodograms of almost periodically correlated (cyclostationary) processes. Digital Signal Processing, 81, 186–197.
34. Mahmoudi, M. R., Heydari, M. H., Avazzadeh, Z., & Pho, K. H. (2020). Goodness of fit test for almost cyclostationary processes. Digital Signal Processing, 96, 102597.
35. Mahmoudi, M. R., Maleki, M., Borodin, K., Pho, K. H., & Baleanu, D. (2020). On comparing and clustering the spectral densities of several almost cyclostationary processes. Alexandria Engineering Journal, 59(4), 2555–2565.
36. Zhou, R., Mahmoudi, M. R., Mohammed, S. N. Q., & Pho, K. H. (2020). Testing the equality of the spectral densities of several uncorrelated almost cyclostationary processes. Alexandria Engineering Journal, 59(5), 3545–3550.
37. Mahmoudi, M. R., Heydari, M. H., & Pho, K. H. (2020). Fuzzy clustering to classify several regression models with fractional Brownian motion errors. Alexandria Engineering Journal, 59(4), 2811–2818.
38. Roohi, R., Heydari, M. H., Aslami, M., & Mahmoudi, M. R. (2018). A comprehensive numerical study of space-time fractional bioheat equation using fractional-order Legendre functions. The European Physical Journal Plus, 133, 412.
39. Mahmoudi, M. R., Nematollahi, A. R., & Soltani, A. R. (2015). On the detection and estimation of the simple harmonizable processes. Iranian Journal of Science and Technology, 39(2), 239–242.
40. Maleki, M., Mahmoudi, M. R., Wraith, D., & Pho, K. H. (2020). Time series modelling to forecast the confirmed and recovered cases of COVID-19. Travel Medicine and Infectious Disease, 37, 101742. https://doi.org/10.1016/j.tmaid.2020.101742
41. Jalali, S. M. J., Karimi, M., Khosravi, A., & Nahavandi, S. (2019). An efficient neuroevolution approach for heart disease detection. In 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC) (pp. 3771–3776). IEEE.
42. Jalali, S. M. J., Khosravi, A., Alizadehsani, R., Salaken, S. M., Kebria, P. M., Puri, R., et al. (2019). Parsimonious evolutionary-based model development for detecting artery disease. In 2019 IEEE International Conference on Industrial Technology (ICIT) (pp. 800–805). IEEE.
43. Jalali, S. M. J., Ahmadian, S., Khosravi, A., Mirjalili, S., Mahmoudi, M. R., & Nahavandi, S. (2020). Neuroevolution-based autonomous robot navigation: A comparative study. Cognitive Systems Research, 62, 35–43.
44. Mousavirad, S. J., Schaefer, G., Jalali, S. M. J., & Korovin, I. (2020). A benchmark of recent population-based metaheuristic algorithms for multi-layer neural network training. In Proceedings of the 2020 Genetic and Evolutionary Computation Conference Companion (pp. 1402–1408). Association for Computing Machinery.
45. Jalali, S. M. J., Ahmadian, S., Kebria, P. M., Khosravi, A., Lim, C. P., & Nahavandi, S. (2019). Evolving artificial neural networks using butterfly optimization algorithm for data classification. In Neural information processing: 26th International Conference, ICONIP 2019, Sydney, NSW, Australia, December 12–15, 2019, proceedings, Part I (pp. 596–607). Springer.
46. Abbasi, A. R., Mahmoudi, M. R., & Avazzadeh, Z. (2018). Diagnosis and clustering of power transformer winding fault types by cross-correlation and clustering analysis of FRA results. IET Generation, Transmission & Distribution, 12(19), 4301–4309.
47. Baleanu, D., Ghanbari, B., Asad, J. H., Jajarmi, A., & Pirouz, H. M. (2020). Planar system-masses in an equilateral triangle: Numerical study within fractional calculus. Computer Modeling in Engineering & Sciences, 124(3), 953–968.
48. Baleanu, D., Jajarmi, A., Sajjadi, S. S., & Asad, J. H. (2020). The fractional features of a harmonic oscillator with position-dependent mass. Communications in Theoretical Physics, 72(5), 055002.
49. Sajjadi, S. S., Baleanu, D., Jajarmi, A., & Pirouz, H. M. (2020). A new adaptive synchronization and hyperchaos control of a biological snap oscillator. Chaos, Solitons & Fractals, 138, 109919.

[DOI: 10.71885/ijorlu-2026-1-744]