A Comparative Analysis of Forecasting Models on COVID-19

Müjde Erol Genevois and Michele Cedolin

Abstract The COVID-19 spread all around the world, causing more than a million deaths and reaching over 50 million confirmed cases. A forecast of these numbers is vital for the adequate preparations of health care capacities and for the governments to take the necessary decisions. In this study, it is aimed to predict the evolution of COVID-19 figures, employing alternative statistical models such as the Holt-Winters, ARIMA, and ARIMAX while using the time series corresponding to different parameters of this disease such as daily cases, daily deaths, and the stringency index. Considered are the John Hopkins University epidemiological world data and the top ten countries with the highest cases, along with China. The fitting of the time series and the upcoming 10 ~~days~~ projections resulted in a high level of accuracy, presented with alternative error metrics and comparisons between the situations of countries. Holt-Winters is the best performing model, while ARIMAX gives the worst accuracy results. Moreover, it was found that the use of coefficient determination and Bayesian information criterion alone are not suitable, and scale independent metrics should be employed when the data ranges differ. The results of this study would be useful to set up benchmark results for other studies and the projections may be used for medical, economic, and social precaution and preparation.

Keywords COVID-19 · Forecasting · Epidemiological forecasting · Holt-Winters · Econometric models · ARIMA · ARIMAX

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1 Introduction

Since December 2019, the world is in combat with COVID-19, which started in Wuhan, China and spread to more than a 100 countries. According to the data collected by the World Health Organization (WHO)[1] on February 14th, 2021, there have been 108,153,741 confirmed cases of COVID-19, with 2,381,295 cases resulting in death~~s~~. While some countries are going through the second wave, some states started the vaccination process, and governments responded to the global pandemic with different measures.

Apart from the clinical researchers, academics approached the COVID-19 problem in different ways. While the pandemic spread and 1 year of living with COVID-19 passed, the social impact and economic aspects of the virus have become critical (Bruns et al., 2020). The diagnosis of the virus with the artificial intelligence image processing techniques became important (Bhattacharya et al., 2021). Similarities between the SARS and other epidemics were investigated (Peeri et al., 2020). Some part of the studies concentrated on estimating the cases and deaths per country, and a significant forecasting literature was formed.

Because there was no data available at the start of this epidemic, predicting and projections were difficult. However, the spread of COVID-19 is highly dangerous and necessitates strict plans and government policies. Therefore, forecasting confirmed cases and deaths in the future days is crucial in order to manage health resource capacities and put in place the necessary protection procedures. Consequently, this study tries to apply alternative forecasting models for the daily reported COVID-19 confirmed cases and deaths of the most affected 10 countries and China. It employs, namely Holt-Winters, ARIMA, and ARIMAX models, providing accuracy results in alternative error metrics.

The rest of the study is organized as follows: The second section consists of literature review. The third section presents the employed methods with the application, and the fourth section gives the concluding remarks and discussions.

2 COVID-19 Forecasting Literature Review

Forecasting the outcomes of a pandemic is important for governments in order to take the necessary restriction measures while preparing the appropriate health infrastructure (e.g. intensive care units for COVID-19 cases). The countries shared their data despite their discordance, with the public and WHO. Many researchers employed this data (worldwide or in specific countries) to forecast cases, deaths, and recovery numbers. In the last year, a solid forecasting literature was built where researchers alternated approaches such as machine learning approaches, statistical

[1] https://COVID19.who.int/

and epidemiological models. These articles focused on a selected country or a group of countries' case and death data (daily or cumulative), while some articles aimed to forecast the worldwide data generally in alternative forecasting horizons and training scales were written.

Al-Qaness et al. (2020) proposed an Adaptive Neuro-Fuzzy Inference System (ANFIS), which uses an enhanced flower pollination algorithm (FPA) with the help of the Salp Swarm Algorithm (SSA) to forecast the confirmed cases in China for the upcoming 10 days. Ankarali et al. (2020) employed ARIMA, Simple Exponential Smoothing, Holt's Two Parameter Model, and Brown's Double Exponential Smoothing Model to forecast 10 days of cumulative cases, cumulative deaths, daily cases, daily deaths, cumulative recovered and active cases of 25 countries, which exceed 1000 as cumulative cases in March 15. Ayinde et al. (2020) focused on the Nigeria data set and tried to forecast 2 months of confirmed cases, discharged cases, and death cases using classic, quadratic, cubic, and quartic versions of linear regression, logarithmic regression, logistic regression, and exponential linear regression. Ayyoubzadeh et al. (2020) predicted the COVID-19 cases in Iran using the Google Trends data. They employed the linear regression model and long short-term memory (LSTM) models and obtained a strong correlation for keywords like "hand sanitizer," "handwashing," and "antiseptic."

Benvenuto et al. (2020) employed ARIMA to forecast the next 2 days of COVID-19 confirmed cases and indicated that "if the virus does not develop new mutations, the number of cases should reach a plateau." Crokidakis (2020) employed a susceptible–infectious–quarantined–recovered (SIQR) model to estimate confirmed cases, ratio of infectious individuals, the reproduction number, and the epidemic doubling time of Brazil. Dandekar and Barbastathis (2020) built a neural network aided quarantine control model to test the impact of strict quarantine measures on the reproduction number in Wuhan. Their simulation results showed that rigid quarantine measures helped China on the new case numbers. Hernandez-Matamoros et al. (2020) built ARIMA models to forecast total case numbers per million, grouping countries according to their continents. Hu et al. (2020) used modified autoencoders for modeling the number of the cumulative and newly confirmed cases. They outlined the immense difference between the immediate and late interventions on total active cases and suggested a case ending time of January 10, 2021 under immediate aggressive interaction. Ibrahim et al. (2021) employed a variational Long Short-Term Memory (LSTM) autoencoder to forecast the spread of the coronavirus across the globe for the next day and 10 days ahead that employs historical data with the urban characteristics and stringency index measures. Ivorra et al. (2020) developed a new θ-SEIHRD model containing the characteristics of COVID-19, to identify the unknown parameters of the pandemic~~s~~ that fit the total cases of China, to estimate the reproduction rate, and to find the maximum number of hospitalized people.

Jia et al. (2020) employed a Logistic model, the Bertalanffy and the Gompertz model to estimate the new cases and death toll of China. Among these mathematical models, the logistic model is the best fitting-one. Kafieh et al. (2020) trained alternative machine learning models as random forest, multi-layer perceptron, LSTM with regular and extended features, and multivariate LSTM to estimate daily number of confirmed, death, and recovered COVID-19 cases. Kolozsvari et al. (2020) used recurrent neural networks with LSTM units to create prediction models of 17 countries' daily infection numbers per 100,000 habitants, outlining the effect of the repeated peaks of the epidemic. Kumar et al. (2020) employed ARIMA and Richard's model to estimate new cases, new deaths, and recovery rates of India. Liu et al. (2020) used related internet search activity in their combined mechanistic and machine learning model to estimate the real-time COVID-19 cases of the Chinese provinces. Liu et al. (2021) modeled the coronavirus in China, South Korea, Italy, Germany, and the UK, and under different scenarios, simulated their new cases. Milhinhos and Costa (2020) employed nonlinear regression to estimate the active cases and total deaths of Portugal and built a comparative model with South Korea, outlining the similarities. Pandey et al. (2020) employed SEIR and a regression model to predict the expected cases in India within 2 weeks.

Petropoulos and Makridakis (2020) employed exponential smoothing to forecast global confirmed cases, deaths, and recoveries with a forecasting horizon of 10 days. Roosa et al. (2020) used the generalized logistic growth model (GLM) and the Richards model to estimate 5-, 10-, and 15- days of cumulative cases of China. Sameni (2020) employed SEIR and the compartmental model to estimate the propagation. They simulated seven different scenarios and tried to find the reproduction and fatality rates of COVID-19. Xu et al. (2020) used the SEIQRPD model which divided the population into susceptible, exposed, infectious, quarantined, recovered, insusceptible, and deceased individuals to estimate the USA COVID-19 cases. Yang et al. (2020) used the SEIR model helped by a trained LSTM in SARS-2003, to predict COVID-19 peaks and sizes in China. Yonar et al. (2020) employed exponential smoothing and ARIMA to forecast the number of COVID-19 cases of the G8 countries. Table 1 summarizes the existing literature per country (forecasting target), the employed method, and the forecasting horizon.

As can be observed from Table 1, most of the studies focused on a single country data, with a forecasting horizon ranging from 2 to 15 days, while there are articles that aim only to fit the training data set. Along with the epidemiological models, regression models are widely used in the literature. Literature outlines that statistical models are simple but effective tools to forecast COVID-19 numbers with the highest proportion. Machine learning models such as LSTM or ANFIS, epidemiological models such as SEIR and combinations like SIR and SIQR are the other common approaches.

In this study, double exponential smoothing (Holt-Winters), ARIMA, and exogenous version ARIMAX models are employed to fit and forecast the daily case and daily death numbers of the selected countries and global data.

Table 1 COVID-19 forecasting literature

References	Country	Method	Forecasting horizon
Al-Qaness et al. (2020)	USA, China	ANFIS, FPA,SSA	10 days
Ankarali et al. (2020)	25 countries	ARIMA, exponential smoothing	10 days
Ayinde et al. (2020)	Nigeria	Linear regression models and versions	2 months (fitting)
Ayyoubzadeh et al. (2020)	Iran	LSTM, logistic regression	35 days (fitting)
Benvenuto et al. (2020)	World	ARIMA	2 days
Crokidakis (2020)	Brazil	SIQR	1 month (fitting)
Dandekar and Barbastathis (2020)	China	NN aided SIR	40 days (fitting)
Hernandez-Matamaros et al.	145 countries	ARIMA	15 days
Hu et al. (2020)	World	Modified auto-encoder	5 days
Ibrahim et al. (2021)	World	Variational-LSTM autoencoder	1–10 days
Ivorra et al. (2020)	China	θ-SEIHRD	1.5 months (fitting)
Jia et al. (2020)	China	Logistic, Bertalanffy, Gompertz models	2 months (fitting)
Kafieh et al. (2020)	Iran	RF, MLP, LSTM	10 days
Kolozsvari et al. (2020)	17 countries	RNN with LSTM	11–12 days
Kumar et al. (2020)	India	ARIMA, Richard's model	1 month
Liu et al. (2020)	7 countries	SIRU	2 days
Milhinhos and Costa (2020)	Portugal	Nonlinear regression	140 days (fitting)
Pandey et al. (2020)	India	SEIR, regression	2 weeks
Petropoulos and Makridakis (2020)	World	Exponential smoothing	10 days
Roosa et al. (2020)	China	Logistic growth, Richard's sub-epidemic wave models	5, 10, and 15 days
Sameni (2020)	USA	SIR	–
Xu et al. (2020)	USA	SEIQRP	2 weeks
Yang et al. (2020)	China	SEIR, LSTM	3 months (fitting)
Yonar et al. (2020)	G8 countries	ARIMA, exponential smoothing	10 days

3 Methodology and Application

3.1 Data Characteristics

The data employed in this study is available at the Coronavirus Research Center at the Johns Hopkins University website.[2] A total of 192 countries deal~~s~~ with the virus; however, in this study, only the first ten countries with the highest case numbers on February 9th, 2021 and China are considered. The first case dates differ among the countries, and the reporting process of these cases is somehow problematic. Therefore, the first day of the training set is selected as the day when cumulative cases reached "100" for each country, which is considered to be a more robust option. The training set length differs for each country and ends on January 30th, 2021. The remaining days are separated for the forecasting part. Table 2 shows the countries, with their cumulative case and death numbers, the initial date with data length and the fatality rate.

As is observed in Table 2, the countries have combatted the virus since March 2020. The USA is the most effected country by case and death numbers. The average fatality rate is 2.2%, while the maximum fatality rate is observed in China and Italy, 4.8% and 3.5%, respectively. The minimum fatality rates are in India and Turkey with 1.4% and 1.6%, which may be linked to the average population age of these countries. China is the virus-source (the virus' source) country. The virus spread after approximately 1 month to Europe, starting with Italy, France, the UK, Germany, and Spain. At last, it affected Russia and Turkey. The last affected countries had more time to prepare, while countries like Italy, which was the first effected, experienced more difficulties in the initial days of the spread of the virus. The countries show some similarities; however, they all have different COVID-19 wave~~s~~ lengths and population properties. In the appendix, charts belonging to daily case vs daily death numbers of the countries can be referenced to investigate these differences. To mathematically evaluate the resemblances between the case and death time series, a correlation test between the countries' data and world data is done. However, due to the initial day differences, the test is applied for the first 316 days of the pandemic. The outcomes for the new cases and new death~~s~~ correlations are as follows.

Table 3 shows that for most of the countries, a correlation between the country based new cases and worldwide new cases can be obtained; however, this hypothesis is not true for the daily death numbers of the countries. China is acting as an outlier in every aspect. The Spain data is corrupted since it contains negative values for the new deaths and new cases along with zeroes. In terms of the case numbers USA, UK, Germany, and Russia are highly correlated with the World. In terms of the death numbers, there is no country that is linearly correlated with the worldwide death numbers. To sum up, worldwide data is not an explanatory variable to yield better

[2] https://coronavirus.jhu.edu/map.html

Table 2 COVID-19 details of the countries

	Initial day	Total case	Total death	Data length	Fatality rate
World	28.01.2020	103, 554, 872	2, 268, 415	369	0.022
USA	7.03.2020	26, 558, 791	451, 416	330	0.017
India	18.03.2020	10, 790, 555	154, 701	319	0.014
Brazil	17.03.2020	9, 335, 247	227, 467	320	0.024
Russia	20.03.2020	3, 858, 234	73, 499	317	0.019
UK	4.03.2020	3, 844, 233	109, 308	333	0.028
France	3.03.2020	3, 307, 342	77, 628	334	0.023
Spain	5.03.2020	2, 871, 140	60, 161	332	0.021
Italy	25.02.2020	2, 586, 016	89, 768	341	0.035
Germany	4.03.2020	2, 253, 819	59, 642	333	0.026
Turkey	21.03.2020	1, 677, 723	26, 345	316	0.016
China	28.01.2020	98, 930	4783	369	0.048

Table 3 Correlation test results

	USA	**India**	**Brazil**	**Russia**	**UK**	**France**
New Case	0.917	0.203	0.693	0.811	0.836	0.517
New Death	0.494	0.232	0.636	0.742	0.179	−0.086
	Spain	**Italy**	**Germany**	**Turkey**	**China**	
New Case	0.696	0.663	0.832	0.547	−0.327	
New Death	−0.394	0.075	0.589	0.388	−0.395	

results when it comes to individual country data. The time series of the countries show obvious differences; therefore, they should be examined separately, and they should have their own model configurations. The figures in this study show the charts belonging to the worldwide data, and in the appendix the figures belonging to the other countries may be found. Figure 1 shows the New Case vs Daily Death numbers of the World and USA.

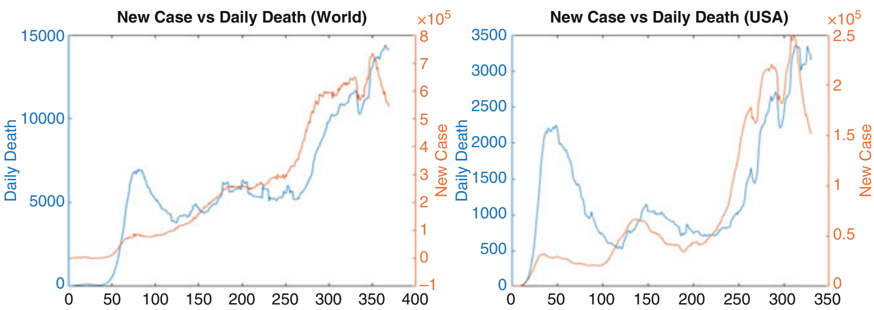


Fig. 1 Training data: left—World, right—USA

3.2 Error Metrics

Alternative error metrics are employed in the COVID-19 forecasting literature. All the statistical models based their study on R^2 which is the coefficient of determination that represents the proportion of the variance for dependent variable by the regression variable. RMSE and bic are the other error metrics that are used by Ankarali et al. (2020), Kumar et al. (2020), and Yonar et al. (2020). In this study, the results are provided according to these metrics. However, these metrics are scale dependent and are not suitable to compare the forecasting accuracies by countries. Therefore, the results are also shown in SMAPE and MAPE. The formulae of the employed metrics are provided next.

- *Bayesian Information Criterion (bic)*

The bic or Schwarz information criterion (SIC) is a criterion for model selection based on the likelihood function like AIC (Schwarz, 1978). The general notation is ~~as~~

$$\mathrm{BIC} = k \ln(n) - 2 \ln\left(\hat{L}\right) \tag{1}$$

- *Root Mean Squared Error (RMSE)*

RMSE or root mean-squared deviation (RMSD) is the square root of the averaged squared errors. It is scale dependent and highly sensitive to the outliers. When there is a set of time series, it is a difficult metric to interpret.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \tag{2}$$

- *Symmetric Mean Absolute Percentage Error (SMAPE)*

SMAPE is an accuracy measure based on percentage errors where the absolute difference between the A_t and F_t is divided by the half sum of absolute values of the A_t and F_t. This value is summed for every t and divided by the number of fitted points n.

$$\mathrm{SMAPE} = \frac{100\%}{n}\sum\nolimits_{t=1}^{n}\left|\frac{F_t - A_t}{\left(|A_t| + |F_t|\right)/2}\right| \tag{3}$$

The main advantage of the SMAPE is the interpretability (values range between 0 and 1) and the scale independency, which are necessities when dealing with multiple time series. The drawbacks are that when the actual value is zero, this metric is undefined because of the denominator.

- *Mean Absolute Percentage Error (MAPE)*

MAPE or mean absolute percentage deviation (*MAPD*) is a prediction measure where the difference between the actual value (A_t) and forecast value (F_t) is divided by the actual value. The absolute value of division is summed for every t and divided by the number of fitted points n. This value may be multiplied by 100% for a percentage error.

$$M = \frac{1}{n}\sum\nolimits_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{4}$$

- *Coefficient of Determination (R^2)*

The coefficient of determination denoted as R^2 is a widely used error metric in regression statistics, based on the proportion of variance in the dependent variable that may be justified by the independent variable. It is known also as the goodness of fit and it is the square of the correlation coefficient.

3.3 Holt-Winters Model

Holt-Winters is a statistical model that employs exponential smoothing to encode past values, used to predict the training data and forecasting. When the data is not stationary, in other words when there is a trend factor in data, simple exponential smoothing remains insufficient and the use of double exponential smoothing, or the Holt-Winters model becomes necessary (Holt, 1957). The COVID-19 data does not yet show any seasonality. Therefore, the seasonal parameter of the model is not included. With this adjustment, the method comprises the forecast equation with two smoothing equations for the level l_t and for the trend b_t, with corresponding parameters α and β between 0 and 1. The component form of the Holt-Winters model is

$$\hat{y}_{t+\mathrm{hIt}} = l_t + hb_t \tag{5}$$

$$l_t = \alpha\,(y_t) + (1-\alpha)\,(l_{t-1} + b_{t-1}) \tag{6}$$

$$b_t = \beta\,(l_t - l_{t-1}) + (1-\beta)\,b_{t-1} \tag{7}$$

The equations are done in MS Excel with generalized reduced gradient nonlinear solver method that looks at the slope of the objective function (decreasing selected error metrics) as the input values change and determine the optimality when the partial derivatives are zero (Abadie, 1978). Table 4 gives the results accuracy in R^2, RMSE, SMAPE, and MAPE.

As is observed from Table 4, for each time series, three alternative double exponential smoothing models are solved to decrease the RMSE, SMAPE, and

Table 4 Holt-Winters accuracy results and parameters

	World case	**World death**	**USA case**	**USA death**	**India case**	**India death**	**Brazil case**	**Brazil death**
α	1.000	1.000	0.801	1.000	0.885	1.000	1.000	0.913
β	0.525	0.224	0.589	0.512	0.383	0.050	0.022	0.043
RMSE	4621.620	149.704	2613.511	46.550	633.241	22.953	1528.380	31.745
α	1.000	0.893	0.817	0.936	0.926	0.942	1.000	0.970
β	0.523	0.470	0.881	0.691	0.325	0.083	0.117	0.162
SMAPE	0.026	0.027	0.021	0.030	0.023	0.039	0.042	0.040
alpha	0.962	0.893	0.849	0.936	0.922	0.942	1.000	0.969
beta	0.597	0.470	0.821	0.691	0.310	0.083	0.102	0.152
MAPE	0.025	0.027	0.020	0.030	0.023	0.039	0.042	0.039
R^2	0.9996	0.9983	0.9985	0.9970	0.9995	0.9958	0.9902	0.9897
	Russia case	**Russia death**	**UK case**	**UK death**	**France case**	**France death**	**Spain case**	**Spain death**
α	0.951	1.000	1.000	0.796	1.000	1.000	0.624	1.000
β	0.719	0.304	0.594	0.411	0.000	0.000	0.364	0.155
RMSE	98.039	4.565	452.017	15.948	1882.908	28.010	693.694	29.679
α	0.816	0.742	1.000	0.995	1.000	1.000	0.922	1.000
beta	1.000	0.531	0.648	0.321	0.015	0.001	0.166	0.155
SMAPE	0.009	0.032	0.028	0.058	0.108	0.097	0.081	0.123
α	0.816	0.845	1.000	0.996	1.000	1.000	0.881	0.908
β	1.000	0.357	0.597	0.299	0.024	0.001	0.233	0.420
MAPE	0.009	0.030	0.028	0.055	0.113	0.097	0.084	0.744
R^2	0.9999	0.9993	0.9991	0.9978	0.9739	0.9862	0.9928	0.9770
	Italy case	**Italy death**	**Germany case**	**Germany death**	**Turkey case**	**Turkey death**	**China case**	**China death**
α	1.000	1.000	0.887	0.867	1.000	0.967	1.000	0.999
β	0.568	0.441	0.050	0.033	0.549	1.000	0.132	0.000
RMSE	230.277	9.850	716.699	20.551	598.717	0.914	164.609	14.012
α	0.981	1.000	0.955	0.932	1.000	1.000	0.945	0.895
beta	0.444	0.127	0.308	0.229	0.949	1.000	0.486	0.672
SMAPE	0.029	0.066	0.050	0.086	0.019	0.016	0.113	0.094
α	0.974	1.000	0.949	0.957	1.000	1.000	0.882	–
β	0.439	0.129	0.305	0.179	0.949	1.000	0.662	–
MAPE	0.029	0.070	0.049	0.084	0.018	0.016	0.102	–
R^2	0.9995	0.9983	0.9908	0.9932	0.9943	0.9998	0.9526	0.8455

MAPE, respectively. The objective error metric highly effects the parameters α and β and the accuracy of the model. RMSE is a scale dependent measure, thus it is not suitable for comparison. When case predictions are observed, SMAPE ranges between 0.9% (Russia) and 11.3% (France). For the death predictions, the maximum SMAPE is 12.3% (Spain, corrupted data with negative values) and the minimum SMAPE is 1.6% (Turkey). For the world data, SMAPE and MAPE values are around 2.5%. For the all-time series, the R^2 shows the power of the correlation with 99.99%, with a poor discriminating power. SMAPE and MAPE values show

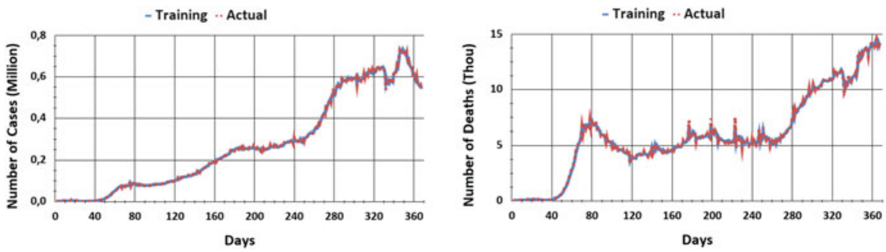


Fig. 2 Fitting Curves for the World: left—New Case, right—New Death

the suitability of the model to the COVID-19 data set. The fitting charts for the World are in Fig. 2.

The forecasting values by the parameters, optimized for SMAPE are in Tables 5 and 6 for daily cases and daily deaths, respectively.

3.4 ARIMA

The ARIMA model describes a univariate time series as a combination of autoregressive (AR) and moving average (MA) lags which capture the autocorrelation within the time series. The order of integration denotes how many times the series has been differenced to get a stationary series. An ARIMA(p,d,q) model where p is the autoregressive lag, d is the degree of differencing, and q is the number of moving average lags can be denoted as:

$$\Delta^D y_t = \sum_{i=1}^{p} \varphi_i \Delta^D y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t, \quad \epsilon_t \sim N\left(0, \sigma^2\right) \tag{8}$$

The (p,d,q) parameters of the model are found by an iterative algorithm that tries to minimize the Bayesian information criterion (bic) values, considering the autocorrelation values. The sample and partial autocorrelation functions belonging to the World are given in Fig. 3.

ARIMA configurations and results for the new cases and new deaths are given in Tables 7 and 8, respectively. These and the following tables show the result by five different error metrics. Bic values are the goodness of fit measure that evaluate the performance of the selected model compared to other models. R^2 represents the proportion of the variance for a dependent variable that is explained by the independent variable. RMSE is the square root of the mean of the squared errors. The existing literature share their results with these three metrics; however, these metrics are scale dependent, and they are not suitable to compare accuracy results for different countries. Therefore, in this study, the scale independent error metric MAPE is calculated. The “Inf” values on MAPE are based on the instability at near

Table 5 Daily case forecasting (Holt-Winters)

Daily cases	World	USA	India	Brazil	Russia	UK	France	Spain	Italy	Germany	Turkey	China
31.01.2021	536,686	147,402	13,007	51,560	18,562	24,104	20,491	34,675	12,348	12,391	6798	125
1.02.2021	528,767	143,587	12,904	51,589	18,306	22,602	20,545	34,555	12,322	12,370	6943	118
2.02.2021	520,847	139,771	12,801	51,617	18,049	21,099	20,598	34,436	12,297	12,348	7088	111
3.02.2021	512,927	135,955	12,699	51,646	17,793	19,597	20,651	34,317	12,271	12,326	7232	104
4.02.2021	505,008	132,140	12,596	51,674	17,537	18,095	20,705	34,197	12,246	12,304	7377	97
5.02.2021	497,088	128,324	12,493	51,703	17,281	16,592	20,758	34,078	12,220	12,283	7522	90
6.02.2021	489,168	124,508	12,390	51,731	17,025	15,090	20,812	33,959	12,195	12,261	7667	84
7.02.2021	481,249	120,693	12,287	51,760	16,769	13,587	20,865	33,839	12,169	12,239	7811	77
8.02.2021	473,329	116,877	12,185	51,788	16,513	12,085	20,918	33,720	12,144	12,218	7956	70
9.02.2021	465,409	113,061	12,082	51,817	16,257	10,583	20,972	33,601	12,118	12,196	8101	63

Table 6 Daily death forecasting (Holt-Winters)

Daily Deaths	World	USA	India	Brazil	Russia	UK	France	Spain	Italy	Germany	Turkey	China
31.01.2021	14,113	3090	129	1079	515	1167	427	420	442	744	131	2
1.02.2021	14,090	3025	125	1087	509	1154	427	429	439	748	129	2
2.02.2021	14,067	2960	121	1094	504	1140	427	437	435	752	127	2
3.02.2021	14,043	2895	117	1102	498	1127	428	446	432	757	125	2
4.02.2021	14,020	2830	113	1109	493	1114	428	455	429	761	122	2
5.02.2021	13,997	2765	109	1117	487	1101	428	463	425	765	120	2
6.02.2021	13,973	2700	105	1125	482	1088	428	472	422	769	118	2
7.02.2021	13,950	2636	101	1132	476	1075	428	481	419	773	116	2
8.02.2021	13,927	2571	97	1140	471	1062	428	489	415	777	114	2
9.02.2021	13,903	2506	93	1147	465	1048	429	498	412	782	112	2

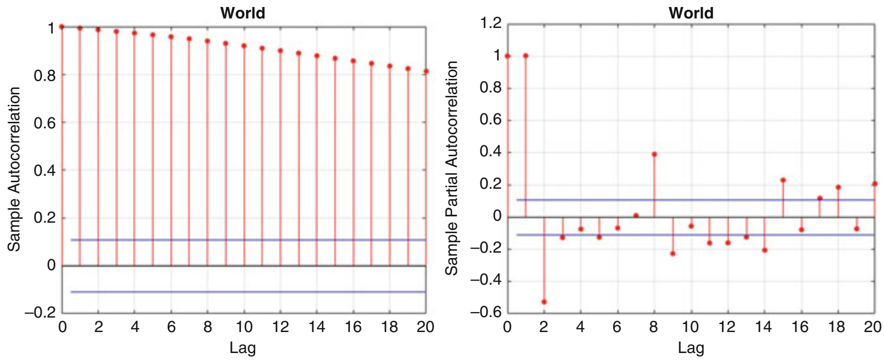


Fig. 3 ACF and PACF charts (World)

Table 7 ARIMA results for the new cases

New case	Configuration	bic	R^2	RMSE	SMAPE	MAPE
World	(7,1,6)	7161.60	0.9997	4141.62	0.0398	0.0367
USA	(7,1,6)	6000.20	0.9991	2390.19	0.0367	0.0587
India	(7,0,7)	4887.30	0.9997	511.21	0.0619	0.0479
Brazil	(7,1,7)	5471.40	0.9939	1297.05	0.0670	0.0836
Russia	(7,2,7)	3660.60	0.9999	76.52	0.0079	0.0080
UK	(7,2,7)	4873.20	0.9994	394.27	0.0401	0.0404
France	(6,1,7)	5785.40	0.9873	2140.64	0.1909	0.1483
Spain	(7,1,4)	5235.50	0.9944	649.56	0.1521	0.1370
Italy	(7,2,7)	4573.00	0.9996	204.75	0.0322	0.0317
Turkey	(6,0,7)	4741.40	0.9972	490.62	0.0259	0.0260
Germany	(6,1,7)	5185.10	0.9950	627.06	0.0805	0.0797
China	(7,1,7)	4574.80	0.9800	117.33	0.4119	0.6388

zero of the time series. To overcome this problem, the symmetric version SMAPE is considered.

When the configurations of the models are investigated, most of the models show a non-stationarity characteristic, which is supported also with the augmented Dickey–Fuller test. For the new cases, the algorithm does not integrate the Turkey and India data and for the daily deaths does not differ between the India and Spain data. A second degree of differentiation is only required for the new cases for Russia, the UK, and Italy, and new deaths for Spain. In general, a seven-lag order is selected by the model for the autoregressive and moving average degrees. However, when the data is decomposed, the seasonality is found to be approximately 0; therefore, a SARIMA model is not necessary. China gives the maximum error values, and the reliability of their values is often discussed in public, therefore in the comments, China will be excluded due to data instability. Most of the countries fit the ARIMA model quite well. The focus of the study is not decreasing the errors as much as

Table 8 ARIMA results for the new deaths

New death	Configuration	bic	R^2	RMSE	SMAPE	MAPE
World	(7,1,7)	4602.40	0.9989	122.43	0.0360	0.0348
USA	(7,1,7)	3335.80	0.9980	37.42	0.0378	0.0321
India	(7,0,7)	4887.30	0.9997	352.87	0.3741	4.2665
Brazil	(7,1,7)	2987.40	0.9937	25.32	0.0371	0.0403
Russia	(6,1,7)	1704.10	0.9996	3.49	0.0383	0.0336
UK	(7,1,7)	2678.30	0.9985	13.28	0.1186	Inf
France	(7,0,7)	2973.30	0.9932	20.40	0.1837	0.1675
Spain	(6,2,7)	3148.90	0.9824	27.31	0.3677	Inf
Italy	(7,1,7)	2428.30	0.9990	8.38	0.0638	0.0643
Turkey	(7,1,7)	664.80	0.9999	0.71	0.0147	0.0150
Germany	(7,1,7)	2708.80	0.9969	13.90	0.2560	Inf
China	(7,1,7)	2769.90	0.9611	10.17	1.1200	Inf

possible but providing an easy and fast fitting and forecasting solution and offering a comparative platform to the researchers and readers to discuss.

The R^2 values greater than 99% show the robustness of the model to explain the variance. The RMSE values may be used for each country to interpret fitting and forecasting intervals. The model performances over countries are done by SMAPE values. For the daily case numbers, the lowest SMAPE is for Russia with 0.79% and Turkey with 2.59%. France and Spain are the worst fitting countries, with 19.09% and 15.21%, respectively. Remaining countries and the world are within acceptable limits, their SMAPE ranging between 1% and 7%. The fitting of the death numbers is not as successful as the new cases fitting. In Table 6, the worst fitting countries are India and Spain with 37.41% and 36.77%, respectively. Turkey (1.47%) and Brazil (3.71%) are the best fitting countries using ARIMA. These countries may be grouped in alternative ways. One way of it is considering the fitting error closeness of the country with the world error term. The countries which have numerically close SMAPEs can be considered as coherent countries. When SMAPEs are too low, the countries may be grouped as negative coherent countries and when SMAPEs are too high, they may be grouped as positive coherent countries, where the necessity of building more sophisticated models arises. Table 9 gives this classification. Spain's data set is corrupted and contains negative values along zeroes, which reflects directly the model results.

Table 9 Classification of the countries by coherence to the world

	Coherent	Positive coherent	Negative coherent
New case	USA, India, Brazil, UK, Italy, Turkey, Germany	France, Spain, China	Russia
New death	USA, Brazil, Russia, UK, Italy	India, France, Spain, Germany, China	Turkey

The ARIMA 10-days forecasting outcomes are in Tables 10 and 11 for daily cases and daily deaths, respectively.

Tables 10 and 11 show that world daily case and death numbers of the virus reached a steady plateau for the first days of the February 2021. USA and UK case and death numbers are decreasing, while the situation is worsening for India and Brazil. Turkey and Russia have a slightly negative slope, where the numbers seem to decrease.

3.5 ARIMAX

ARIMAX is an extension of the ARIMA model where there are suitable explanatory variables that can be incorporated into fitting and forecasting problems. In practice, these additional exogenous variables X create a multivariate time series model instead of a univariate model and improve the prediction performance. An ARIMAX(p,d,q) model for a time series y_t with an exogenous series X can be written as

$$\Delta^D y_t = \sum_{i=1}^{p} \varphi_i \Delta^D y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \sum_{m=1}^{M} \beta_m X_{m,t} + \epsilon_t, \quad \epsilon_t \sim N\left(0, \sigma^2\right) \tag{9}$$

New cases and new deaths are correlated time series and may be meaningful for each other as an exogenous variable fit and forecast better. Another significant data is the stringency index of the countries. The stringency index reflects the government attitudes of the countries and is calculated as a function of school and workspace closures, cancellation of public events, restrictions on public gatherings, closures of public transport, stay at-home requirements, public information campaigns, restriction on internal movements and international travel controls.[3] To test the effectiveness of using these exogenous variables, the Granger-causality test is applied among the time series.

The Granger-causality test is a statistical hypothesis test to determine the usefulness of a time series for forecasting another series (Granger, 1969). A time series X is said to Granger-cause Y, when it provides statistically significant information about the future of the Y The notation is.

$$p\,[Y\,(t+1) \in A|I\,(t)] \neq p\,[Y\,(t+1) \in A|I_{-X}(t)] \tag{10}$$

where p is probability, A is an arbitrary non-empty set, and $I(t)$ and $I_{-X}(t)$ denote the information as of time t in the universe, and in the modified universe where X is excluded. In this study this test is employed to detect in which series ARIMAX can be employed. In total, six hypotheses are built. These hypotheses are, respectively,

[3] https://ourworldindata.org/COVID-government-stringency-index

Table 10 Daily case forecasting (ARIMA)

Daily case	World	USA	India	Brazil	Russia	UK	France	Spain	Italy	Germany	Turkey	China
2021-01-31	541,044	150,053	13,061	51,798	18,467	24,193	21,249	34,287	12,392	12,341	6642	112
2021-02-01	533,534	145,656	12,866	52,644	18,278	23,473	21,315	33,026	12,443	12,071	6631	96
2021-02-02	530,433	143,884	12,957	52,558	18,093	23,208	21,277	32,830	12,598	12,243	6542	80
2021-02-03	530,139	143,415	13,214	52,561	17,886	22,669	21,309	31,410	12,608	12,426	6301	69
2021-02-04	532,153	143,319	12,285	53,833	17,679	21,934	24,121	30,880	12,727	12,542	5921	58
2021-02-05	528,806	140,978	12,363	53,392	17,493	21,094	22,883	29,853	12,934	12,456	5854	41
2021-02-06	528,633	141,601	12,729	53,400	17,288	20,695	21,658	28,554	13,029	12,053	5867	23
2021-02-07	528,731	141,320	12,554	53,736	17,067	20,437	21,864	28,028	13,190	12,267	5787	10
2021-02-08	527,357	140,361	12,529	53,781	16,803	20,381	23,076	26,415	13,401	12,249	5707	2
2021-02-09	527,713	140,703	12,463	53,985	16,541	20,233	22,942	25,720	13,591	12,183	5641	13

Table 11 Daily death forecasting (ARIMA)

Daily deaths	World	USA	India	Brazil	Russia	UK	France	Spain	Italy	Germany	Turkey	China
2021-01-31	14,235	3131	173	1090	519	1171	430	442	447	781	131	0
2021-02-01	14,326	3119	228	1108	520	1157	443	426	440	694	130	−1
2021-02-02	14,230	3062	303	1105	517	1126	462	425	439	784	130	0
2021-02-03	14,346	3070	399	1123	513	1112	444	420	439	792	129	−2
2021-02-04	14,287	3053	507	1134	512	1096	499	425	438	696	129	−3
2021-02-05	14,369	3039	625	1143	514	1076	454	416	437	804	128	−3
2021-02-06	14,368	3062	749	1132	516	1051	465	433	435	764	127	−3
2021-02-07	14,416	3070	854	1147	516	1034	467	437	435	715	127	−4
2021-02-08	14,434	3069	940	1153	516	1019	461	440	433	822	127	−4
2021-02-09	14,447	3058	1007	1159	517	999	455	439	433	763	126	−4

Table 12 The Granger-causality test results on case to death and vice versa

Case → Death	h	*p*-value	Stat	Death → Case	h	*p*-value	Stat
World	**1**	0.001	10.657	World	**1**	1.12E−19	8.24E+01
USA	**1**	0.002	9.405	USA	**0**	2.68E−01	1.23E+00
India	**1**	0.000	19.041	India	**0**	5.90E−01	2.90E−01
Brazil	**0**	0.147	2.101	Brazil	**0**	6.60E−01	1.93E−01
Russia	**1**	0.000	36.213	Russia	**1**	3.62E−05	1.71E+01
UK	**1**	0.000	14.606	UK	**0**	6.78E−01	1.73E-01
France	**1**	0.000	98.141	France	**1**	2.00E−04	1.38E+01
Spain	**0**	0.090	2.883	Spain	**1**	1.85E−05	1.83E+01
Italy	**1**	0.000	27.930	Italy	**1**	1.18E−06	2.36E+01
Turkey	**0**	0.161	1.968	Turkey	**0**	4.37E−01	6.05E−01
Germany	**0**	0.869	0.027	Germany	**1**	1.96E−02	5.45E+00
China	**0**	0.585	0.299	China	**1**	9.10E−03	6.80E+00

Table 13 The Granger-causality test results on case to stringency and vice versa

Case → Stringency	h	*p*-value	Stat	Stringency → Case	h	*p*-value	Stat
USA	**0**	0.759	0.094	USA	**0**	0.484	0.489
India	**1**	0.015	5.974	India	**1**	0.000	25.564
Brazil	**0**	0.184	1.762	Brazil	**0**	0.927	0.008
Russia	**0**	0.829	0.047	Russia	**1**	0.021	5.310
UK	**0**	0.217	1.522	UK	**0**	0.145	2.127
France	**0**	0.104	2.651	France	**0**	0.055	3.694
Spain	**0**	0.755	0.097	Spain	**0**	0.374	0.790
Italy	**0**	0.069	3.313	Italy	**1**	0.000	13.800
Turkey	**0**	0.890	0.019	Turkey	**0**	0.996	0.000
Germany	**1**	0.007	7.356	Germany	**0**	0.054	4.500
China	**0**	0.705	0.143	China	**0**	0.915	0.011

"case" Granger-causes "deaths" and vice versa, "case" Granger-causes "stringency index" and vice versa, and "deaths" Granger-cause "stringency index" and vice versa.

Tables 12, 13, and 14 show the results of these tests, where h value 1 indicates the acceptance of the hypothesis, which does not neglect the Granger-cause effect between the time series for a *p*-value lower than 0.05.

The first hypothesis is based on the strong correlation idea between the case and death numbers. However, as can be observed from Table 13, only for seven countries "case" has a Granger-cause on the "death" numbers. Similarly, only for seven countries the "death" numbers can be employed to estimate the "case" numbers. In addition, these countries are not the same, and this Granger-cause cannot be generalized for countries; therefore, it will not be included in the ARIMAX model.

The second hypothesis is based on the effect of the government restrictions on the case number and vice versa. Although this idea makes sense in theory, when the test is applied, it is found that it does not make sense statistically. Only in two countries

Table 14 The Granger-causality test results on death to stringency and vice versa

Death → Stringency	h	p-value	Stat	Stringency → Death	h	p-value	Stat
USA	**0**	0.783	0.076	USA	**1**	7E−06	2E+01
India	**0**	0.098	2.746	India	**1**	3E−02	5E+00
Brazil	**0**	0.081	3.053	Brazil	**1**	1E−03	1E+01
Russia	**0**	0.965	0.002	Russia	**1**	6E−03	8E+00
UK	**0**	0.870	0.027	UK	**1**	3E−06	2E+01
France	**0**	0.331	0.945	France	**1**	5E−05	2E+01
Spain	**0**	0.227	1.459	Spain	**1**	4E−05	2E+01
Italy	**0**	0.337	0.921	Italy	**1**	9E−23	1E+02
Turkey	**0**	0.550	0.357	Turkey	**1**	2E−06	2E+01
Germany	**0**	0.645	0.212	Germany	**1**	4E−05	2E+01
China	**0**	0.991	0.000	China	**0**	7E−01	1E−01

Table 15 ARIMAX scores on new cases (stringency index as exogenous variable)

New case	Configuration	bic	R^2	RMSE	SMAPE	MAPE
India	(7,0,7)	4509.09	0.9998	583.90	0.0243	0.0242
Russia	(7,2,7)	3652.34	0.9996	77.64	0.0082	0.0084
Italy	(7,2,7)	4552.71	0.9999	198.12	0.0348	0.035

"case" is the Granger-cause of the stringency index, and only in three states the stringency has a significant effect on the "case" numbers estimation. These three countries will be modeled with ARIMAX to measure the impact on the forecasting accuracy.

As is clear from Table 14, death has no impact on the stringency index in each country, however when the vice versa situation is considered, for all the countries (except China), the stringency index is a Granger-cause of the death numbers, therefore should be used in the ARIMAX as an exogenous variable to increase the forecasting accuracy. Based on the Granger-causality test, the results of the ARIMAX model are given in Table 15.

The SMAPE values of the ARIMA model belonging to India, Russia, and Italy were 6.19%, 7.9%, and 3.22%, respectively. ARIMAX results shows that, the only significant contribution of the stringency index on the estimation process, obtained in India, by an added value of 3.76%. This can be considered as warning not to employ complex models when the forecasting accuracy satisfactory.

The Granger-cause effect between the stringency index and new deaths is common for countries. Table 16 shows the results of the ARIMAX model where the stringency index is considered as an exogenous variable to predict the new deaths.

Spain gives the worst performance. When the data of Spain is investigated the negative values of new deaths are observed. This corruption of the data set is reflected directly on the solutions. Therefore, this country necessitates a data cleaning process rather than a sophisticated model. MAPE does not perform well

Table 16 ARIMAX scores on new deaths (stringency index as exogenous variable)

New death	Configuration	bic	R^2	RMSE	SMAPE	MAPE
USA	(7,1,7)	3348.17	0.9980	37.62	0.0757	0.2032
India	(7,0,7)	2766.18	0.9967	17.42	0.1312	0.6431
Brazil	(7,1,7)	3008.07	0.9931	25.67	0.0798	1.1843
Russia	(6,1,7)	1756.71	0.9996	3.55	0.0696	0.0633
UK	(7,1,7)	2703.46	0.9982	13.32	0.7225	Inf
France	(7,0,7)	2998.08	0.9938	20.38	0.2933	0.5039
Spain	(6,2,7)	3161.37	0.9670	27.58	0.9295	Inf
Italy	(7,1,7)	2464.41	0.9989	8.44	0.1269	0.1566
Germany	(7,1,7)	2734.91	0.9968	13.98	0.3149	Inf
Turkey	(7,1,7)	760.35	0.9999	0.71	0.0160	0.0161

Table 17 Daily death forecasting (ARIMAX)

	USA	India	Brazil	Russia	UK	France	Spain	Italy	Germany	Turkey
2021-01-31	3105	129	1089	520	1201	408	549	445	784	131
2021-02-01	3048	110	1106	521	1226	397	660	432	694	130
2021-02-02	2935	116	1087	520	1241	388	809	426	777	130
2021-02-03	2877	123	1093	517	1278	337	967	423	783	129
2021-02-04	2789	134	1104	519	1330	356	1165	414	682	129
2021-02-05	2701	127	1100	522	1381	272	1373	403	787	129
2021-02-06	2635	110	1071	526	1443	236	1636	394	746	129
2021-02-07	2562	106	1080	528	1509	200	1821	385	687	130
2021-02-08	2478	104	1074	530	1592	151	2012	372	788	131
2021-02-09	2381	103	1068	533	1676	100	2207	363	727	132

because of the near zero values. UK is not suitable to be fitted with ARIMAX with a SMAPE of 72.25%, which is far greater than the simple ARIMA process (Table 17).

Tables 18 and 19 show the Holt-Winters outperforming performance for the new case and new deaths except for Spain. For the new deaths ARIMAX is an overfitting method and should not be used in the prediction of the COVID-19 numbers.

The ARIMA and Holt-Winter models may be used for fitting and forecasting the cases and deaths, they can be employed as benchmark results for alternative forecasting methods. Figures 4 and 5 draw the 10-days forecasting outcomes of the employed models with the test data for World, USA, and UK.

4 Conclusion

The COVID-19 studies are an ongoing literature in alternative branches. This study is among the first efforts that compiles forecasting research. COVID-19, having completed its first year, employs a satisfactory large training data set and shows

Table 18 Comparative results (new death)

	SMAPE			MAPE		
New death	Holt-Winters	ARIMA	ARIMAX	Holt-Winters	ARIMA	ARIMAX
World	0.027	0.036	–	0.027		–
USA	0.03	0.0378	0.0757	0.03	0.0321	0.2032
India	0.039	0.3741	0.1312	0.039	4.2665	0.6431
Brazil	0.04	0.0371	0.0798	0.039	0.0403	1.1843
Russia	0.032	0.0383	0.0696	0.03	0.0336	0.0633
UK	0.058	0.1186	0.7225	0.055	Inf	Inf
France	0.097	0.1837	0.2933	0.097	0.1675	0.5039
Spain	0.744	0.3677	0.9295	0.744	Inf	Inf
Italy	0.066	0.0638	0.1269	0.07	0.0643	0.1566
Germany	0.086	0.256	0.3149	0.084	Inf	Inf
Turkey	0.016	0.0147	0.016	0.016	0.015	0.0161
China	0.094	1.2	–	–	Inf	–

Table 19 Comparative results (new case)

	SMAPE		MAPE	
New case	Holt-Winters	ARIMA	Holt-Winters	ARIMA
World	0.026	0.0398	0.025	0.0367
USA	0.021	0.0367	0.02	0.0587
India	0.023	0.0619	0.023	0.0479
Brazil	0.042	0.067	0.042	0.0836
Russia	0.009	0.0079	0.009	0.008
UK	0.028	0.0401	0.028	0.0404
France	0.108	0.1909	0.113	0.1483
Spain	0.081	0.1521	0.084	0.137
Italy	0.029	0.0322	0.029	0.0317
Germany	0.05	0.0259	0.049	0.026
Turkey	0.019	0.0805	0.018	0.0797
China	0.113	0.4119	0.102	0.6388

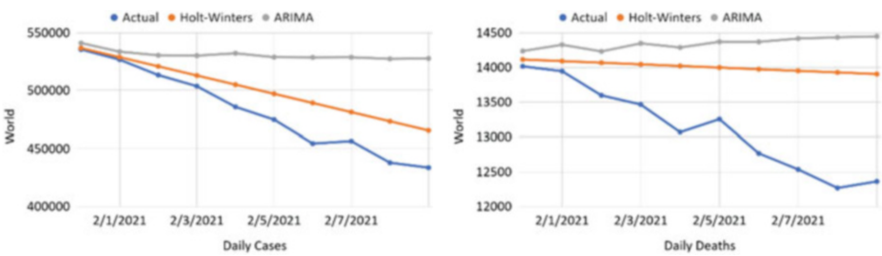


Fig. 4 Forecasting world COVID-19 data: left—New case, right—New death

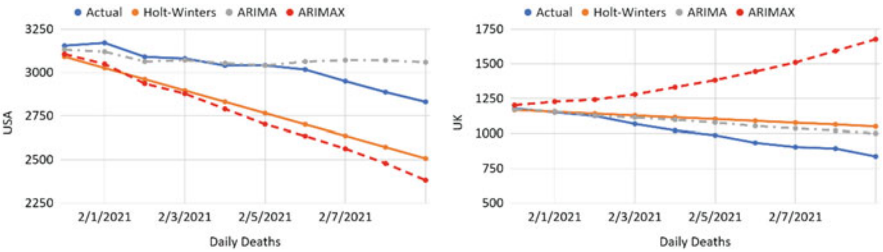


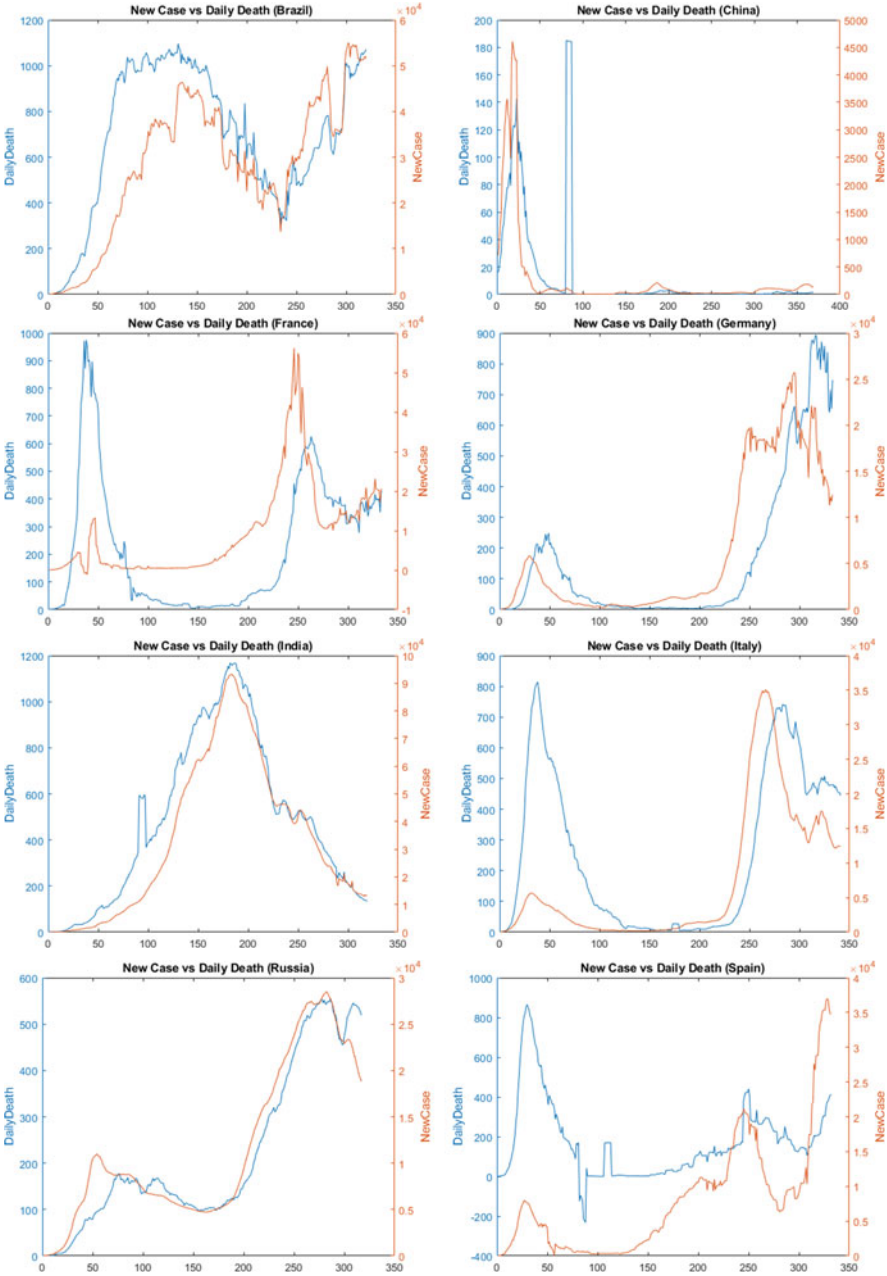
Fig. 5 Forecasting daily deaths: left—USA, right—UK

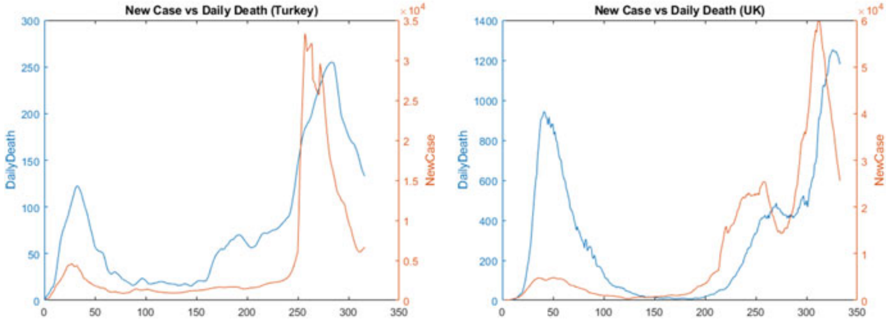
the accuracy results of simple but successful statistical forecasting models on a total of 24 time series (12 for new cases and 12 for new deaths). This paper employs three different models, those being the Holt-Winters, the ARIMA, and the ARIMAX models, with five different error metrics, bic, R^2, RMSE, SMAPE, and MAPE. All the models provide satisfactory results where percentage errors are generally lower than 10% and R^2 is approximately 99.9% showing the power of regression-based models. In general, the Holt-Winters (known as double exponential smoothing) outperforms the ARIMA, and although an introduction of an exogenous variable in the estimation process exists, ARIMAX is the lowest performing model, still with the acceptable results for most of the countries (see Figs. 4 and 5).

The correlation of the most effected countries' data is calculated with the world data. The Granger-causality tests show the importance of the correct exogenous variable selection. Statistically, the new cases and new deaths are dependent variables; however, in the estimation process they cannot be used for each other as auxiliary inputs. The stringency index consisting of government attitudes towards combatting the virus, statistically does not affect the case numbers; however, it has a Granger-cause effect in death numbers.

With the available data set and all the parameter details, this study provides reproducible results, where outcomes may be used by other researchers as benchmark results. Further researchers may classify the countries according to their response to statistical models, and with a more focused attention, such as data cleaning or machine learning approaches, they can improve the fitting and forecasting accuracy performances. The finding of a meaningful exogenous variable in the estimation would be beneficial to increase the ARIMAX performance.

Appendix


New Case vs Daily Death (Brazil)
New Case vs Daily Death (China)
New Case vs Daily Death (France)
New Case vs Daily Death (Germany)
New Case vs Daily Death (India)
New Case vs Daily Death (Italy)
New Case vs Daily Death (Russia)
New Case vs Daily Death (Spain)
DailyDeath
NewCase
$\times 10^4$



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