Analyzing Response Efficiency to COVID-19 and Underlying Factors of the Outbreak With Deep Assessment Methodology and Fractional Calculus

ERTUĞRUL KARAÇUHA¹, ESRA ERGÜN¹, NİSA ÖZGE ÖNAL TUĞRUL¹, KAMIL KARAÇUHA¹, VASIL TABATADZE¹

¹Informatics Institute, Istanbul Technical University, Istanbul 34467, TURKEY
Corresponding author: Esra Ergün (e-mail: ergunesr@itu.edu.tr).

This work was supported by the Vodafone Future Laboratory, Istanbul Technical University (ITU), under Grant ITUVF20180901P11.

ABSTRACT This study focuses on modeling the daily deaths per new case of COVID-19 by using the Fractional Calculus and the Least Squares Method. Based on our prior work, we proposed a new modeling approach, assessed the strength of outbreak response, and analyzed possible underlying factors of the outbreak for 8 countries including China, France, Germany, Italy, Russia, Spain, the UK, and the US. First, we modeled weekly deaths per new case of COVID-19 using our new modeling method Deep Assessment Methodology - Second Derivative (DAM-SD). Later, we defined a performance indicator to understand how well each country copes with the pandemic. Lastly, Pearson correlations between the performance indicator and several economic, social, and environmental indices, such as Human Development Index, Human Freedom, Democracy, Competitiveness, and Trust Index are computed, and \( p \)-values are reported. Results showed that DAM-SD successfully models the daily new cases of COVID-19 with 3.7390% Mean Average Precision Error and outperforms the DAM by 1.5678% MAPE. China is the best-modeled country with 4.0975e-08% MAPE whereas the model produced the highest error rate for France as 8.8317% MAPE. According to the analysis with the performance indicators, China is the most successful country against the pandemic while the United States and France fail to confine COVID-19 outbreak compared to the others. Indicators such as Human Development Index, Human Freedom, Human Democracy, GINI Index, Workers Rights, the Trust Index, and Air Pollution are found significant for COVID-19 response according to the \( p \)-values. In the correlation analysis, Average Class Size, Government’s Long Term Vision, Responsiveness to Change, Better Life Index, and Population Density were the least significant indicators. Long Term Care Beds, Social Capital, and Global Social Mobility indicators are found correlated with the COVID-19 response. Household Spending and Student Skills are found insignificant.

INDEX TERMS COVID-19, Deep Assessment Methodology (DAM), Fractional Calculus, Mathematical Modelling, Correlation Analysis.

I. INTRODUCTION

COVID-19 disease was first identified in Wuhan, capital of Hubei province of China, in December 2019 and declared as a global pandemic by the World Health Organization on March 11, 2020. As of October 2021, the disease has infected 244 million people and caused more than 4 million deaths worldwide. Governments, institutions, and policymakers are trying to design the optimal outbreak response to curb the spread of the disease and ultimately reduce the number of people becoming infected. Therefore, understanding the dynamics of the outbreak and response are crucial for effective filtering and evaluation of candidate strategies.

Computational, statistical, and mathematical methods have attracted researchers for decades in analyzing the characteristics of any natural phenomena, including biological epidemics. Because of the ongoing COVID-19 crisis, scientific institutions, universities, and companies are...
actively investigating various mathematical methodologies for predicting the trend, estimating the peaks, the end, and modeling the course of the pandemic. For instance, in [1], three types of mathematical models, the logistic model, Bertalanffy model, and Gompertz model, were adopted for fitting COVID-19 data. A compartmental model that takes super-spreaders into account is proposed, and the proposed model is evaluated with the data from Wuhan in [2].

Reference [3] combines ARIMA and wavelet-based predicting techniques for short-term future prediction of Canada, France, India, South Korea, and the UK. In [4], a method based on a dictionary learning and online non-negative matrix factorization is proposed to predict the COVID-19 outbreak, and the near future is extrapolated by one step recursive predictions. Reference [5] investigates the early transmission dynamics of COVID-19 in Wuhan by fitting a stochastic transmission dynamic model using sequential Monte Carlo simulation and obtains the basic Reproduction number $R_t$. Schüttler et al. [6] proposed a Gauss Model to map the time to the Gauss function, modeled the daily deaths per day, and forecasted the further progression of the fatalities per country. In [7], authors use a mean-field model to understand the temporal dynamics of the epidemic spread and predict the time of the peak of confirmed cases for Mainland China, Italy, and France. In [8], the mortality rate is estimated with the ARIMA and the regression models. Further, [9] focuses on uncovering persistent dynamics of COVID-19 cases by using the Switching Kalman Filter algorithm to predict the future of the infection. The family of compartmental models is being investigated for mathematical modeling of COVID-19 [10]–[12], as well. For instance, the SIR model that uses three variables (susceptible $(S)$, infected $(I)$, and recovered $(R)$) is employed to predict the epidemic characteristics in mainland China and estimate the final size of the COVID-19 pandemic [13], [14]. In the original SIR model, transmission rate, $\beta$ and recovery rate, $\gamma$ are constant variables and do not change by time. In [15], the authors formulate the transmission and recovery rates as time-dependent variables to track and control the disease spread better. Further, a version of the SIR model, “SEIR” which has an additional element $E$ for exposed, is introduced in [16], and the evolution of the epidemic in Hubei Province is shown. Another compartmental mathematical model with six variables including asymptotic $(A)$, isolated infected $(I_a)$, and quarantine susceptible $(S_q)$ is proposed and sensitivity analysis of parameters is carried out in [17].

Also, the mathematical models are used to identify the effect of co-morbidities on COVID-19 mortality rates too. In [18], the authors have estimated the link of demographic and co-morbidities with COVID-19 test positivity alone, or with mortality, with logistic regression. An Elastic Net regularized binary classification is performed to select for the most important elements such as co-morbidities and demographics in [19].

Fractional Calculus (FC) is a branch of mathematics that allows operations over arbitrary positive order of integrals and derivatives and extends the concept of calculus to the entire real and complex axis. Fractional operators are superior to their integer-order counterparts for two reasons. First, fractional operators provide flexibility and are capable of modeling systems with complex dynamics. Also, conventional integer-order operators have no memory because their locality properties and solutions of integer order differential equations do not depend on past values. On the other hand, fractional operators have non-locality properties effective for modeling systems that possess historical dependence. Hence, fractional operators have attracted various disciplines of science and engineering including mechanics, biology, biomedical devices, nanotechnology, diffusion, diffraction, economics, and control theory [20]–[39].

Fractional Calculus (FC) has been widely utilized for analyzing the characteristics of various epidemics such as Measles, Tuberculosis, Malaria, Dengue, and Ebola [20]–[24] in the literature. Recently, [25] presented a mathematical model based on Fractional Calculus for the transmission rate of the COVID-19 pandemic. Also, [26] illustrated that the fractional operators are superior to their integer-order counterparts for exploring the hidden dynamics of the infection by using the data of India.

Several studies are published recently on the containment of COVID-19 and optimal COVID-19 response. [27] argues that game-theoretic modeling should be used for obtaining the best policy response to control the COVID-19 pandemic. Another study [28] proposes an epidemiological model on a social network to study how the COVID-19 epidemics evolve and how it is contained by different vaccination strategies.

Earlier, we introduced various mathematical modeling and prediction methods that employ Fractional Calculus where we focused on analyzing time series such as children’s physical growth, subscriber numbers of operators, GDP per capita, and compared the results to other modeling approaches such as Fractional Model-1, and Polynomial Models [30], [31]. Results showed that Fractional models had superior results when compared to Polynomial Models and Fractional Model-1 [31], [30]. Most recently, we used Deep Assessment Methodology (DAM), our previously proposed modeling and prediction method that exploits Fractional Calculus, for analyzing COVID-19 [33]. In this paper, the non-locality property of fractional operators, existing research on employing FC for infections, and our previous modeling results with DAM and FC are the foundations of our motivation for analyzing COVID-19 by using FC.

Previously, we proposed Deep Assessment Methodology (DAM), a modeling and prediction method, which exploits Fractional Calculus and Least Squares Method. In [33], we showed that the DAM performs better than Polynomial Method and vanilla Long Short-Term Memory (LSTM) for modeling and prediction, respectively. DAM represents any function by its previous values and its derivative. In this paper, we propose a new approach Deep Assessment Methodology - Second Derivative (DAM-SD) which we
extend the function representation of DAM with second-derivative.

The main objectives of this study are assessing the performance of DAM-SD, modeling daily deaths per new COVID-19 case, and analyzing the correlation between various social and economic indicators with the combat against COVID-19 outbreak. To achieve these goals, we modeled the daily deaths per new case trend of COVID-19 for China, France, Germany, Italy, Spain, Russia, the UK, and the US using our new modeling method, DAM-SD. Later, we defined a performance indicator using the modeled functions to understand how well each country fights against the COVID-19 spread. The performance indicator is formulated based on the assumption that the daily new case curve is a wave with symmetrical left and right-hand sides around the peak day. This indicator is referred to as \( \beta_p \) throughout the paper. Lastly, we investigated possible underlying factors behind the success against COVID-19 outbreak by computing the Pearson correlation between \( \beta_p \) and various indicators related to the capacity of coping with a pandemic, social-economical status, educational and behavioral status, and vulnerabilities.

The organization of this paper is as follows. Section II introduces our new methodology DAM-SD and performance indicator \( \beta_p \). Section III reports the modeling results and values of the performance indicators and analyzes the correlation between \( \beta_p \) and the picked subset of indicators. Lastly, in Section IV, the conclusion is given.

II. OUR APPROACH

A. DEEP ASSESSMENT METHODOLOGY WITH SECOND DERIVATIVE

As aforementioned, we previously proposed a mathematical method for modeling and prediction, DAM, which exploits the first-order derivative of functions and their Taylor series expansion in [33]. DAM represents any time instance of a function \( g(x) \) as a weighted sum of its previous values and its first-order derivatives. Here, we propose including the second-derivative in the function representation as well as the first-order derivative. We refer to this model as DAM-Second Derivative (DAM-SD). Let \( g(x) \) be continuous and differentiable. With DAM-SD, the function \( g(x) \) is represented as shown in (1).

\[
g(x) \approx \sum_{k=1}^{l} \alpha_k g(x-k) + \sum_{k=1}^{l} \beta_k g'(x-k) + \eta_k g''(x-k) \quad (1)
\]

We can express \( g(x) \) as follows using Taylor Series expansion:

\[
g(x) = \sum_{n=0}^{\infty} a_n x^{n\alpha} \quad (2)
\]

Likewise, any previous time instance of \( g(x) \) is written as:

\[
g(x-k) = \sum_{n=0}^{\infty} a_n (x-k)^{n\alpha} \quad (3)
\]

By substituting the Taylor expansion into (1), \( g(x) \) and its derivative \( g'(x) \) are expressed as shown in (4) and (6), respectively.

\[
g(x) \approx \sum_{k=1}^{l} \alpha_k \sum_{n=0}^{M} a_n (x-k)^{n\alpha} + \sum_{k=1}^{l} \beta_k \sum_{n=0}^{M} a_n \alpha(x-k)^{n\alpha-1} + \sum_{k=1}^{l} \gamma_k \sum_{n=0}^{M} a_n \alpha(n\alpha-1)(x-k)^{n\alpha-2} \quad (4)
\]

We can re-write the equation above as:

\[
g(x) \approx \sum_{k=1}^{l} \sum_{n=0}^{M} \tilde{a}_{kn} (x-k)^{n\alpha} + \sum_{k=1}^{l} \sum_{n=0}^{M} \tilde{b}_{kn} \alpha(x-k)^{n\alpha-1} + \sum_{k=1}^{l} \sum_{n=0}^{M} \tilde{c}_{kn} \alpha(n\alpha-1)(x-k)^{n\alpha-2} \quad (5)
\]

Substituting Taylor expansion into derivative \( g'(x) \) yields,

\[
\frac{dg(x)}{dx} \approx \sum_{k=1}^{l} \sum_{n=0}^{M} \tilde{a}_{kn} n\alpha(x-k)^{n\alpha-1} + \sum_{k=1}^{l} \sum_{n=0}^{M} \tilde{b}_{kn} \alpha(n\alpha-1)(x-k)^{n\alpha-2} + \sum_{k=1}^{l} \sum_{n=0}^{M} \tilde{c}_{kn} (n\alpha-1)(n\alpha-2)(x-k)^{n\alpha-3}. \quad (6)
\]

The next step is including the heritability property with fractional calculus. DAM-SD employs Caputo’s description of the fractional derivative as shown in (7).

\[
D^{\gamma} g(x) = \frac{d^n g(x)}{dx^n} = \frac{1}{\Gamma(n\alpha-\gamma)} \int_0^x g^{(j)}(k) \frac{dk}{(x-k)^{\gamma-n\alpha+1}}, \quad (j-1 < \gamma < j) \quad (7)
\]

Here, \( \Gamma \) is the Gamma function and \( \gamma \) suggests the order of the fractional derivative. The \( j \)-th order derivative with respect to \( x \) is referred to as \( g^{(j)} \). This way, the derivative in (5) is generalized by changing the first-order derivative into fractional-order \( \gamma \) as in [29]–[31]. In DAM-SD, the order of derivative, \( j \), is set to 1, and the fractional-order \( \gamma \) changes in the range of \([0,1]\). This study consists of two parts of numerical analysis as explained in Section III. For the first part, it is assumed that function \( f(x) \) represents the daily deaths per daily new cases of COVID-19 pandemic over time which is equal to \( \tilde{b}_{kn} \). For the second part, it is assumed that function \( f(x) \) represents the daily new cases.
of the pandemic. 

\[ f(x) \approx \sum_{k=1}^{l} \sum_{n=0}^{M} a_{kn}(x-k)^{n\alpha} + \sum_{k=0}^{l} \sum_{n=0}^{M} b_{kn}n\alpha(x-k)^{n\alpha-1} \]

+ \sum_{k=0}^{l} \sum_{n=0}^{M} c_{kn}n\alpha(n\alpha - 1)(x-k)^{n\alpha-2} \]

(8)

The function \( f(x) \) that satisfies (9) models any time instant of the discrete daily new COVID-19 dataset similar to the arbitrary continuous \( g(x) \) function is given in (6).

\[ \frac{d^n f(x)}{dx^n} = \sum_{k=1}^{l} \sum_{n=0}^{M} a_{kn}n\alpha(x-k)^{n\alpha-1} \]

+ \sum_{k=1}^{l} \sum_{n=1}^{M} b_{kn}n\alpha(n\alpha - 1)(x-k)^{n\alpha-2} \]

(9)

+ \sum_{k=1}^{l} \sum_{n=1}^{M} c_{kn}n\alpha(n\alpha - 1)(n\alpha - 2)(x-k)^{n\alpha-3} \]

Equation (9) is the fractional-order derivative of function \( f(x) \) where \( x \) denotes the time. Exploiting the fractional-order \( \gamma \) parameter in (9) provides more general and flexible modeling compared to (6) [32]. Compared to the integer counterparts, the fractional derivative has one additional parameter \( \gamma \) to optimize that helps to achieve better optimality. Next, (9) needs to be converted to an algebraic form. Here, we use the Laplace Transform. After taking the inverse Laplace Transform of the transformed algebraic equation, we get the final form of \( f(x) \) as:

\[ f(x, \gamma) \approx f(0) + \sum_{k=1}^{l} \sum_{n=0}^{M} a_{kn}A_{kn}(x, \gamma) \]

+ \sum_{k=1}^{l} \sum_{n=1}^{M} b_{kn}B_{kn}(x, \gamma) + \sum_{k=1}^{l} \sum_{n=1}^{M} c_{kn}C_{kn}(x, \gamma) \]

(10)

where,

\[ A_{kn}(x, \gamma) = \frac{\Gamma(n\alpha + 1)}{\Gamma(n\alpha + \gamma)}(x-k)^{n\alpha+\gamma-1} \]

\[ B_{kn}(x, \gamma) = \frac{\Gamma(n\alpha + 1)}{\Gamma(n\alpha + \gamma - 1)}(x-k)^{n\alpha+\gamma-2} \]

\[ C_{kn}(x, \gamma) = \frac{\Gamma(n\alpha + 1)}{\Gamma(n\alpha + \gamma - 1)}(x-k)^{n\alpha+\gamma-3} \]

(11)

Now, the representation for function \( f(x) \) can be obtained by finding the unknown coefficients \( a_{kn}, b_{kn}, c_{kn} \) and \( f(0) \), and parameters \( M, l, \) and \( \gamma \) by minimizing the squared total error between the real data. The squared total error referred to as \( \epsilon^2_T \), is found by summing the error of each instance in the dataset and calculated as shown in (12):

\[ \epsilon^2_T = \sum_{i=1}^{m}(P_i - f(i, \gamma))^2 \]

(12)

where \( m \) is the total number of instances in the dataset and \( P_i \) and \( f(i) \) denote the real and approximated data instances, respectively. The square of total error, \( \epsilon^2_T \), is minimized with a gradient-based approach and the unknown coefficients are found by solving a linear system of equations. Readers can find detailed explanation in [33].

B. MEASURING THE SUCCESS OF THE FIGHT AGAINST COVID-19

Understanding the performance against the COVID-19 pandemic is crucial for policymakers to pick optimal measurements and take necessary actions to stop further progression. In this section, we define a performance indicator \( \beta_p \) for understanding how well each country copes with the pandemic. We introduced this indicator by assuming the daily new cases curve of a pandemic is a curve with a single symmetrical wave that decays after the peak point with an inverse trend of its rise. By this assumption, the pandemic is restrained after the first wave of the daily new cases curve.

Fig. 1 illustrates both the expected daily new cases curve we assumed to be ideal and the real daily new cases curve, represented by \( f_{cm} \) and \( f_c \), respectively. Horizontal axis refers to time where \( x_0, x_p \) and \( x_t \) represent the initial day of the pandemic, the peak, and today, respectively. The expected curve, \( f_{cm} \), is a symmetric curve around the day of the peak, \( x_t \). Here, \( f_{cm} \) is obtained by modeling the real data starting in the range \([x_0, x_p]\) and mirroring the modeled curve around \( x = x_p \).

We calculate the \( \beta_p \) indicator as shown in (13) as the ratio of area under the expected daily new cases curve to the area under the actual daily new cases curve. We used a similar notation as Fig. 1. The magnitude of \( \beta_p \) is a measure of the success of a country’s fight against the pandemic. A value close to 0 is a sign of an ineffective response.

\[ \beta_p = \frac{\int_{x_0}^{x_p} f_{cm}(x)dx}{\int_{x_0}^{x_p} f_c(x)dx} \]

(13)

Multiple peaks on the daily new case curve produce a larger area under the curve when compared to the ideal expected state. The multiple peaks also produce a \( \beta_p \) closer to 0. On the other hand, the \( \beta_p \) indicator is close to 1 when the actual data curve has symmetrical left and right-hand sides around \( x = x_p \). The magnitude of \( \beta_p \) hints at the overall situation of the pandemic. The greater values of \( \beta_p \) indicate the pandemic is relatively under control. Similarly, smaller values of \( \beta_p \) imply poor performance against COVID-19.

III. NUMERICAL RESULTS

In this section, we provide the modeling results of the daily deaths per case ratio using plain DAM and DAM-SD, compute the performance indicator \( \beta_p \), and discuss the correlation between \( \beta_p \) various social, economic, governmental, educational, and behavioral indicators possibly linked to the outbreak of the pandemic. We acquired the data of daily new cases of COVID-19 from [40]. The proposed approach DAM-SD is implemented on MATLAB.
TABLE I: Modeling errors and optimized $M$, $l$, and $\gamma$ values of daily death per new COVID-19 cases of China, France, Germany, Italy, Spain, Russia, the UK, and the US for DAM and DAM-SD.

| Models | Results | China | France | Germany | Italy | Spain | Russia | UK | US |
|--------|---------|-------|--------|---------|-------|-------|--------|-----|----|
| DAM-SD | MAPE (%) | 4.0975e-08 | 8.8317 | 5.0044 | 4.3832 | 3.9074 | 1.5394 | 4.4907 | 1.7198 |
| $\alpha$ value | 0.7260 | 0.5766 | 0.3649 | 0.9128 | 0.0972 | 0.9938 | 0.4521 | 0.3525 |
| $M$ | 40 | 50 | 50 | 50 | 50 | 40 | 50 | 50 |
| $l$ | 5 | 20 | 19 | 21 | 21 | 20 | 20 | 21 |
| DAM | MAPE (%) | 4.5e-6 | 12.6112 | 6.8411 | 4.7526 | 6.4717 | 1.7756 | 6.2310 | 1.8632 |
| $\alpha$ value | 0.7260 | 0.5766 | 0.3649 | 0.9128 | 0.0972 | 0.9938 | 0.4521 | 0.22 |
| $M$ | 40 | 50 | 50 | 50 | 50 | 40 | 50 | 50 |
| $l$ | 5 | 20 | 19 | 21 | 21 | 20 | 20 | 21 |

FIGURE 1: Illustration of the optimal curve of daily new cases $f_{cm}$ and the real curve of daily cases $f_c$. The $x$-axis represents time. Performance indicator $\beta_p$ is computed as the ratio of area under $f_{cm}$ curve to the area under $f_c$ curve. This indicator takes values in $[0,1]$. A successful response against the pandemic produces a larger $\beta_p$'s.

A. MODELING OF DAILY DEATHS/NEW CASE RATIO

In Section II, briefly, we introduced our new modeling method Deep Assessment Methodology Second Derivative (DAM-SD). In this section, we report the modeling results of the COVID-19 daily deaths per case ratio and assess the performance of DAM-SD by comparing it with DAM. To eliminate the variables of the day of the week, we averaged the weekly data and reported the modeling results of the weekly deaths/new case ratio. We denote the weekly deaths per new case ratio as $r$. For week $i$, the ratio $r$ is computed as:

$$r_i = \frac{\sum_{j=0}^{7} \text{DailyDeath}(j)}{\sum_{j=0}^{7} \text{DailyNewCase}(j)}$$

Daily new cases and daily deaths are obtained from [40]. The dataset starts from the initial day of the pandemic until March 11, 2021. For China, daily deaths are mainly zero after April 30, 2020. Therefore, China is modeled until 30 April, 2020. Other countries are modeled until March 2021. Weeks with no daily new case values are omitted.

In [33], we showed the superiority of DAM to vanilla LSTM and Polynomial method. Here, we compare our new approach DAM-SD to DAM [33]. Table I reports the modeling errors, optimized $M$, $l$ and $\gamma$ values of both DAM and DAM-SD methods for modeling weekly deaths per new COVID-19 case. As shown in the table, the DAM-SD models the deaths per case ratio with 3.7390% average MAPE. For all countries, DAM-SD yields a smaller MAPE and is superior to DAM. Fig. 2 illustrates the DAM-SD modeling curves of the deaths per case ratios. We employed grid search for finding the optimal fractional-order $\gamma$ values. Optimal $\gamma$ values are reported in row 4 and row 8. For both models, $\alpha$’s different from 1, demonstrating the advantage of fractional-order derivatives compared to integer-order counterparts. Both DAM and DAM-SD methods model China with the minimum error. Modeling France yields the largest error for both models with 8.8317% and 12.6112% error rates for DAM-SD and DAM, respectively. For DAM-SD, the largest $\gamma$ is found for Russia as 0.9938 and the smallest value of $\gamma$ is found for Spain as 0.0972. As mentioned in and publicly available at [41]. The countries are selected considering two main factors: virus transmission risks and economic activity. The selected countries have large tourist rates, carry a large number of air passengers, and have a high amount of population. The countries are members of the G-20, except Spain.

We report the results using the Mean Absolute Percentage Error (MAPE) metric computed as follows:

$$\text{MAPE} = \frac{1}{k} \sum_{i=1}^{k} \left| \frac{P(i) - f(i)}{P(i)} \right| \times 100$$

where $k$ is the total number of samples, $P(i)$ is the real value and $f(i)$ is the predicted value for $i^{th}$ sample.
Modeling of daily cases for China. (Jan. 22, 2020 - Apr. 30, 2020)

Modeling of daily cases for France. (Feb. 24, 2020 - March 11, 2021)

Modeling of daily cases for Germany. (Feb. 24, 2020 - March 11, 2021)

Modeling of daily cases for Italy. (Feb. 22, 2020 - March 11, 2021)

Modeling of daily cases for Spain. (Feb. 24, 2020 - March 11, 2021)

Modeling of daily cases for Russia. (Feb. 24, 2020 - March 1, 2021)
Modeling of daily cases for the UK. (Feb. 25 - 2020 - Feb. 26, 2021)

Modeling of daily cases for the US. (Feb. 25 2020 - March 11, 2021)

FIGURE 2: Illustration of modeling curves of Daily New Deaths/Case by Deep Assessment Methodology-Second Derivative for China, France, Germany, Italy, Spain, Russia, UK, and the US. The DAM-SD models the deaths per case ratio with 3.7390\% average MAPE outperforming plain DAM by 1.5678\% MAPE. The best-modeled country is China with 4.0975e-08\% MAPE. Modeling both France and Germany yields larger error rates compared to the other countries due to the large data variance.

| Performance Indicators | Country   | $\beta_p$ |
|------------------------|-----------|-----------|
| China                  | 0.3206    |
| United Kingdom         | 0.0975    |
| Russia                 | 0.0550    |
| Spain                  | 0.0301    |
| Germany                | 0.0191    |
| Italy                  | 0.0164    |
| France                 | 0.0124    |
| United States          | 0.0082    |

TABLE II: Performance indicator values of China, France, Germany, Italy, Spain, Russia, the UK, and the US.

B. ANALYSIS OF COVID-19 RESPONSE

In this section, we assess the effectiveness of the COVID-19 response using the performance indicator $\beta_p$. For computing $\beta_p$, we need to determine the expected curve of the daily new cases of each country. We assumed that the expected daily new cases curve is a single peak curve with symmetric left and right-hand sides. Our purpose is to understand the relative performance benefit of the analyzed countries among themselves. The performance indicator $\beta_p$ measures how close the real data curve is to the ideal daily new cases curve.

Fig. 3 illustrates the real data and the ideal expected curves of daily new cases for China, France, Germany, Italy, Spain, Russia, the UK, and the US. Red dashed vertical lines denote the day with the maximum daily new cases during the first wave, except for China. For China, we treat the second-largest number of daily new cases as the peak. To find the expected curves, we modeled the data from the initial day until the peak day using DAM-SD. Later, we mirror the curve found by modeling around the peak day and obtain a symmetric expected curve. Lastly, we measured the COVID-19 response performance at 11th of March by computing the performance indicator $\beta_p$ as described in section II.

Table III reports the Performance indicators for China, France, Germany, Italy, Spain, Russia, the UK, and the US. The largest $\beta_p$ is produced by China as 0.3206 whereas the lowest is produced as 0.0082 by the US. As mentioned earlier, $\beta_p$ is a measure of how effectively a country combats with COVID-19. A larger $\beta_p$ indicates a better COVID-19 response.
performance. According to the results, the most successful country against the pandemic is China, whereas France, the US, Spain, and the UK are fighting inadequately.

C. ANALYZING POSSIBLE UNDERLYING FACTORS OF THE OUTBREAK

For analyzing possible factors of the outbreak, we picked various indicators linked to the COVID-19 spread and analyzed the Pearson correlations with performance indicator $\beta_p$ by reporting their $p$-values. Indicators consist of Competitiveness, Infrastructure, Institutions, Government’s Long Term Vision, Government’s Response to Change, Public Health Coverage, Efficiency Enhancers, Basic Requirements, number of Long Term Care Beds, Better Life Index, Health Expenditure as a Share of Total Government Income, Mean Years of Education, Critical Thinking, Average Class Size, Student’s Skills, Educational Attainment, The trust Index, Air Pollution, Population Density, Top Passenger Countries by Region, Global Social Mobility, Human Development Index, Human Freedom, Human Democracy, Worker’s Rights, Labor Market, Market Size, Social Capital, Household Spending, Employment, Annual Household Income per Capita, Gini Index and Household Size.

The aforementioned indicators are grouped into four main categories: indicators of coping with the pandemic, social-economical indicators, educational and behavioral indicators, and indicators of vulnerability against the pandemic. Table III, IV, V, and VI reports the indicators and corresponding $p$-values. Indicator data are provided in terms of either score or rank. The values are converted to scores by taking the multiplicative inverse of the data when only ranks are provided. Lower $p$-values indicate strong correlations between the indicator and the performance coefficient. Regarding Long Term Care Beds, Population Health Coverage, Better Life Index, Average Class Size, and Lack of Social Support indicators, values for China or Russia were not available. Therefore we computed correlations by excluding the missing country/countries for these indicators.

Indicators of Coping with the pandemic show strength of governments’ effort and existing structure. Infrastructure indicator measures the quality of transportation and communications infrastructure. Institutions indicate the level of basic security, enforcing property rights, transparency, and efficiency. The government’s Long-Term Vision indicates the capability of carrying out long-term projects. Respond to Change indicator measures to what extent the government responds effectively to the technological, economic, societal, and security changes. Efficiency enhancers is the indicator of goods market and labor market efficiency, higher education and training, technological readiness. Basic requirements indicator considers features related to the macroeconomic environment, health and primary education, institution, and infrastructure status. The better life index allows comparing well-being across countries based on topics including health, education, safety, access to services.

As illustrated in Table III $p$-values for all indicators of

| Indicators of Coping with the Pandemic | $p$ |
|---------------------------------------|----|
| Infrastructure [42]                   | .1937 |
| Institutions [42]                     | .3480 |
| Government’s Long Term Vision [42]    | .6222 |
| Respond to Change [42]                | .9663 |
| Competitiveness [42]                  | .5959 |
| Population Health Coverage [44]       | .4306 |
| Efficiency Enhancers [45]             | .7132 |
| Basic Requirements [45]               | .8648 |
| Long Term Care Beds [46]              | .2014 |
| Better Life Index [43]                | .7873 |
| Health Expenditure as a Share of Total| .3547 |
| Government Income* [47]               | ||

| TABLE III: $p$-values of various indicators of coping with the pandemic and the performance indicator $\beta_p$ for China, France, Germany, Italy, Spain, Russia, the UK, and the US. |

| Social/Economic Indicator | $p$ |
|---------------------------|----|
| Top Passenger Countries by Region [48] | .3422 |
| Global Social Mobility [42] | .1132 |
| Human Development Index [42] ** < .05 | ** < .05 |
| Human Freedom [49] ** < .05 | ** < .05 |
| Human Democracy [50] ** < .05 | ** < .05 |
| Worker’s Rights [42] * < .1 | |
| Labor Market [42] | .5267 |
| Market Size [42] | .1614 |
| Social Capital [42] | .1124 |
| Household Spending [52] | .5490 |
| Employment [53] * | .4647 |
| Annual Household Income per Capita [54] | .2066 |
| GINI Index [55] ** < .05 | |

| TABLE IV: $p$-values of various social and economic indicators and the performance indicator $\beta_p$ for China, France, Germany, Italy, Spain, Russia, the UK, and the US. |
(a) The real and the expected daily new cases curves for China. The day of the peak is Feb-3.

(b) The real and the expected daily new cases curves for France. The day of the peak is April-1.

(c) The real and the expected daily new cases curves for Germany. The day of the peak is March-28.

(d) The real and the expected daily new cases curves for Italy. The day of the peak is March-22.

(e) The real and the expected daily new cases curves for Spain. The day of the peak is March-21.

(f) The real and the expected daily new cases curves for Russia. The day of the peak is April-12.
(g) The real and the expected daily new cases curves for UK. The day of the peak is April-11.

(h) The real and the expected daily new cases curves for the US. The day of the peak is April-25.

FIGURE 3: The real daily cases (blue) and the ideal expected daily cases (yellow) of China, France, Germany, Italy, Spain, Russia, UK, and the US. Red dashed lines indicate the day of the first peak. The performance of COVID-19 response is measured for March 11th by computing the performance indicator $\beta_p$. The largest $\beta_p$ is computed as 0.3206 for China, while the smallest $\beta_p$’s are computed as 0.0124 and 0.0082 for France and the US, respectively.

This category are larger than 0.1. The smaller the $p$-value, the stronger the evidence that one should reject the null hypothesis. By implication, the least significant indicators for the performance against the pandemic are Government’s Respond to Change and Basic Requirements. Better Life Index, Basic Requirements, and Efficiency Enhancers did not find significant in this analysis. The most significant indicator of this category is Infrastructure. Long Term Care Beds is the second most significant indicator under the category.

Table IV reports $p$-values for various social and economic indicators. Social/Economic indicators are related to social and economical features of populations that affect the quality of life. Top passenger countries by region show the number of passengers carried per country. The Social Capital index is the sum of social stability and the well-being of the population. Social Mobility is an assessment of the impact of socio-economic background on an individual’s outcomes in life. The Human Development Index measures average achievement in key aspects of human development such as long and healthy life, being knowledgeable and having a decent quality of living. Worker’s rights measure the level of protection of Labour standards. Labour Market measures the efficiency of labor-employer relations. Market Size is defined as a combination of country size and foreign markets.

Results indicate Human Development Index, Human Freedom, Human Democracy, Worker’s Rights, GINI Index, Trust Index, and Air Pollution indicators are significant for the COVID-19 battle. The global impacts of COVID-19 are highly unpredictable, and decisions concerning the outbreak are made in a rapidly evolving environment. Policymakers may embrace these findings for designing rational strategies against COVID-19 or a further pandemic.

IV. CONCLUSIONS

In this paper, we proposed a new modeling approach Deep Assessment Methodology SD (DAM-SD) and, modeled the weekly deaths per case data of COVID-19 for China, France, Germany, Italy, Russia, Spain, the UK, and the US. We assessed the performance of our new method by comparing it with DAM [33]. Later, we assumed the daily new cases of a pandemic would be a single wave curve, symmetric around its peak, and defined a performance indicator to measure how well each of the 8 countries copes with the ongoing COVID-19 pandemic. Lastly, we investigated the possible underlying factors of the outbreak control by
### TABLE VI: p-values of various educational and behavioral indicators and the performance indicator $\beta_p$ for China, France, Germany, Italy, Spain, Russia, the UK, and the US.

| Educational and behavioral Indicators | p    |
|--------------------------------------|------|
| Mean Years of Education [42]         | .1033|
| Critical Thinking [42]               | .8130|
| Average Class Size [57]              | .9444|
| Student Skills [42]                  | .7069|
| Educational Attainment* [58]         | .2799|
| The Trust Index [60]                 | ** < .05|

### TABLE VII: p-values of various vulnerability indicators and the performance indicator $\beta_p$ for China, France, Germany, Italy, Spain, Russia, the UK, and the US.

| Vulnerability Indicators | p    |
|--------------------------|------|
| Air Pollution [61]       | ** < .05|
| Lack of Social Support [59] | .2728|
| Population Density [62]  | .6266|

Computing Pearson correlation between various indicators of the capability of coping with the pandemic, vulnerability, behavioral, educational, social, and economic status of a country, and the performance indicator, $\beta_p$. We reported p-values to highlight the significance of indicators. Results show that Deep Assessment Methodology SD models the daily new cases of COVID-19 with 3.7930% mean absolute error and outperforms DAM by 1.5678% MAPE. The best-modeled country was China with 4.0975e-08% average error and outperforms DAM by 1.5678% MAPE. The performance indicator is found for China as 0.3206, suggesting the performance of China against the pandemic was relatively poorly against the virus. Computed p-values values to highlight the significance of indicators. Results show that Deep Assessment Methodology SD models the daily new cases of COVID-19 with 3.7930% mean absolute error and outperforms DAM by 1.5678% MAPE. The best-modeled country was China with 4.0975e-08% average error and outperforms DAM by 1.5678% MAPE. The performance indicator is found for China as 0.3206, suggesting the performance of China against the pandemic was superior compared to the others. The smallest performance indicators were found for France and the US as 0.0124 and 0.0082, meaning that France and the US performed relatively poorly against the virus. Computed p-values revealed that Human Development Index, Human Freedom, Human Democracy, Worker’s Rights, GINI Index, Trust Index, and Air Pollution indicators are significant for the fight against the COVID-19 pandemic. In the correlation analysis, Average Class Size, Government’s Long Term Vision, Responsiveness to Change, Better Life Index, and Population Density were the least significant indicators. Long Term Care Beds, Social Capital, and Global Social Mobility indicators are found correlated with the COVID-19 response. Household Spending and Student Skills are found insignificant.

### REFERENCES

[1] L. Jia, K. Li, Y. Jiang, X. Guo, and T. Zhao, “Prediction and analysis of coronavirus disease 2019,” 2020, arXiv:2003.05447. [Online]. Available: http://arxiv.org/abs/2003.05447

[2] P. Namkung, I. Are, J. J. Nieto, D. M. Torres, “Mathematical modeling of COVID-19 transmission dynamics with a case study of Wuhan,” Chaos, Solitons & Fractals, vol. 135, Jun. 2020, Art. no. 109846, doi:10.1016/j.chaos.2020.109846

[3] T. Chakraborty and I. Ghosh, “Real-time forecasts and risk assessment of novel coronavirus (COVID-19) cases: A data-driven analysis,” Chaos, Solitons & Fractals, vol. 135, Jun. 2020, Art. no. 109850, doi:10.1016/j.chaos.2020.109850

[4] H. Liu, C. Strohmeier, G. Menz, and D. Needell, “COVID-19 time-series prediction by joint dictionary learning and online NMF,” 2020, arXiv:2004.09112. [Online]. Available: http://arxiv.org/abs/2004.09112

[5] A. J. Kucharski, T. W. Russell, C. Diamond, Y. Liu, J. Edmunds, S. Funk, R. M. Eggo, F. Sun, M. Jit, J. D. Munday, and N. Davies, “Early dynamics of transmission and control of COVID-19: A mathematical modelling study,” Lancet Infect. Dis., vol. 20, pp. 553–558, Mar. 2020, doi:10.1016/S1473-3099(20)30144-4

[6] J. Schüttler, R. Schlickeiser, F. Schlickeiser, and M. Kröger, “Covid-19 critical thinking indicators revealed that Human Development Index, Human Freedom, People’s Health, and Economic Freedom are significant for the fight against the virus.”

[7] D. Fanelli and F. Piazza, “Analysis and forecast of COVID-19 spreading in China, Italy and France,” Chaos, Solitons & Fractals, vol. 134, p. 109761, May 2020, doi:10.1016/j.chaos.2020.109761

[8] Chaurasia V, Pal S. “COVID-19 Pandemic: ARIMA and Regression Model-Based Worldwide Death Cases Predictions,” SN Comput. Sci. vol. 1, no. 5, pp. 288, Aug. 2020, doi:10.1007/s42979-020-00298-6

[9] Zeng, X., Ghaniem, R., “Dynamics identification and forecasting of COVID-19 by switching Kalman filters,” Comput. Mech., vol. 66, no. 5, pp. 1179–1193, 2020, doi:10.1007/s00466-020-01911-4

[10] G. C. Calafate, C. Novara, and C. Possenti, “A modified SIR model for the COVID-19 contagion in Italy,” 2020, arXiv:2003.14391. [Online]. Available: http://arxiv.org/abs/2003.14391

[11] M. Sinkala, P. Nkhoma, M. Zulu, D. Kafta, R. Tembo, and V. Daka, “The COVID-19 pandemic in Africa: Predictions using the SIR model indicate the cases are falling,” medRxiv, 2020, doi:10.1101/2020.06.01.20118993

[12] J. Wangping, H. Ke, S. Yang, C. Wenzhe, W. Shengshu, Y. Shanshan, W. Jianwei, K. Fuyin, T. Penggang, L. Jing, M. Liu, and H. Yao, “Extended SIR prediction of the epidemic trends of COVID-19 in Italy and compared with Hunan, China,” SSRN Electron. J., May 2020. doi:10.2139/ssrn.3556691

[13] I. Nesteruk, “Statistics based predictions of coronavirus 2019-nCoV spreading in mainland China,” medRxiv, Feb. 2020, doi:10.1101/2020.02.12.20021931

[14] M. Batista, “Estimation of the final size of the coronavirus epidemic by the SIR model,” medRxiv, Feb. 2020, doi:10.1101/2020.02.16.20023605

[15] Chen, Y. C., Lu, P. E., Chang, C. S., & Liu, T. H., “A time-dependent SIR model for COVID-19 with undetectable infected persons,” IEEE Trans. Inf. Tech. Sci., vol. 7, no. 4, pp. 3279-3294, Oct./Dec. 1, 2020, doi:10.1109/TNSRE.2020.3024723

[16] He, S., Peng, Y. & Sun, K., “SEIR modeling of the COVID-19 and its dynamics,” Nonlinear Dyn. vol. 101, no. 3, pp. 1667–1680, Aug. 2020, doi:10.1007/s11071-020-05743-5

[17] K. Sarkar, S. Khajanchi, J. J. Nieto, “Modeling and forecasting the COVID-19 pandemic in India,” Chaos, Solitons & Fractals, vol. 139, Oct. 2020, Art. no. 110049, doi:10.1016/j.chaos.2020.110049

[18] Y. Huang, D. Radenkovic, K. Perez, K. Nadeau, E. Verdin, and D. Furman, “Modeling predictive age-dependent and age-independent symptoms and comorbidities of patients seeking treatment for COVID-19: Model development and validation study,” J. Med. Internet Res., vol. 23, no. 3, Mar. 2021. doi:10.2196/25696

[19] K. L. Atkins, J. A. MacLaren, J. Delgado, L. C. Pilging, C.-L. Koo, G. A. Kuchel, and D. Melzer, “Preexisting comorbidities predicting COVID-19 and mortality in the UK Biobank Community cohort,” J. Gerontol. A, vol. 75, no. 11, pp. 2224–2230, Nov. 2020, doi:10.1093/gerona/glaa183

[20] M. R. Islam, A. Peace, D. Medina, and T. Oraby, “Integer versus fractional order SEIR deterministic and stochastic models of measles,” Int. J. Environ. Res. Public Health, vol. 17, no. 6, p. 1404, Jan. 2020, doi:10.3390/ijerph17061404

[21] F. Sun, M. Jit, J. D. Munday, and N. Davies, “Early dynamics of transmission and control of COVID-19: A mathematical modelling study,” Lancet Infect. Dis., vol. 20, pp. 553–558, Mar. 2020, doi:10.1016/S1473-3099(20)30144-4
ERTÜRLÜ KARAÇUHA graduated from the Electronics and Telecommunication Engineering Department, Istanbul Technical University, in 1986. He received the master’s and Ph.D. degrees from Istanbul Technical University, Çukurova University, and Istanbul University, in 1990, 1992, 1993, and 1996, respectively. From 1988 to 1989, he was a Research and Development Engineer with Teletaş. From 1989 to 1996, he was a Research Assistant with Istanbul Technical University. From 1994 to 2001, he was an Assistant Professor with the Gebze Advanced Technology Institute. From 2002 to 2013, he was the Head of the Tariffs Department and the Vice-President of the Information and Communication Technologies Authority. He was also with the Informatics Institute, Istanbul Technical University, where he was a Professor. He is currently the Dean of the Informatics Institute, Istanbul Technical University.

ESRA ERGÜN received the bachelor’s and the master’s degrees in Electronics and Telecommunications Engineering and Computer Science departments from Istanbul Technical University, in 2017 and 2020, respectively. She is currently pursuing the Ph.D. degree in Computer Science. She is also a Research Assistant with Istanbul Technical University. Her research interests include continual learning, representation learning, and domain adaptation for deep neural networks.

NİSA ÖZGE ÖNAL TUĞRUL graduated from the School of Business, Istanbul University, in 2016. She received the M.Sc. degree from the Department of Applied Informatics, Istanbul Technical University, Turkey, in 2018, where she is currently pursuing the Ph.D. degree with the Department of Applied Informatics, Informatics Institute. She is also a Research Assistant with Istanbul Technical University. Her research interests include computational and applied mathematics.

KAMİL KARAÇUHA was born in Istanbul, Turkey, in 1993. He got his B.Sc. and double major degrees from the Electrical & Electronics and physics departments of the Middle East Technical University (Ankara) in 2017 and 2018, respectively. Then, he obtained Ph.D. in 2021 at Istanbul Technical University. He is working on Electromagnetic Theory, Scattering and Diffraction Problems in Electromagnetics and Antenna design. Currently, he is an associate researcher at Istanbul Technical University.

VASIL TABATADZE was born in Georgia, in 1982. He received his B.Sc., M.Sc., and Ph.D. from the physics department of Tbilisi State University (Tbilisi) in 2003, 2005, and 2009, respectively. His research interests are the computer simulations of electromagnetic radiation and the scattering phenomena, direct and inverse Problems in electrodynamics, and computational electromagnetics. Previously, he was an academic staff of Samtskhe-Javakheti State University and Tbilisi State University, all in Georgia. Currently, he is working as an invited associate professor at Istanbul Technical University.

[62] The World Bank, “Population density,” World Bank Data, 2020. [Online]. Available: https://data.worldbank.org/indicator/EN.POP.DNST?view=chart [Accessed: 26-Oct-2021].