Policy Simulator Methodology

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Model overview

The *COVID-19 Simulator* uses a validated system dynamics (compartment) model to simulate the trajectory of COVID-19 at the state level from March 15, 2020 onwards in the United States. Utilizing the most recent reported data for each state, the *COVID-19 Simulator* considers state-specific disease spread dynamics. Specifically, to reproduce the observed trends and project future cases of COVID-19, time-varying and state-specific effective reproduction numbers are estimated using curve fitting algorithms and fed as inputs into a compartment model. The compartment model is defined using Susceptible, Exposed, Infectious, and Recovered compartments (i.e., SEIR model) with continuous time progression. Model programming and analysis were performed in R (version 3.6.2), and the package "deSolve" was used to solve the ordinary differential equation system.

The *COVID-19 Simulator* evaluates the impact of different non-pharmaceutical intervention strategies to reduce the spread of COVID-19 under varying intensity and timing at the state and national level. For each selected strategy, the model projects and visualizes the total number of deaths from COVID-19, daily count of cases, cumulative number of cases, number of active cases, and the number of hospital beds and intensive care unit (ICU) beds needed for COVID-19 patients.

Model structure

For each state, we developed a system dynamics model, also known as a compartment model,[1] to project the trajectory of the COVID-19 pandemic. Figure 1 shows the schematic of the SEIR model.

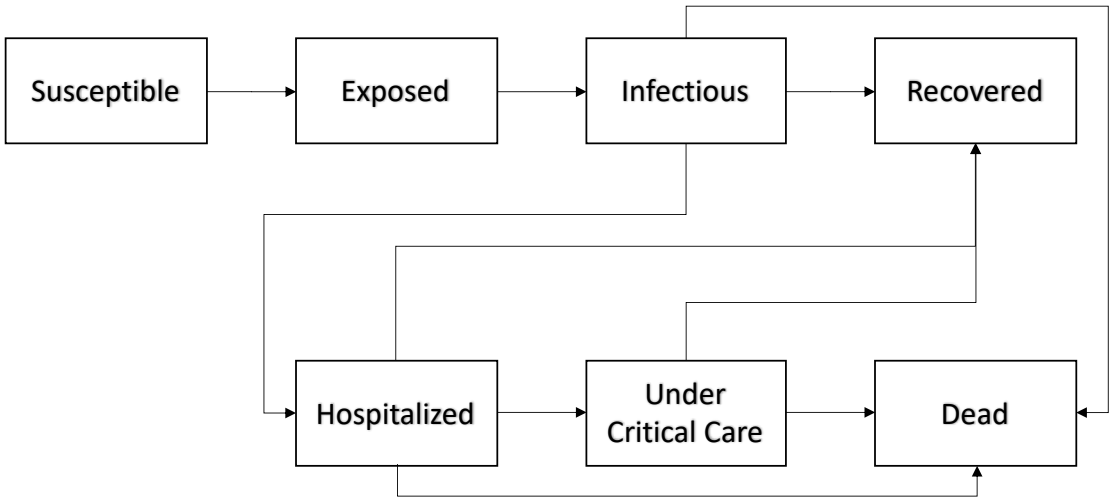

Figure 1. Schematic of SEIR model of COVID-19

The transmission force of the epidemic was controlled by a parameter called the *effective reproduction number* (R_E) of the model. The effective reproduction number is defined as the average number of secondary cases from a single infected individual under a specific level of interventions. To reproduce the observed trends of COVID-19 cases in each state, we allowed the effective reproduction number to be a function of time to account for time-trends and the effects from various interventions (e.g., social

distancing) over time on the spread of COVID-19. Specifically, we considered a stepwise function of time for the value of the reproduction number as defined below:

$$R_E(t) = \begin{cases} R_0, & 0 < t \leq \tau_1, \\ R_E^1, & \tau_1 < t \leq \tau_2, \\ R_E^2, & \tau_2 < t \leq \tau_3, \\ & \dots \\ R_E^{10}, & t > \tau_{10}, \end{cases}$$

where R_0 (*basic reproduction number*; the value under no implemented intervention), $R_E^1, R_E^2, \dots, R_E^{10}$ are the time-varying values of $R_E(t)$, and $\tau_1, \tau_2, \dots, \tau_{10}$ are the time points at which the reproduction number takes a new value, distributed uniformly from time 0 to the present time.

For each state, the spread of COVID-19 is modeled based on the following set of differential equations:

$$\frac{dS}{dt} = -\frac{R_E}{p_I} \cdot \frac{S \cdot I}{S_0}$$
$$\frac{dE}{dt} = \frac{R_E}{p_I} \cdot \frac{S \cdot I}{S_0} - \frac{E}{p_E}$$
$$\frac{dI}{dt} = \frac{E}{p_E} - \frac{I}{p_I}$$

where:

S : Number of susceptible individuals at time *t*,
S_0 : Initial population of the state,
E : Number of exposed (latent) individuals at time *t*,
I : Number of infectious (diagnosed plus undiagnosed) individuals at time *t*,
R_E : Effective reproduction number,
p_I : Duration of the infectiousness period,
p_E : Duration of the exposed (latent) period.

Time progresses continuously in the model. Model programming and analysis was performed in R (version 3.6.2). We used the "deSolve" package to solve the system of ordinary differential equations.[2]

Though there is uncertainty about the possibility of re-infection with COVID-19, we assume that immediate re-infection of COVID-19 is not feasible within the time frame of this study based on expert opinion.[3]

Estimation of total infections from deaths using infection fatality rate

As discussed in the next paragraph, we calibrate to the time series of cumulative total cases (diagnosed plus undiagnosed cases). Since undiagnosed cases are unobserved, we estimate the cumulative total cases on a given day t as the cumulative deaths on day $t + 16$ divided by the age-weighted infection fatality rate (IFR), where IFR is the ratio of confirmed deaths to total COVID-19 infections. We obtain an IFR value of 0.00769 based on the current best estimates from the CDC's COVID-19 Pandemic Planning Scenarios.[16]

The IFR is weighted based on the national population age distribution. The time shift of 16 days is the mean duration between diagnosis and death.[12]

Calibration of unobserved parameters

Because several parameters in the model were not directly observable, we estimated the values of these parameters using a calibration approach. In particular, we calibrated the values of the following parameters by first defining clinically plausible ranges:

- Initial number of infections (range: 0–1,000 cases)
- Latent period duration (range: 4.5–5.8 days)
- Infectious period duration (range: 2.1–7 days)
- Basic reproduction number (R_0) (range: 2.0–2.4 cases)
- Effective reproduction number ($R_E^1, R_E^2, \ldots, R_E^{10}$) (range: 0.1–2.4 cases)

We applied a directed search algorithm, Generalized Simulated Annealing (package "GenSA"),[4] to optimize the values of parameters such that the model outcomes closely matches the cumulative total cases (diagnosed plus undiagnosed). The optimization objective function is the weighted sum of the absolute relative errors between the model output and the calibration target. To account for uncertainty in the calibrated parameter values, we repeat the calibration process 100 times, resulting in 100 unique sets of parameter values. We take the median outcome as point estimates and compute the 95% credible interval at each time point.

Table 1. Key model parameters used in COVID-19 Simulator

Parameter	**Value or range**	**Source**
Basic reproduction number	2.4 cases per infections	[5]
Latent period duration	4.5–5.8 days	[6]
Infectiousness period duration	2.1–7 days	[7]
Effective reproduction number of *Lockdown*	0.3 case per infections	[8]
Effective reproduction number of *Stay Home Orders*	state specific	estimated
Effective reproduction number of *Current Interventions*	state specific	estimated
Effective reproduction number of *Minimal Restriction*	1.68 case per infections	[9]
Infection fatality rate	0.00769	[16]
Hospitalization rate upon diagnosis	state specific	[10]
Rate of hospitalization per death	state specific or 10.02	[10] and [11]
Number of patients in ICU per death	state specific or 3.15	[10] and [11]

Mean hospitalization (non-ICU) duration	8 days	[12]
Mean duration of stay in ICU	10 days	[12]
Mean duration between diagnosis and death	16 days	[12]
Threshold to suppress the epidemic	10 new cases per million inhabitants	assumption

Estimation of diagnosed infections from total infections using diagnosis rate

We predict future diagnosed cases by multiplying total cases by a diagnosis rate. We estimate the future diagnosis rate as the average diagnosis rate in the last 10 days of data.

Back-calculation of hospitalization and ICU patient volume from deaths

We estimated hospitalizations and intensive care unit (ICU) bed usage using a back-calculation approach such that model-predicted past hospitalizations and ICU bed usage matched the reported values from the COVID Tracking Project.[10] We assumed a lag of 16 days between hospitalization and death[12], and that hospitalized patients would use a regular hospital bed for 6 days on average before transitioning to an ICU bed, spending a total of 10 days on average in the hospital (including ICU).[12] For states that did not report past hospitalizations, we used the national averages of 10.02 hospitalizations per death and 3.15 ICU admissions per death.[11]

Intervention strategies

In the current version of the COVID-19 Simulator, we evaluate the impact of different state-level non-pharmaceutical intervention strategies defined by varying intensity and timing as defined below:

1. Minimal restrictions: This strategy assumes that there is minimal social distancing in place to reduce the spread of COVID-19, but there is an assumed level of learned social awareness (handwashing, avoiding close contact when sick, etc.). We assume the $\boldsymbol{R_E}$ of this intervention will be 1.68, which is 30% lower than the basic reproduction number.[9]

2. Current intervention: This strategy captures the level of opening or closing that is currently happening in each state.[13] We used the current value of the $\boldsymbol{R_E}$ from the website rt.live to make future projections under this scenario.[14] Each week, we update the projections of each states based on the current $\boldsymbol{R_E}$ of the state.

3. Stay-at-home orders: This strategy assumes a statewide stay-at-home order. We used rt.live to estimate the $\boldsymbol{R_E}$ for the states who declared stay-at-home orders. For each state, we used the minimum $\boldsymbol{R_E}$ value observed since the beginning of epidemic as the $\boldsymbol{R_E}$ value of the stay-at-home orders for that state.[14]

4. Lockdown: This strategy assumes a complete ban on travel, including cancelling flights and closing inter-state travel and local travel (except for limited time for essential needs such as grocery shopping and picking up prescriptions needs), as has been done in countries such as Italy, China, and India. We used the $\boldsymbol{R_E}$ of 0.3, as estimated in Wuhan after the lockdown of the region.[8]

We simulate different combinations of two sequential interventions, each of which could last for 1–16 weeks. After the interventions, the effective reproduction number is changed to that of the public awareness only scenario ($\boldsymbol{R_E}$ of 1.68).

Assumptions

First, due to uncertainty about the possibility of re-infection with COVID-19, we assumed that immediate re-infection of COVID-19 is not feasible within the time frame of this study (9 months), based on the opinions of several experts.[3] Second, after each intervention, we check whether or not the epidemic is suppressed based on a pre-defined daily case count threshold. This threshold is defined as the number of daily COVID-19 cases in a given state falling below 1 new case per 100,000 people. If this threshold is met, we assume all cases can be isolated and therefore transmission of coronavirus in the community is stopped.

Model outcomes

For each state, the model generates the following outcomes from March 15, 2020 onwards:

- Cumulative deaths from COVID-19 infection
- Daily new cases of COVID-19 infection
- Cumulative cases of COVID-19 infection
- Active cases of COVID-19 infection
- Number of hospital beds needed for COVID-19 patients
- Number of ICU beds needed for COVID-19 patients

Hospital beds Capacity

Data on hospital beds and capacity were extracted from the annual cost reports (fiscal years 2016 through 2019) that hospitals file to the Centers for Medicare & Medicaid Services (CMS). The data from these reports is then made available through CMS's Healthcare Cost Report Information System (HCRIS).[15] Data were analyzed over a period of years to allow for corrections of both missing and inaccurate data. Hospitals that were deemed unlikely to be able to assist greatly in a pandemic were not counted in this analysis (alcohol and drug treatment hospitals, psychiatric hospitals, community mental health hospitals, hospice, religious non-medical hospitals, and skilled nursing facilities and homecare). For Intensive Care Unit (ICU) beds, we also included beds in similar units that could be repurposed as general intensive care in the event of a pandemic (cardiac critical care, burn ICU, and surgical ICU units).

To get the estimated number of beds available to COVID-19 patients, we calculated the average number of available beds (hospital beds or ICU beds) in each hospital on a single day. This was done using reported bed days and reported inpatient days for each type of bed. If the hospital reported bed numbers but did not report bed utilization numbers, we used the state average occupancy rate (calculated from all states that provided this data) to calculate the estimated number of beds available to coronavirus patients.

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