# A New Model for COVID-19 Propagation and Simulating Response Strategies

By Franz Busse | fdbusse@gmail.com | 29 March 2020

## 1 Abstract

This paper has three goals: 1) introduce a model of the spread, 2) using the model to identify the parameters defining the transmission and severity of COVID-19, and 3) use the model to explore mitigation alternatives. The paper uses data from JHU CSSE, and focuses on death rates rather than confirmed cases. A model derived from the standard SIR epidemiological model including exposure and quarantine "compartments" is presented, but includes asymptomatic and isolation states as well, to better capture real disease dynamics. Using this data and model, it is shown that current model parameters underestimate the severity of COVID-19. By fitting model parameters to the observed death rates in 8 countries, it is found that COVID-19 has an R0 value of 4-5, and death rate of 0.4% (with an expected CFR of about 4%). Unmitigated, this would lead to a 3% total population fatality rate, which would be worse than the Spanish Flu of 1918 (which was 2.5%). Using the model, an initial study is conducted looking at the impact of varying contact rates of symptomatic and asymptomatic populations. It is shown that by reducing asymptomatic contact by 50% and symptomatic by 90%, COVID-19 should be controllable to levels like the seasonal flu.

## 2 Introduction

There is significant concern world-wide about the spread and impact of COVID-19. Governments are taking drastic actions to help curb its impact. There is no clear end in sight for these measures, and they are driving the entire globe into economic depression and will have immense long-term effects on health and well-being of the global population.

It is critical to "right-size" the response to the crisis. To do this, it is important to understand the disease and its severity, as well as the parameters regarding its spread and lethality. With these understood, a more targeted response can be proposed.

## 3 SEACQRD Model

A standard way of modeling disease is by defining "compartments" of the population as Susceptible, Infectious, and Recovered (SIR). Literature also has more advanced models beyond the standard SIR model, which include other various states (or "compartments") of the population.[1][2] This has also been expanded upon in a SEIR model, and applied to COVID by Wu et al, where the "E" represents "exposed."[3]

For COVID-19, one of the key challenges includes an asymptomatic contagious period.[4] By explicitly compartmentalizing that state, different contact rates can be explored for that stage. Most countries also try to isolate symptomatic individuals, which can greatly change the contact rate as well, which also justifies a new compartment.

In the popular media, there is some obfuscation of key disease behavior parameters (for example, confusing incubation period and latent period). This model is focused on disease spread and lethality, which is not the same as symptoms. To clarify, Figure 1 illustrates the different timeline terms used in this paper.

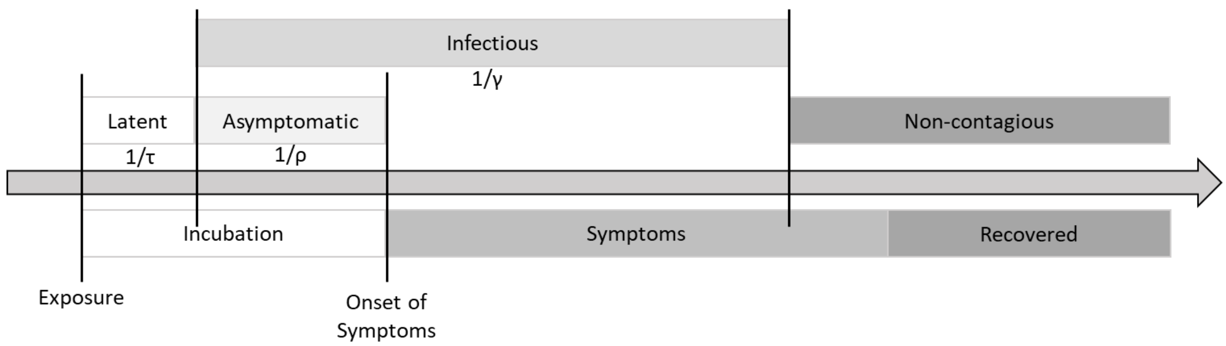


*Figure 1: Timeline Definitions*

For this work, a model will be used to capture additional dynamics by including the exposed state (time between exposure and contagiousness) as well as a quarantine state (when contact rate goes effectively to zero). This model, shown in Figure 2, is named SEACQRD, rather than SEIR, for Susceptible – Exposed – Asymptotic – Contagious – Quarantined – Recovered – Dead.[5] The Dead compartment simply assists in tracking that trend. The model also includes a birth rate $\Lambda$ and mortality rates, $\mu$, for each compartment, but are currently set to 0 for this work. The added states A and Q also enable experimenting with containment strategies.

[1] Blackwood, Childs, "An introduction to compartmental modeling for the budding infectious disease modeler," Journal Letters in Biomathematics, Vol. 5, 2018, Issue 1, 23 Mar 2018
[2] Lotfi, Maziane, Hattaf, Yousfi, "Partial Differential Equations of an Epidemic Model with Spatial Diffusion," International Journal of Partial Differential Equations, Vol. 2014, Article ID 186437
[3] Wu, Leung, Leung, "Nowcasting and forecasting the potential domestic and international spread of the 2019-nCoV outbreak originating in Wuhan, China: a modelling study," The Lancet, Vol. 395, Issue 10225, P689-697, Feb 29, 2020.
[4] Anderson, Heesterbeek, Klinkenberg, Hollingsworth, "How will country-based mitigation measures influence the course of the COVID-19 epidemic?" The Lancet, Vol. 395, Mar. 21, 2020.
[5] Contagious is a misleading name, but "symptomatic" would reuse "S," and quarantine could also more correctly been labelled "isolated," but reused "I."

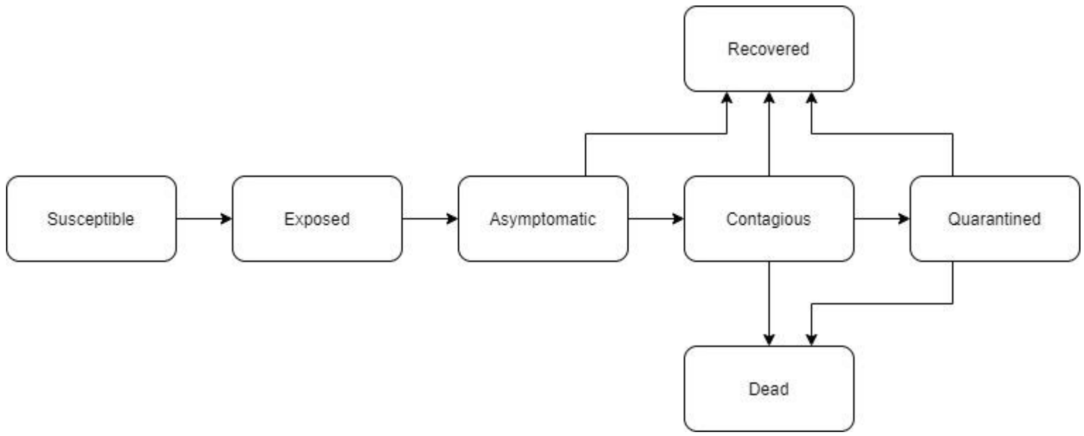


*Figure 2: SEAQRD Compartment Model Diagram*

The model has several parameters, including:

- $\beta$: the contact rate, defined as the percentage of the susceptible infected per infected person per day. This includes both transmission likelihood as well as social interactions.
- $\tau$: the contagion rate, defined as the percentage of those exposed who become contagious per day, or the reciprocal of the latent period.
- ρ: the symptomatic rate, defined as the percentage of those asymptomatic who begin to express symptoms per day.
- ξ: the quarantine rate, defined as the percentage of symptomatic contagious population put into isolation each day.
- $\gamma$: the recovery rate, defined as the percentage of infectious people (symptomatic, asymptomatic, and isolated) who recover each day, or the reciprocal of the total infectious period.
- $\delta$: the death rate, defined as the percentage of infected who die each day.

The model allows these rates to be different for the different compartments, e.g., the contact rate for asymptomatic and symptomatic populations may be different. The well-known $R_0$ term is defined as $R_0 = \beta/\gamma$, or the number of people infected per day times the average number of days one is contagious.

The governing differential equations are:

$$\frac{dS}{dt} = \Lambda - \mu S - [\beta_A SA + \beta_C SC + \beta_Q SQ]$$

$$\frac{dE}{dt} = [\beta_A SA + \beta_C SC + \beta_Q SQ] - \tau E - \mu E$$

$$\frac{dA}{dt} = \tau E - \gamma_A A - \delta_A A - \rho A - \mu A$$

$$\frac{dC}{dt} = \rho A - \gamma_C C - \delta_c C - \xi C - \mu C$$

$$\frac{dQ}{dt} = \xi C - \gamma_Q Q - \delta_Q Q - \mu Q$$

$$\frac{dR}{dt} = \gamma_A A + \gamma_C C + \gamma_Q Q - \mu R$$

$$\frac{dD}{dt} = \delta_A A + \delta_C C + \delta_Q Q$$

The compartments are all normalized values so they represent a proportion of the total population. When the birth rate $\Lambda$ and the natural death rate $\mu$ are 0, then S+E+A+C+Q+R+D = 1. An example of the model output for a contagious disease, where it runs its course without any change in population behavior, as modeled, is shown in Figure 3. For this work, it is assumed there is no quarantine leakage ($\beta_Q = 0$), the recovery rate is the same for all compartments ($\gamma_A = \gamma_C = \gamma_Q$), the asymptomatic death rate is zero ($\delta_A = 0$), and that the contagious symptomatic and quarantined death rates are equal ($\delta_C = \delta_Q$).

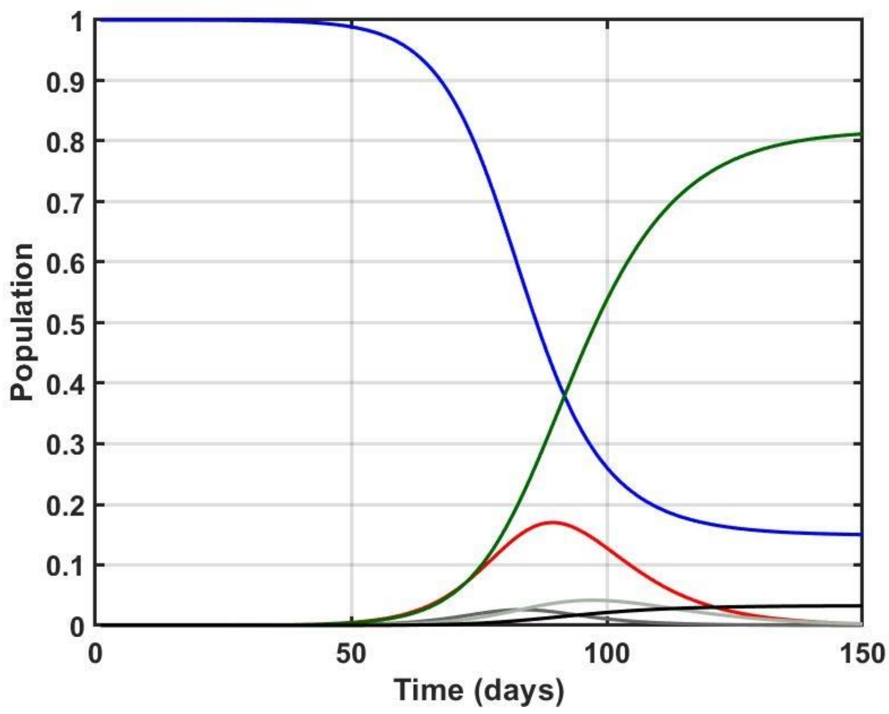


*Figure 3: Example of SEACQRD Model Output*

In this example, the overall Crude Population Fatality Rate would be 3.25%, which would make it worse than the Spanish Flu of 1918. The blue line shows the susceptible population, the green line is the recovered population, the red line is the contagious population, the dark grey the quarantined number, and the light grey those exposed (but not yet contagious). The black line is those that are dead. Of course, this model does not account for changes in behavior; China demonstrated the ability to go from a “Spanish Flu” to less than a “Seasonal Flu” event, as seen in the data below.

# 4 Anchoring Model Parameters

The data from [JHU Center for System Science and Engineering (CSSE) on Github](), retrieved on March 25, 2020, 5 PM MDT. 2 data sets are used from this repository: Confirmed Cases and Deaths. Confirmed Cases will be greatly affected by the amount of testing; also, presumably, if symptoms are mild, then it is less likely one will be tested. Therefore, it should be expected that Confirmed Cases may be under-reported, especially if it is a less-severe illness. Therefore, the Case Fatality Rate (CFR), which is deaths per confirmed cases is a worrisome metric because this denominator is so uncertain. Deaths are presumed to be a more reliable number, though some critics point out that even the death count may be unreliable as different officials may attribute a death to Corona in different ways. The other problem with deaths is it takes on the order of 2 weeks before one dies (and often longer); therefore it is a lagging indicator. Nevertheless, the population fatality ratio (PFR) is still deemed to be a better overall metric; with the caveats that it is lagging and also because it assumes a uniform distribution across the population denominator.

Figure 4 shows cumulative deaths divided by the country population. This metric combines transmission as well as lethality of the disease. Hubei is shown in place of all of China, because that is a more concentrated case, and more severe (not diluted by the total Chinese population).

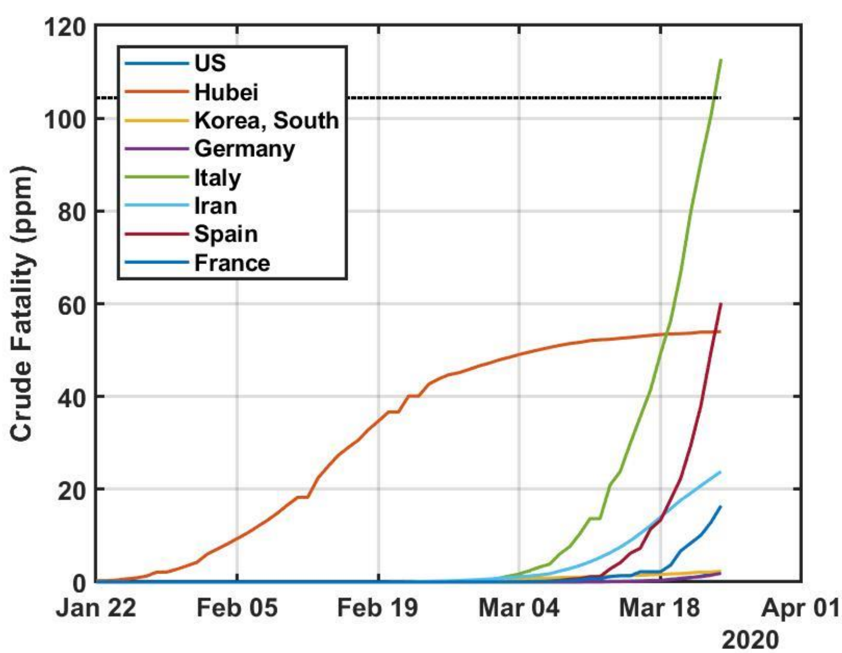


*Figure 4: Population Fatality Rate ("Crude") for 8 Countries*

The figure explicitly shows the narrative that the world knows: Hubei is containing the outbreak; Italy is of deep concern, with a greater growth rate than Hubei ever had, and no signs of slowing.

Iran and Spain are a little behind Italy, but on the same trend. South Korea is exemplary in their containment, and the US and Germany are still relatively early, so hard to see on this scale.

The dashed black line indicates the PFR of the US seasonal flu (about 34K die per year from the flu in the United States). Based on this chart, it appears that when controlled the way China controlled the outbreak, Corona is half as lethal as the seasonal flu. On the other hand, Italy was less controlled, leading to a much higher lethality (we won't know just how bad until the trend "bends down").

As of March 28, most literature places COVID-19 $R_0$ at around 2-3, with a death rate ($\delta$) ~0.1%, and a two week infectious period ($\gamma$=1/14).[6][7] However, if we use these parameters in the model, we see the following result for the US shown in Figure 5.

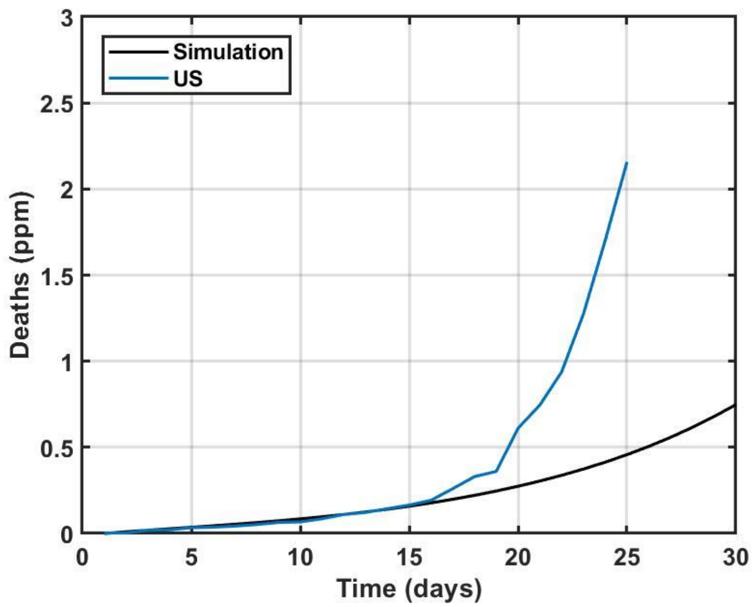


*Figure 5: Current $R_0$ model values do not fit observed COVID fatalities*

These values seem to underestimate the severity of the disease observed in the actual data. This same underestimation was also observed for all of the other countries (except South Korea).

Therefore, a search process was undertaken to find the parameters to best match the various country profiles. Parameters related to the disease were assumed to be constant globally, while parameters related to behavior (specifically, b, the contact rate) were varied from country to country.

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[6] Li, Guan, Wu, Wang, Zhou, Tong,Ren, Leung, Lau, Wong, Xing, Xiang, et al, "Early Transmission Dynamics in Wuhan, China, of Novel Coronavirus—Infected Pneumonia," New England Journal of Medicine, Jan 29, 2020.

[7] Ciarochi, "How COVID-19 and Other Infectious Diseases Spread: Mathematical Modeling," Mar 12, 2020, https://triplebyte.com/blog/modeling-infectious-diseases#fn1

The parameters used to generate these simulation curves are as follows. General parameters used for all countries:

- $\rho = 1/3$ (or an asymptomatic infectious period of 3 days)
- $\tau = 0.5$ (or a latent period of 2 days)
- $\gamma = 1/10$ (or a 10-day infectious period)
- $\delta_C = 0.004$ (which would result in a CFR of about 4%)

For individual countries, the conditions are set to begin with the first reported COVID-19 death (with the exception of Hubei). Note that because $\gamma$ is 0.1, the $R_0$ value is simply ten times the $\beta$ values shown in the table.

*Table 1: Model Parameters for 8 Countries*

| Country | Start date | Seed infection | $\beta_C$ | $\beta_A$ | $\xi$ |
|---|---|---|---|---|---|
| **US** | Feb 29 | 425 | 5 | 5 | 0 |
| **Hubei** | Jan 22 | 8,204 | 2.5 | 2.5 | 0 |
| **South Korea** | Feb 20 | 669 | 2 | 2 | 0.06 |
| **Germany** | Mar 9 | 745 | 5 | 5 | 0 |
| **Italy** | Feb 21 | 2,298 | 3.8 | 4.5 | 0 |
| **Iran** | Feb 19 | 812 | 4 | 4 | 0 |
| **Spain** | Mar 3 | 1,633 | 6 | 6.5 | 0 |
| **France** | Feb 15 | 34 | 0.45 | 0.5 | 0 |

Figure 6 shows the model result for each of the eight countries. The blue line shows the actual data. The black line shows the simulated trend, using the parameters in Table 1.

It should be noted that some countries (Hubei, Italy, Iran) show a divergence after about 20 days with the real data trending below the simulation. This is expected and represents the beginning of response efforts to take effect; generally reducing the contact rate. South Korea includes a quarantine state already, even in this early phase, as a way to emulate the flat curve seen in the real data.

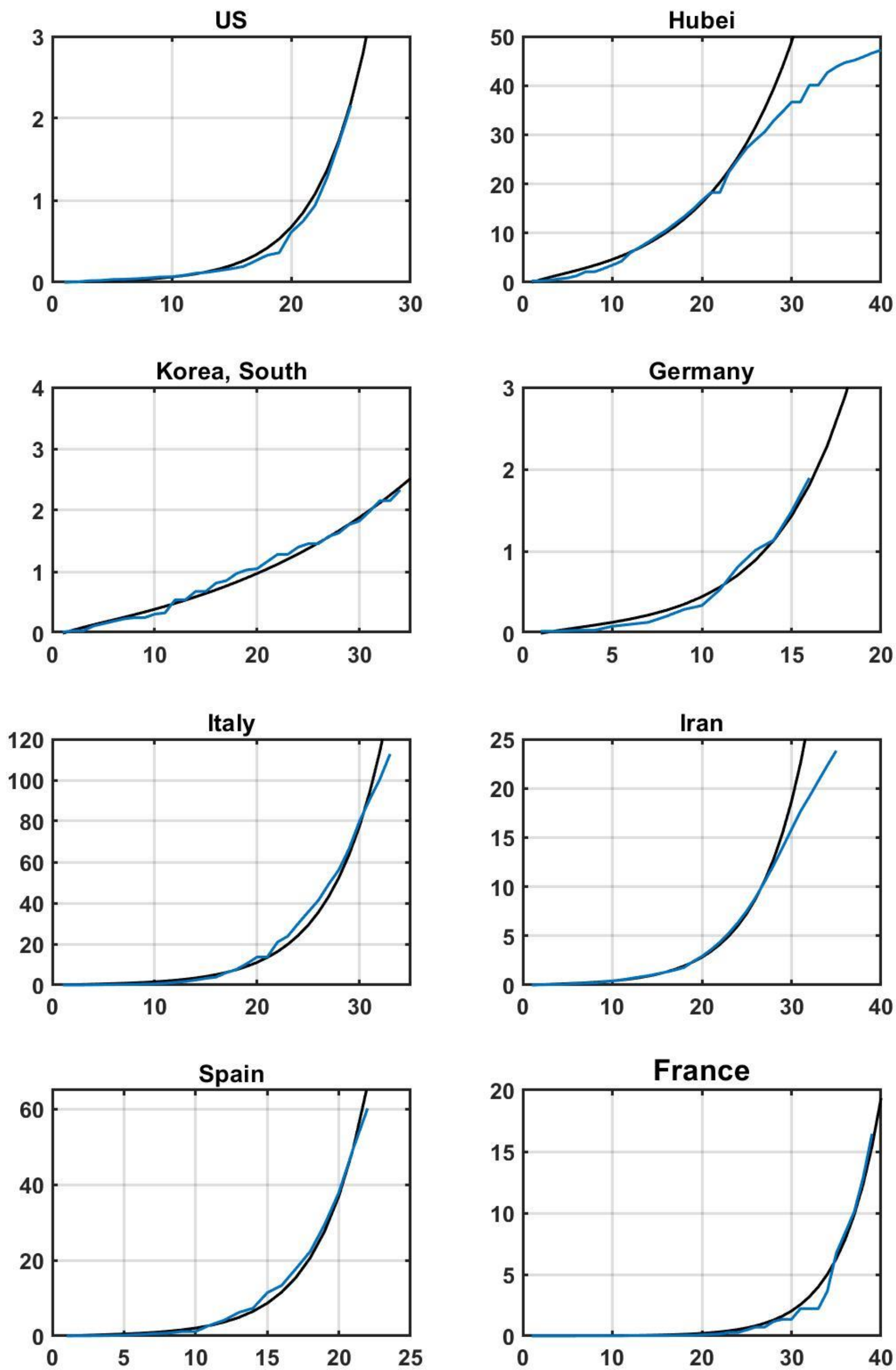


*Figure 6: Model fits for 8 countries using updated parameters*

The fact that the parameters are so common across the different countries, at least for these early pre-response stages, provides some confidence in their accuracy.

# 5 Response Alternatives

Public media has advanced the concept of "flattening the curve" of the epidemic. The model easily demonstrates this goal. By simply changing the contact rate from $\beta = 2.5$ to $\beta_C = 1.5$ and $\beta_A = 2.0$, we see the resulting contagious propagation.

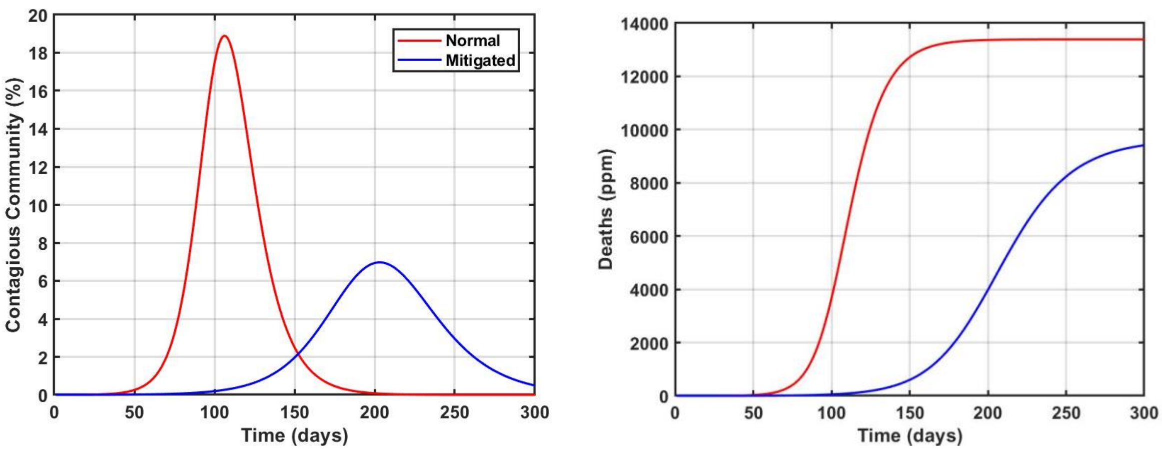


*Figure 7: Notional example of "flattening the curve" by reducing contact rate*

The model can be used to explore a variety of response strategies. As an example, consider the degree of beta contact reduction during the asymptomatic and symptomatic phases.

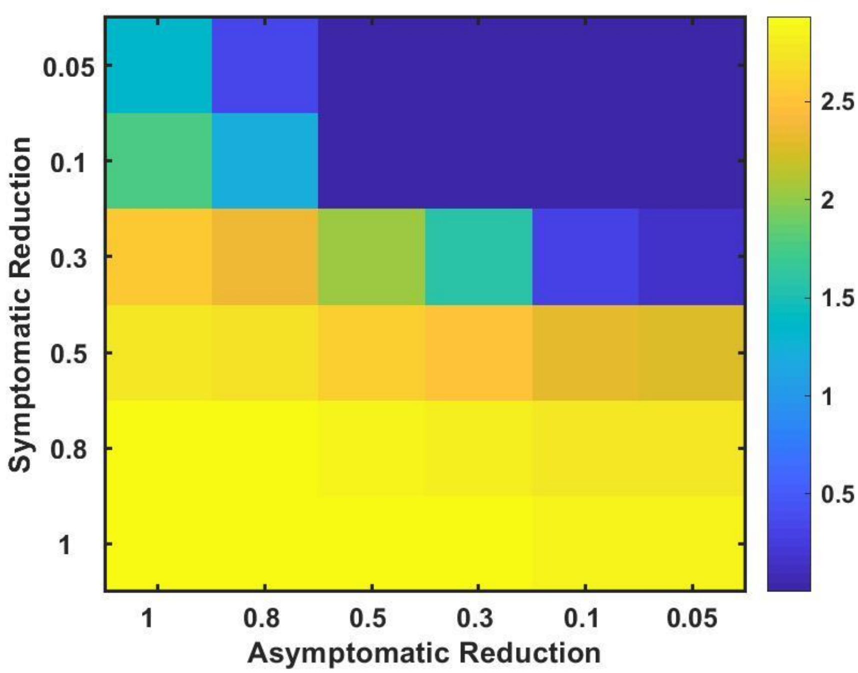


*Figure 8: Impact of contact rate reduction both symptomatic and asymptomatic phases*

In Figure 8 we see that if action is only taken to reduce β for symptomatic population, even with a reduction to 0.05 the current levels (reducing contacts to 1/20 current levels), that without any change to asymptomatic contacts, at best the PFR can go from 2.93% to 1.36%, which is still too high.

It really requires reduction of $\beta_A$ to at least 50% current levels, and then reducing $\beta_C$ to 10% current levels to achieve even close to seasonal flu levels of PFR. Fortunately, it is easier to reduce contact rates for individuals with symptoms through self-isolation than it is to reduce asymptomatic contacts, which require limitations on the entire population.

# 6 Conclusion

A new model is presented that can capture essential dynamics of epidemics, by introducing new compartments to the traditional SIR or SEIR models. This model shows that, when compared to actual death data from 8 countries, that the R0 parameter is likely much higher than many public reports indicate, which suggest that COVID-19 may be even more deadly than many estimate.

The model also provides a tool to explore alternative mitigation strategies. For example, it is shown that a combination of reducing contact rates for the asymptomatic population by 50% and symptomatic population to 10% current levels, can control the virus to levels similar to the seasonal flu.

Future work includes looking at duration of mitigation strategies, quarantine rates, and other explorations to find additional recommendations for public health officials. The input and output travel between locations will also be added, to not only improve the location dynamics, but also spread between locations.