Towards a COVID-19 model to inform healthcare policy

School of Electrical & Information Engineering
University of the Witwatersrand
Private Bag 3, 2050
Johannesburg, South Africa
University of the Witwatersrand

Marindi Kaddy (1416262)
Supervisor: Prof. Anton van Wyk
Co-Supervisor: Dr. Yin-Chi Chan

ELEN4011A: Information Engineering Design II
10 August 2021

Abstract

COVID-19 is a disease caused by the SARS-CoV-2 virus which was first reported in Wuhan, China, at the end of 2019. Since then, COVID-19 has spread across the world resulting in the ongoing pandemic. This paper identifies two COVID-19 tipping points: COVID-19 (re-)emergent wave outbreaks and exceeding hospital capacity. Early warning signal (EWS) is used for predicting an approaching (re-)emerging wave outbreaks tipping point using three indicators: lag-1 autocorrelation and variance and index of dispersion. Effective reproduction number (R_t) is used alongside the three indicators as a confirmation signal. The index of dispersion and variance is found to be the most effective EWS when doing an empirical analysis using Italy and South African COVID-19 real-time data. The indicators provides at least more than 20 days EWS before (re-)emergent of COVID-19 wave. SEI[H]RD compartmental model is used for COVID-19 modeling, that expands a hospital compartment [H] into hospitals regular beds, ICU beds, and ventilator beds. This enables a thorough evaluation of the hospitals capacity.

Contents

1 Introduction

At the end of 2019, the first case of a new severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) was reported in Wuhan, China [1]. SARS-CoV-2 is a virus that causes a very contagious coronavirus disease 2019 (COVID-19), which has since spread across the world resulting in the ongoing pandemic. The World Health Organization (WHO) has reported 216,229,741 Covid-19 confirmed cases and 4,496,681 deaths due to Covid-19 by the 25 of August 2021 [3]. One of the challenges countries faces when fighting COVID-19 is surprising outbreaks that occur without any warning signal. COVID-19 outbreaks often happen so rapidly, resulting in a number of people who need mild and serious medical attention exceeding a healthcare capacity. When an infected individual cannot get the medical attention they need, it amplifies the mortality rate. In order to fight COVID-19 effectively, a government needs concise indicators to identify the critical transmission (tipping points) leading to a new COVID-19 wave and a fairly accurate epidemiological model that can predict the infection numbers and the severity of the upcoming wave.

This paper presents a design project to identify COVID-19 critical tipping points leading to a catastrophic failure that is costly in terms of human lives, and economic hardship. In addition, it implements early warning signals (EWS) based on the phenomenon of critical slowing down (CSD) alongside effective reproduction number (R_t) for predicting an approaching critical tipping point. SEI[H]DR compartment model is used to predict COVID-19 numbers and to assess COVID-19 hospital demand.

The rest of this paper is organised as follows: First, it looks at two tipping points of interest. Then, it evaluates a different literature review related to COVID-19 modeling, EWS, and R_t. Then, it presents a compartment model design through iterative steps. Thereafter, it evaluates the model in a simulation-based study, and, test the effectiveness of the EWS for a (re-)emergent wave tipping point in a different empirical condition study. Then followed by an evaluation of the economic, environmental, and social impact and sustainability of the project. Lastly, conclude the paper.

2 Background

2.1 Tipping points

COVID-19 poses different tipping points that require swift intervention in order to avoid a catastrophic failure that can result in a severe loss of human life, economic suffering, and strain in human emotion. There are two tipping points of interest that will be investigated in this project: (re-)emergent of new wave and COVID-19 patients exceeding healthcare system capacity.

(Re-)emergent of a COVID-19 wave is one of the critical transitions that government should be on the lookout for. COVID-19 outbreaks often required intensive measures to bring the spread under control such as a high-level lockdown. Lockdown measure bares a short to long team economical suffering to those who live in poverty and causes enormous job losses. In addition, lockdown can leave some people depressed due to limited social

interaction.
If a COVID-19 outbreak is not handled timely and adequate measures are not applied, the outbreak can lead to the second tipping point, acceding healthcare capacity. COVID-19 has put even some of the best healthcare systems in the world under intensive stress. Once the healthcare threshold is reached, most people can not get the medical attention they need (ICU beds and ventilators), which results in numerous death as evident in countries like India, Italy, and Brazil [12, 13].

3 Related Study

3.1 On Covid-19

In an early stage of a disease when there is a very limited amount of data, the epidemiological model can provide useful information to understand the dynamic behavior of the disease. There are different epidemiological models that build upon Kermack and McKendrick compartment models to describe the number or proportion of individuals within a population in various compartments using a set of differential equations [8]. One of the simplest compartment models for a disease in which an infected individual die or gain immunity after recovering from the disease is a susceptible-infected-recovered (SIR) model [4]. Several studies have proven that COVID-19 has a latent incubation period before the infection, which is incorporated by adding an exposed (E) compartment [14, 15]. [8] presents SEIHR-model that introduces hospital (H) compartment, which treats all hospitalized individuals as homogeneous subjected to the same recovery and mortality rate. Hospitalized individuals can not continue spreading the disease because of the isolation. In addition to the H compartment, [8] also model the effect of migration to and from each of the various compartments in the SEIHR model. Hospitalized COVID-19 might show mild, severe, or critical symptoms that require medical attention. [9] Presents an age-structured SEIR model that is extended by adding the inner working of the hospital as compartments such as testing, normal hospital beds, severe (ICU), and critical (ventilator) condition wards. [9] model allows explicit modeling of the health care capacity.

3.2 Early Warning Signals

[5] Presents generic early warning signals (EWS) that may indicate if a complex system is approaching a critical threshold. The EWS presented in [5] apply to most complex systems regardless of the difference in the details of each system. In a model study, a tipping point occurs at a bifurcation which marks the shift of a system from a state equilibrium to an acyclic and chaotic tractor. There are leading several indicators that can highlight if a system is approaching catastrophic bifurcation which follows under a family of critical slowing down (CSD). CSD means that when a system is approaching a critical transition, the system recovery is increasingly slow from small perturbations [5]. One of the approaches to measure an increasingly slowing down of system recovery is an increase in auto-correlation, particularly lag-1 autocorrelation [5]. The increase in auto-correlation can be observed long before the system reaches critical transition, this will allow people in power to act timely before catastrophic failure of the system. An increase in variance is another indicator of critical slowing down that signals an approaching tipping point. In addition to the CSD indicator

mention in [5], [6] Presents two additional EWS indicators, namely: coefficient of variation and index of dispersion. Out of four EWS indicators, the variance, auto-correlation, and index of dispersion were found to be more effective in detecting a (re-)emergent of a disease [6].

3.3 Effective reproduction number as EWS

One of the key parameters for describing a virus spread is an effective reproduction number, R_t, defined as a number of secondary cases caused by a typical infected person at a given time, t [6]. R_t differs from a basic reproduction number, R_0, which is used in an early stage of the disease spread to estimate new secondary cases caused by the presence of one infection in a well-mixed population; fully susceptible [7]. A reproduction number R is a threshold parameter in which if R is less than 1, there will be a limited number of secondary cases leading to the disease dying out. If R is greater than 1, the disease will spread; possibly resulting in an endemic or a pandemic [6]. R changes over time due to a lot of factors such as vaccination, social distancing, lockdown, super-spreading events, and wearing masks. R_t is a useful estimate based on real data which gives good insight into how the disease is spreading over time [7]. R_t goes over one before the wave (re-)emerges and can be used to gauge if the wave has reached the peak or still prevailing [6]. [6] has presented empirical and simulation base study which has proven the existence of critical slowing down indicator before R_t approaches 1, implying (re-)emergent of the disease. Thus, R_t can be used as an EWS in conjunction with CSD [6].

4 Contribution of this paper

This paper presents a compartment model, SEI[H]RD that builds on top of the model present in [8]. The model design starts by introducing a death (D) compartment that allows the breaking down of the removed compartment into two compartments: recovered (R) and D compartment. The E compartment takes the same consideration as in [8], which states that an individual in E is asymptomatic; capable of spreading the disease, and might recover before getting transferred to the I compartment. The I compartment consists of individuals that are tested positive for COVID-19, who are less infectious than E individuals since they are most likely to quarantine after being tested positive.

Some I individuals can recover without needing hospital care while some of them will get admitted to the hospital. The hospitalized individuals can not infect susceptible group because of the strict isolation hospital environment. The model design adapts a simple vision of the approach taken in [9] by modeling a [H] compartment into three different compartments: those showing mild symptoms, severe (ICU beds), and critical (ventilators) conditions. This approach gives detailed modeling of hospital resources for evaluating if a country or region might run out of ICU and ventilation Beds.

In addition, this paper evaluates three EWS indicators based on CSD phenomena that can be used to predict COVID-19 outbreak which is costly in terms of human lives and emotion and economical hardship. Out of three indicators, variance and index of dispersion indicators are found to be effective in predicting the outbreak, while lag-1 autocorrelation is found to be inconclusive.

5 Modeling

5.1 The SEIR Model

The epidemiological model design is initiated from the simplest compartment model that can capture the COVID-19 transmission process, SEIR-model. The individuals within the compartments are assumed to be homogeneous [4], meaning that they are treated the same without considering their age group, pre-existing health conditions and they can equally interact with each other. SEIR-model has four compartments, namely: Susceptible (S), exposed (E), infected (I), and removed (R) compartment. The S compartment is the population that has not been infected by the disease but is prone to infection. E compartment is composed of individuals who have contaminated the disease but are yet asymptomatic and can still transmit the disease. E can recover or die without exhibiting any symptoms. I compartment holds symptomatic individuals (or tested positive) and can still transmit the disease at a lower rate than the E compartment since I individuals are likely to quarantine. R compartment consists of the individuals who are removed from the S compartment when they died or recover and assumed to gain full immunity to the disease after recovering.

5.1.1 SEIR-model formulation

The parameter in equation (1 - 4) are defined in Table 1 below. S(t), E(t), I(t) and R(t) are the number of individual per each compartment at time t such that $S(t)+E(t)+I(t)+R(t) = N(t)$. Where $N(t)$ is a constant population size. Therefore, $\dot{S} + \dot{E} + \dot{E} + \dot{R} = 0$

$$\dot{S} = \left[\alpha k \frac{I}{N} + \eta k \frac{E}{N}\right] S(t) \tag{1}$$

$$\dot{E} = \left[\alpha k \frac{I}{N} + \eta k \frac{E}{N}\right] S(t) - \beta E(t) - \delta_E E(t) \tag{2}$$

$$\dot{I} = \beta E(t) - \delta_I I(t) \tag{3}$$

$$\dot{R} = \delta_E E(t) + \delta_I I(t) \tag{4}$$

Where k is the average number of people a susceptible person interacts with per day. The probability of infection posed by E and I person on susceptible is denoted by α and η. $\frac{1}{\beta}$ is an average number of days for E individual to become I. E person has $\frac{\delta_E}{\delta_E+\beta}$ chance to recover before transferred to I compartment. The average number of days for an infected person to recover or die is $\frac{1}{\delta_I}$.

5.2 The SEIHRD Model

Although the SEIR model can be used to study the dynamic of the disease, it fails to capture a hospitalization demand and death number due to the disease. H and D compartments

Table 1: *Meaning of parameters in the SEIHR model [8].*

Parameters	meaning
η	Transmission rate of exposed (asymptomatic) individual
α	Transmission rate of infected (symptomatic) individual
β	Rate of becoming symptomatic after the latent period
γ	Hospitalization rate of infected people
δ_I	Rate of recovery of infected individual
δ_E	Rate of recovery of exposed individual
δ_H	Rate of recovery of hospitalized infected individual
θ	Mortality rate of the hospitalized individual

are crucial for studying the hospital capacity critical threshold and the death severity as the result of exceeding it. SEIR-model is modified by adding H compartment as done in reference [8] but omit the effect of migration and also adding D compartment to derive SEIHRD model depicted in figure 1 below. This solution explicitly separates D number and recovery (R) instead of adding them up as removed compartment. This model assumes that the only people who die are those in the H compartment.

$$\dot{S} = \left[\alpha\frac{I}{N} + \eta\frac{E}{N}\right] S(t) \tag{5}$$

$$\dot{E} = \left[\alpha\frac{I}{N} + \eta\frac{E}{N}\right] S(t) - \beta E(t) - \delta_E E(t) \tag{6}$$

$$\dot{I} = \beta E(t) + \left[-\gamma - \delta_I\right] I(t) \tag{7}$$

$$\dot{H} = \gamma I + \left[-\delta_H - \theta\right] H(t) \tag{8}$$

$$\dot{D} = \theta H(t) \tag{9}$$

$$\dot{R} = \delta_E E(t) + \delta_I I(t) + \delta_H H(t) \tag{10}$$

All parameters for SEIHRD-model equations above are defined in table 1. The probability of the infected individual to get hospitalised is $\frac{\gamma}{\gamma+\delta_I}$. The mortality rate of those hospitalized is θ.

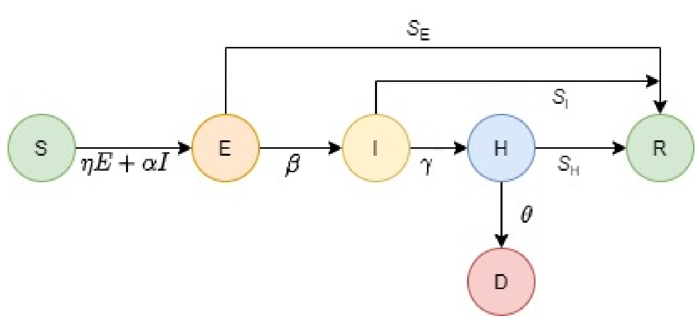


Figure 1: *Graphical depiction of SEIHRD model.*

5.3 SEI[H]RD model with expanded H compartment

The SEIHRD model proposed assumes that hospital compartment (H) is homogeneous. It implies that all hospitalized individuals require the same medical attention and they recover at the same rate δ_S. Infected individuals can exhibit mild symptoms or go into a severe, or critical condition requiring different hospital treatment. Patients in a severe condition require ICU beds and those in a critical condition require ventilators [9]. COVID-19 outbreak can lead to a shortage of limited ICU beds and ventilators which cause catastrophic death and stress. Hence, it is important to capture the entirety of the hospital's capacity so that countries can check if the health care resource is reaching the threshold.SEI[H]RD model with expanded H compartment into regular (H_{bed}), ICU (H_s) and ventilator (H_c) beds is depicted in Fig 2 below.

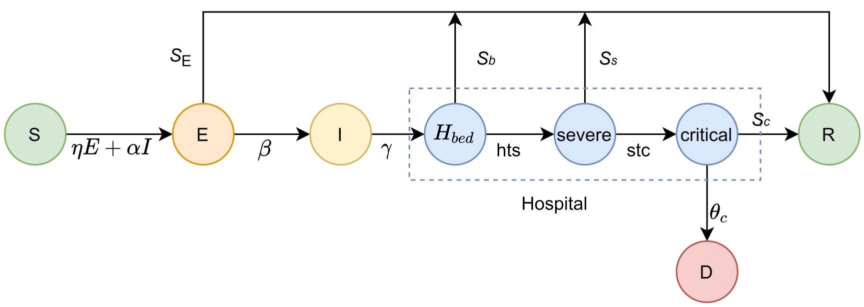


Figure 2: *Graphical depiction of SEI[H]RD model.*

5.4 SEI[H]RD model formulation

SEI[H]RD model builds on equation (5 - 10) by expanding equation (8) into equation (11 - 13) and changing equation (9) and (10) to (14) and (15), respectively. The differential equation (5 - 7) describing the movement of individuals in and out of the S, E, and I compartments remain the same. The movement in and out of the hospital compartment is described by equation (11 -13) below. All the parameters in equations (11 - 15) are defined in table 2 below. It is assumed that the only people who die from COVID-19 are those in the critical condition (ventilator) compartment.

$$\dot{H_{bed}} = \gamma I + [-\delta_b - hts]\, H_{bed}(t) \tag{11}$$

$$\dot{H}_s = [-\delta_s - stc]\, H_s(t) + hts \times H_{bed}(t) \tag{12}$$

$$\dot{H}_c = [-\theta_c - \delta_c]\, H_c(t) + stc \times H_s(t) \tag{13}$$

$$\dot{D} = \theta_c H_c(t) \tag{14}$$

$$\dot{R} = \delta_E E(t) + \delta_I I(t) + \delta_b H_{bed}(t) + \delta_s H_s(t) + \delta_c H_c(t) \tag{15}$$

The recovery rate from H_{bed}, H_s and H_c compartments are defined by the equation (16), (18), and (20), respectively. The transfer rate from H_{bed} to H_s and H_s to H_c compartment is defined by equation (17), and (19). All the parameters from equation (16) to (20) are defined in table 3 below. Equation (16) to (20) formulated as done in reference [9].

$$\delta_b = \frac{1}{t\_s\_r} \times symptomatic\_recovery\_p \tag{16}$$

$$hts = \frac{1}{t\_s\_r} \times (1 - symptomatic\_recovery\_p) \tag{17}$$

$$\delta_s = \frac{1}{t\_sv\_r} \times \frac{severe\_fraction}{severe\_fraction + critical\_fraction} \tag{18}$$

$$stc = \frac{1}{t\_c\_r} \times \frac{severefraction}{severe\_fraction + critical\_fraction} \tag{19}$$

$$\delta_c = \frac{1}{t\_c\_r} \left(1 - \frac{CFR}{critical\_fraction}\right) \tag{20}$$

Table 2: *Meaning of parameters in the SEIHR model [9].*

Parameters	meaning
hts	hospitalized (symptomatic) individual to severe condition (ICU bed) rate
stc	severe (ICU bed) to critical condition (ventilator)
δ_b	Rate of recovery of symptomatic people in hospital beds
δ_s	Rate of recovery of individuals in severe condition (ICU)
δ_c	Rate of recovery of individuals in critical condition (ventilator)
θ_c	Mortality rate of individuals in critical condition

5.5 Parameter estimate

The main parameters of the model, equation (16 - 20) are summarised in Table 3. These parameters are taken from [9], which extracted and estimated them from various sources and studies [21, 22, 23].

Table 3: *The model parameters [9].*

Parameters	meaning	values
t_s_r	Symptomatic to recovery time	11.76 $\pm 2.61 days$
t_sv_r	Severe to recovery time	5.66 $\pm 2.61 days$
t_c_r	Critical to recovery time	17.76 $\pm 2.61 days$
t_s_sv	symptomatic to severe time	4.82 $\pm 0.683 days$
$symptomatic\_recovery\_p$	Rate of recovery of exposed individual	30%
$severe\_fraction$	fraction of individual with severe condition	44%
$critical\_fraction$	Fraction of critical with critical condition	82%
CFR	case fatality ratio	2%

5.6 Basic reproduction number

It is essential to determine a reproduction number (R_0) of the disease propagation process. For homogeneous population, Let $X = (S, E, I, [H], D, R)$ where each value of X_i is always greater than 0. To find R_0, begin by calculating a next-generation matrix composed of two parts: F and V^{-1} matrix [10]. Where matrix F and V are of size $m \times m$. There are only two infection compartments: E and I, giving $m = 2$. According to [10], F is defined as partial differentiation of the rate of new infection with respect infection compartments:

$$F = \begin{bmatrix} \alpha & \eta \\ 0 & 0 \end{bmatrix} \tag{21}$$

The V matrix is defined as the rate of in and out of the infectious compartment with respect to infection compartments, giving [10]:

$$V = \begin{bmatrix} \beta + \delta_E & 0 \\ -\beta & \gamma + \delta_I \end{bmatrix} \tag{22}$$

calculate a next-generation matrix:

$$\begin{aligned} FV^{-1} &= \begin{bmatrix} \eta & \alpha \\ 0 & 0 \end{bmatrix} \times \begin{bmatrix} \frac{1}{\beta+\delta_I} & 0 \\ \frac{\beta}{(\beta+\delta_E)(+\delta_I)} & \gamma + \frac{1}{\gamma+\delta_I} \end{bmatrix} \\ &= \begin{bmatrix} \frac{k\eta}{\beta+\delta_E} + \frac{k\alpha\beta}{(\beta+\delta_E)(\gamma+\delta_I)} & \frac{k\alpha}{\gamma+\delta_I} \\ 0 & 0 \end{bmatrix} \end{aligned} \tag{23}$$

R_0 is the largest eigenvalue or spectral radius of the next-generation matrix [10].

$$\begin{aligned} R_0 &= \rho(FV^{-1}) \\ &= \frac{k\eta}{\beta + \delta_E} + \frac{k\alpha\beta}{(\beta + \delta_E)(\gamma + \delta_I)} \end{aligned} \tag{24}$$

The value of R_0 speaks to the strength of disease spread. R_0 is a number of secondary infections given that the is one person infected. If $R_0 > 1$, the disease outbreak will be sustained, potentially leading to epidemic or pandemic and when $R_0 < 1$, the disease will die out [10].

6 EWS indicators

There critical transition from a state of COVID-19 equilibrium to an abrupt outbreak is considered as one of the tipping points. There are three EWS indicators used to identify an approaching wave outbreak in this paper, namely: variance, lag-1 autocorrelation, and index of dispersion defined by equation (25), (26) and (27), respectively [6].

$$v = m_i((x_j - M_j)^2) \tag{25}$$

where v is a variance.

$$autoc = \frac{m_i((x_j - M_j)(x_{j-i} - M_{j-1})}{(v_i \times v_{i-1})^2} \tag{26}$$

where *auto* is a lag-1 autocorrelation.

$$D = \frac{v_i}{M_i} \tag{27}$$

and D is an index of dispersion.

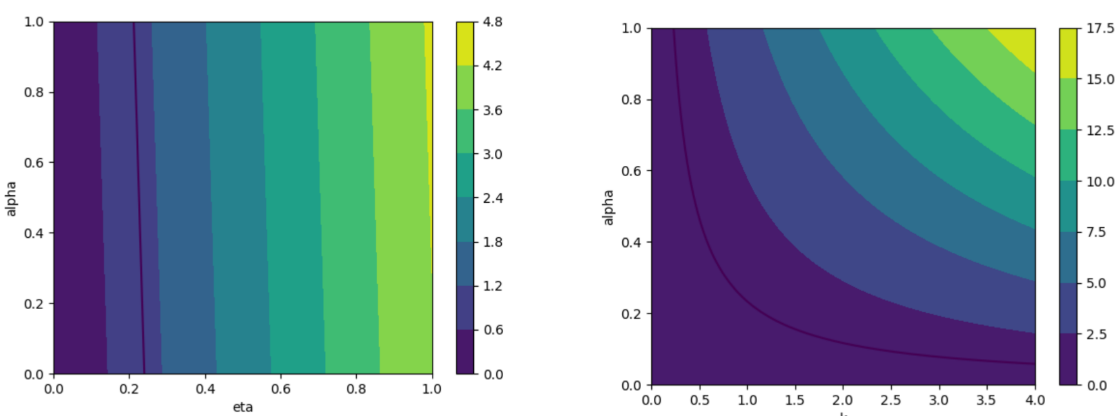
$$M = m_i(x_j) \tag{28}$$

Where M is a rolling mean (moving average) for window of i elements from $(i-j)^{th}$ to j^{th} element.

Analyses of simulation models exposed to stochastic forcing confirm that if the system is gradually getting closer to a catastrophic failure, there is a substantial increase in autocorrelation, variance, and index of dispersion that builds up long before the critical transition occurs [5].

7 Simulation and empirical analysis

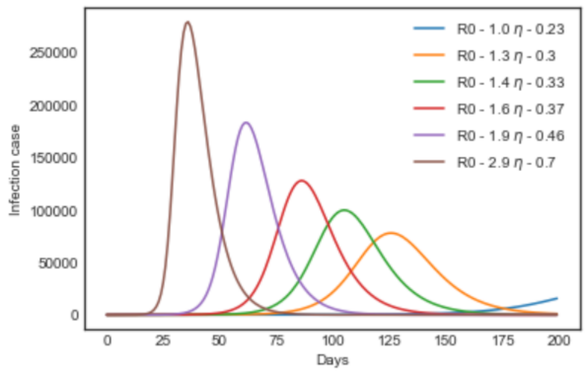
The simulation study of the SEI[H]RD model is carried out for a region with an ideal population size of 1.5 million. The first thing we are going to investigate is how different R_0 affect the infection outbreak and the hospitals' compartments. Different R_0 is simulated by varying the parameter η and keeping α at a constant of 0.1. It can be observed from figure 2, (a) that changing α does not have much impact on $_0$ when k is constant. Figure 4, (a) shows that for very high R_0 the peak of infection is reached early and is very high than for small R_0. Lowering R_0 delays the outbreak and lowers the peak. Figure 4, (b) depicts the distribution of patience in the hospital beds.



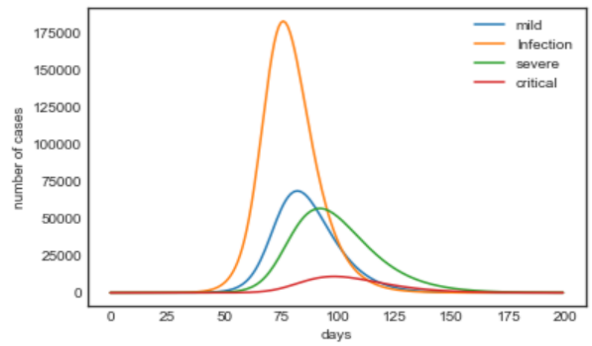
(a) *η vs α, while $k = 1$*

(b) *α vs k*

Figure 3: *Contour plot for R_0 for different parameters. Where $\beta = 0.14$, $\delta_I = \delta_E = 0.1$. Colour represent different values of R_0. A solid black line is $R_0 = 1$.*



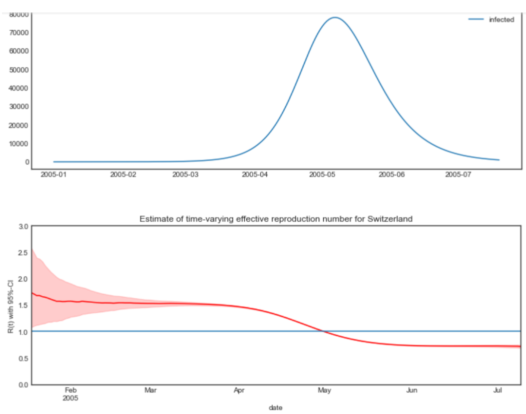
(a) *Number of infection cases for different* R_0



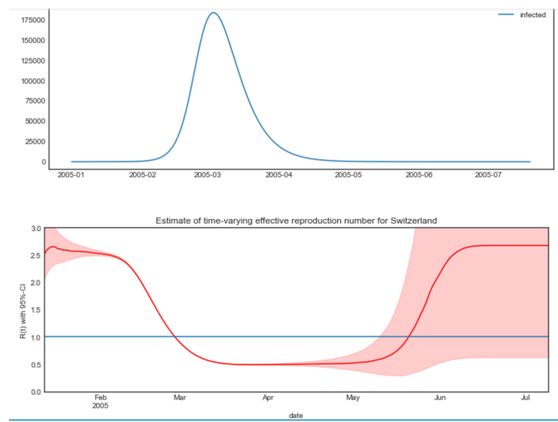
(b) *Number of cases in hospital compartments for* $R_0 = 1.5$ *and* $\gamma = x$

Figure 4: *Simulation*

.



(a) $R_0 = 1.5, \eta = 0.34, \alpha = 0.1$



(b) $R_0 = 2.5, \eta = 0.7, \alpha = 0.1$

Figure 5: R_t *with respect to I numbers simulated for different* R_0. *k= 1*

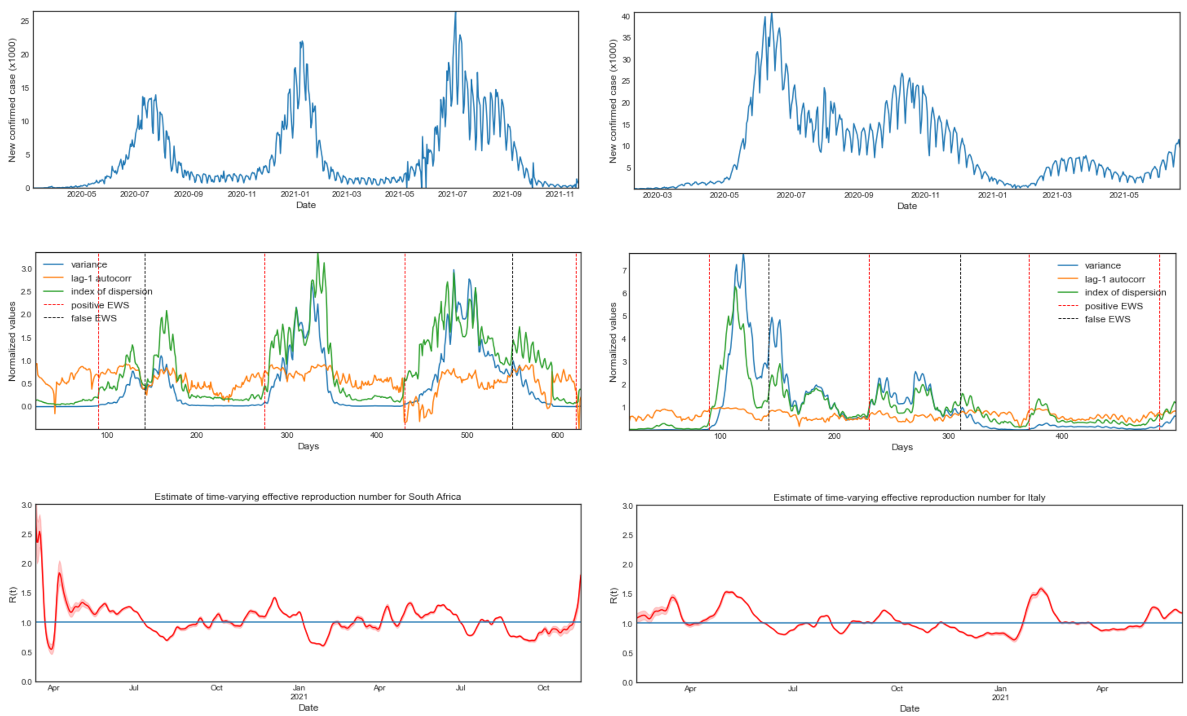
.

uu

R_t speaks to a number of secondary cases caused by an infected person over time. R_t is computed using a python package, Epyestim [17]. It is a Python re-implementation of the method outlined by Huisman et al. [18], making use of the method used in implemting R package EpisEstim by Cori et a. [19]. R_t is simulated using delay distribution that peaks at 4.3 days used by Flaxman et al. [20] and it is smoothed using 21 days window. R_t calculated in Figure 5.a and 5.b accurately estimate R_0 of a calculated for given constant η and α. Therefore, If we didn't know R_0, we could still calculate R_t using the initial data before the wave outbreak to determine how soon and how high the pick would be. As the wave is approaching the peak, R_t goes below 1 which tells that the wave has reached its peak. Thus this proves that R_t is practically useful in determining the intensity of the spread. Figure 5, (b) has a greater R_t than figure 5, (a) and that is supported by how (b) reaches its peak fast than (a) and is greater in magnitude than of (a). Theoretically, R_t should be capable of determining if the wave is going to continue rising until passing the hospitalization threshold.

7.1 EWS empirical analysis

South Africa and Italy are two countries chosen COVID-19 data chosen for an evaluation of EWS indicators to predict approaching wave outbreaks. To date, South Africa has experienced three waves that occurred long after their previous have settled. Italy has experienced a COVID-19 wave quite different from South African's where the third outbreak happened before the previous outbreak settles. According to [6], the outbreaks that occur consecutively before the previous one fully settle are hard to predict due to the indicators producing a lot of false alarms. Thus these two countries are chosen to evaluate the indicators in different wave conditions. 21 days smoothing window (rolling average) is used to clean out noise in the data.



(a) *South Africa* **(b)** *Italy*

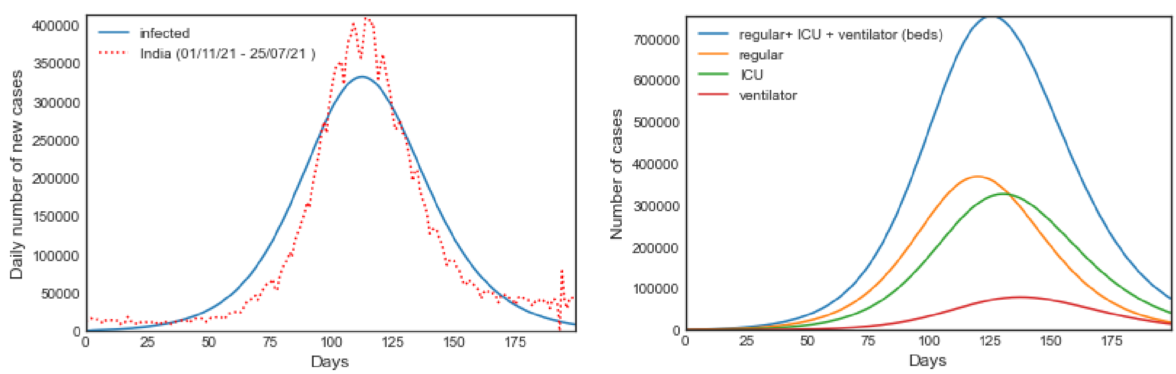
Figure 6: *Real data new COVID-19 case and Three EWS plotted in the bottom figure with respect to the new cases for provided data above. The vertical dotted red line in the bottom figure represents where a positive EWS would have been given*

.

For both South Africa and Italy graphs in Figure 6.a and 6.b, the vertical red and black dotted line in the middle figures indicate a positive and false EWS, respectively. The bottom R_t graph is used as a confirmation indicator, where if the EWS indicator(s) rise when $R_t > 1$, it is positive EWS; if the EWS indicator(s) rise when $R_t < 1$, the signal is considered a false alarm. For South Africa, lag-1 autocorrelation is constantly going up and down which makes it inconclusive as an EWS for COVID-19 outbreaks. the variance and index of dispersion have consistently increased prior to all outbreaks depicted in Figure 6. However, variance always lags behind the index of dispersion, giving a signal only a few days before an outbreak. The index of dispersion consistently gives an early warning 21 days (on average) or more prior to the outbreak. For instance, the index of dispersion started rising more than 40 days prior to the first outbreak that happened in Italy which resulted in enormous death, which could have given policymakers enough time to prevent the catastrophic failure. These graphs prove that variance and index of dispersion alongside R_t are reliable for predicting upcoming waves. Future prediction: R_t has drastically gone over 1 and the index of dispersion also rose this month (11/21) in South Africa, which means South Africa is most likely to experience another COVID-19 wave this coming December.

7.1.1 Hospital beds

For empirical analyzing if SEI[H]RD mode can tell if the wave will lead to exceeding hospital capacity we will use India's second wave that resulted in the county's healthcare capacity being exceeded. According to [24], the estimated India overall hospital capacity is about 1.75 million beds. The number of beds in ICUs, or critical care beds is 5%, which is about 87,979 beds. (Chandna 2020) estimate reports 8,432 ventilators in the government sector and about 40,000 more ventilators across the country mostly in the private sector. Some estimate that there are half as many ventilators as ICU beds in India. This is the total number of beds, not the available beds because people with ailments other than COVID-19 usually occupy at least two-thirds of the bed capacity at any given time. ICUs typically operate at full or close to full capacity because of the high cost, and only a fraction of the existing ICU beds will become available for COVID-19 patients [24].



(a) *Model fitting to real data*

(b) *Hospital Capacity*

Figure 7: *Fitting the model to India's second wave and COVID-19 hospital use during the second wave.*

Figure 7.a gives the good fitting of the model to the daily new case. All the parameters in Table 3 are kept constant when fitting the model. Provided that the model fits/predicts the data well, the hospital compartments numbers will also be well estimated. The estimation of hospital use the model prediction of daily new cases. Figure 7.b shows that the hospital beds are fairly estimated and reasonably correspond with the hospital capacity. But because only a fraction of the hospital capacity is available for COVID-19 patients, it is clear that the hospitalization predicted by the model exceeds the hospital capacity as it happened in India during the second wave.

8 Economic, Environmental and Social impacts

8.1 Economic impacts

The ability to predict critical tipping points transition before they occur can allow the government to apply relaxed lockdown adequate enough to keep the disease under control. If any of the early warning signals indicate the approaching critical point, a thorough assessment can be applied timely to come up with an appropriate response. A relaxed lockdown will allow most economic activities to continue and avoid job losses as a result of unnecessary drastic interventions applied. Moreover, if a critical threshold is acceded unnoticed, a severe outbreak might occur that calls for extensive hard lockdown that limits economic activities. The proposed solution assists with mitigating such possible issues.

8.2 Environmental impacts

The model proposed shows that the disease spread (R_0) can significantly get reduced by reducing the average number of individuals (k) an infected and exposed individual interact with. The only way to reduce k is by applying social distancing which has proven to be an effective measure to fight COVID-19. If people are staying at home and traveling less, ultimately the air pollution caused by traveling get reduced. According to the study done by [11], social distance response to COVID-19 has reduced NO2, and CO nationwide from last year's mean levels by 16.98 g/m3, 21.61 g/m3, 4.16 ppb, and 0.09 ppm, respectively, a decrease by 45.45%, 35.56%, 20.41%, and 17.33%, respectively. The simulation-based study shows that there is E compartment spread the disease at a very high rate I compartment because they quarantine after getting tested. Thus, in order to combat COVID-19, many tests must be conducted. But conducting more COVID-19 tests will contribute to the ongoing plastic waste crisis that has been affecting the environment worldwide.

8.3 Social impacts

The model used for this study does not account for age-structure and the network between regions, this might exaggerate the non-pharmaceutical measure required to keep the spread under control. As a result, people might be in a high level of lockdown than it is required, which inhibits people's social and cultural activities. social distancing can make some people feel depressed because of a lack of social interaction with their beloved ones and friends. Although this model might be very useful, some people tend to broadcast the model's forecasts without thoroughly communicating the assumption taken in the model which might cause unnecessary public panic.

The EWS can be useful in avoiding the catastrophic disasters where a lot of people die because of COVID-19 just like experienced in countries like Italy and India. If many people were to die at the same time, it might inhibit the families to give their loved ones a proper burial because mortuaries will be full. Thus, the deceased will have to get berried on the same day of death. The EWS help to avoid such issue.

9 Design sustainability

The development of the COVID-19 compartment model is not costly in terms of resources but only human capital (time and research). What is required is that the countries commit resources to produce accurate COVID-19 data accounting for new cases, number of death, and hospital capacity. Inaccurate data can yield inaccurate forecasts and EWS. Although few model parameters can be estimated by fitting to real data, most parameters are deduced from studying the disease characteristic, such as latency and incubation time. If a new COVID-19 variance develops that poses slightly different characteristics, the model can make a wrong forecast with respect to new variance. For instance, it is commonly known that COVID-19 is most deadly in the elderly population, but surprisingly in Brazil, they have found that most of the people in ICU beds are young people [12]. Nonetheless, the model does not have to change for new variance, only the parameters.

The EWS proposed in this paper are general EWS that can used be in different complex systems regardless of the details. Therefore, the forecast used for predicting the outbreak can be used for any variance or disease that might emerge in the future without changing the implementation details provided that the is adequate data recorded. Although false signals can cause unnecessary panic if published, the reward ratio is greater because it helps to prevent catastrophic events.

10 Conclusion

This paper has investigated two COVID-19 tipping points that can lead to costly catastrophic failure in terms of economic, human lives, and emotions. The two tipping points investigated is exceeding hospital capacity and (re-)emergent of COVID-19 wave outbreak. This paper also device early warning signals (EWS) for predicting approaching tipping points before it occurs. The EWS is based on three indicators: variance, lag-1 autocorrelation, and index of dispersion. Effective reproduction R_t is also used in cooperation with the three indicators to sever as a confirmation indicator of EWS. In order to evaluate the hospital capacity tipping point, this paper proposes using R_t to check if the wave is going to continue rising. In a simulation study, it is found that a higher value of R_t implies that the wave will rise rapidly and will have very high peak; the wave with small R_t has delayed outbreak and has a smaller peak. SEI[H]DR compartment model with hospital expanded into regular hospital beds, ICU units, and ventilator beds is used to predict COVID-19 numbers and to access if the hospital will be able to cope during a COVID-19 outbreak. lag-1 autocorrelation, variance, and index of dispersion are the indicator used for outbreak EWS. This indicator is tested in South African and Italy COVID-19 data. Index of dispersion and variance is found to be effective in detecting an approaching outbreak by more than 20 days before it happens.

References

[1] Page J, Hinshaw D, McKay B (26 February 2021). "In Hunt for Covid-19 Origin, Patient Zero Points to Second Wuhan Market – The man with the first confirmed infection of the new coronavirus told the WHO team that his parents had shopped there". The Wall Street Journal. Retrieved 27 February 2021

[2] Burke, G. J., Miller, E. K., Poggio, A. J. (2004, June). The numerical electromagnetics code (NEC)-A brief history. In IEEE Antennas and Propagation Society Symposium, 2004. (Vol. 3, pp. 2871-2874). IEEE.

[3] WORLD Health Organization (WHO), WHO Coronavirus (COVID-19) Dashboard.V

[4] Hethcote, Herbert W. "Qualitative analyses of communicable disease models." Mathematical biosciences 28.3-4 (1976): 335-356.

[5] Scheffer, Marten, et al. "Early-warning signals for critical transitions." Nature 461.7260 (2009): 53-59.

[6] Brett, Tobias, et al. "Detecting critical slowing down in high-dimensional epidemiological systems." PLoS computational biology 16.3 (2020): e1007679.

[7] van der Voorn, Tom, and Martin de Jong. "Cope or Perish? Managing Tipping Points in Developing Coping Strategies for Emergency Response during the First Wave of the COVID-19 Outbreak in Europe." COVID 1.1 (2021): 39-70.

[8] Niu, Ruiwu, et al. "Modeling the COVID-19 pandemic using an SEIHR model with human migration." IEEE Access 8 (2020): 195503-195514.

[9] Verma, Veenapani Rajeev, et al. "Capacity-need gap in hospital resources for varying mitigation and containment strategies in India in the face of COVID-19 pandemic." Infectious Disease Modelling 5 (2020): 608-621.

[10] Van den Driessche, Pauline, and James Watmough. "Reproduction numbers and subthreshold endemic equilibria for compartmental models of disease transmission." Mathematical biosciences 180.1-2 (2002): 29-48.

[11] Ju, Min Jae, Jaehyun Oh, and Yoon-Hyeong Choi. "Changes in air pollution levels after COVID-19 outbreak in Korea." Science of the Total Environment 750 (2021): 141521

[12] The BMJ, Covid-19: Brazil's spiralling crisis is increasingly affecting young people, https://www.bmj.com/content/373/bmj.n879, Published 01 April 2021

[13]

[14] Peirlinck, Mathias, et al. "Outbreak dynamics of COVID-19 in China and the United States." Biomechanics and modeling in mechanobiology 19.6 (2020): 2179-2193.

[15] Xin, Hualei, et al. "Estimating the latent period of coronavirus disease 2019 (COVID-19)." Clinical Infectious Diseases (2021).

[16] Harris, Mallory J., Simon I. Hay, and John M. Drake. "Early warning signals of malaria resurgence in Kericho, Kenya." Biology letters 16.3 (2020): 20190713.

[17] https://github.com/lo-hfk/epyestim

[18] Jana S. Huisman, Jeremie Scire, Daniel Angst, Richard Neher, Sebastian Bonhoeffer, Tanja Stadler: A method to monitor the effective reproductive number of SARS-CoV-2 https://ibz-shiny.ethz.ch/covid-19-re/methods.pdf

[19] Anne Cori, Neil M. Ferguson, Christophe Fraser, Simon Cauchemez: A New Framework and Software to Estimate Time-Varying Reproduction Numbers During Epidemics, American Journal of Epidemiology, Volume 178, Issue 9, 1 November 2013, Pages 1505–1512, https://doi.org/10.1093/aje/kwt133

[20] Flaxman, Seth, et al. "Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe." Nature 584.7820 (2020): 257-261.

[21] Khalili M, Karamouzian M, Nasiri N, Javadi S, Sharifi H. Epidemiological characteristics of COVID-19; A systemic review and meta-analysis 1. medrxiv.org [Internet]

[22] K. Prem, A.R. Cook, M. Jit Projecting social contact matrices in 152 countries using contact surveys and demographic data

[23] N. Chow, K. Fleming-Dutra, R. Gierke, A. Hall, M. Hughes Preliminary estimates of the prevalence of selected underlying health conditions among patients with coronavirus disease 2019 — United States February 12–March 28, 2020

[24] Rajagopalan, Shruti, and Abishek Choutagunta. "Assessing healthcare capacity in India." (2020).

Appendices

A Non-Technical Report

A.1 Introduction

The ongoing fight against the notorious COVID-19 pandemic has unsparingly affected everyone. Many people have lost their jobs, beloved ones, and it has significantly affected our livelihood. What makes COVID-19 hard to combat is that is highly infectious, which has resulted in an unexpected outbreak that has caught many countries unprepared. The outbreak has put enormous stress on the health care system, ultimately exceeding the health care capacity. In such cases, people exhibiting treatable symptoms end up dying because they cannot get the medical attention they need. To date (10th September 2021), only 26.9% of the worldwide population has been vaccinated and according to Our World in Data statics, only 1.9% of people in low-income countries have received at least one dose [1]. In order to combat COVID-19, we need ways to predict COVID-19 critical tipping points that can result in catastrophic failure in terms of human life, emotion, and economic hardship. This paper presents early warning signals for predicting approaching outbreaks and if hospitals are about to reach the threshold capacity before it happens. It also used a mathematical model that can forecast COVID-19 numbers and hospital demand due to COVID-19.

A.2 Brief overview

The design uses a compartmental model called SEI[H]IDR, which means that the population is dived into different groups to study the spread of the disease between the groups. The simplest vision of this model is the SIR model where the population is divided into three groups: susceptible (s), infected (I), and removed (R) group. The S compartment consists of people that have not yet been infected by the disease but are prone to get infected. The I compartment consists of individuals who caught the disease and can infect S individuals. R compartment consists of individuals who have died or recovered from the dies. The SEI[H]IDR model follows similar principles to the SIR model. The advantage of using this model is that it divides a hospital into three different beds category: regular beds for those showing mild symptoms, ICU, and ventilator beds for those in critical Ventilator. This allows a detailed forecast of hospital demand for COVID-19 patients.

During a COVID-19 outbreak, the SEI[H]IDR model is useful for estimating the required measure to keep the disease under control. In addition, by using historical COVID-19 data for a particular region, we can calculate the number of people an infected person will infect, this number is called a reproduction number (R). If we know R, we can determine how soon an outbreak is likely going to happen and how severe is it going to be. The model developed allows a simulation of hospital regular beds, ICU, and ventilators that will be needed in an outbreak. This will allow policymakers to implement non-pharmaceutical interventions to prevent the hospital resource shortage.

There are three COVID-19 early warning signal indicators implemented to give a warning of an approaching outbreak. These indicators are based on a statistic formula that uses real-time COVID-19 data which is publicly available to determine. Using publicly available data, we can estimate how many people will an exposed/infected person infect with COVID-19, this number is called the effective reproduction number. This number can be used as a confirmation signal for early warning indicators.

A.3 Economic, Environmental and Social impacts

This solution will allow the government to apply relaxed lockdown knowing that they have a system that will help them guard against an approaching catastrophic outbreak and exceed the health care threshold. By so doing, this will allow some economic activities to take place, small businesses to operate, and reduce job loss. Furthermore, relaxed lockdown will allow fairly limited social and spiritual. The model implemented shows that the might be a lot of asymptomatic people spreading the disease, thus it will be essential to test more people to keep the disease under control. Testing kits are made of plastic, so they might contribute to plastic waste. But the good thing is that if more tests are conducted, the early warning signal will make better predictions. This solution is not expensive to operate, in fact, it only requires a simple personal computer and once the solution is implemented, it doesn't require any maintenance cost. The only required thing is that government keeps on testing people and producing the most accurate data.

A.4 Conclusion

All three indicator indicators were tested on Italy and South Africa data, they were able to predict all the approaching waves in both countries before they happen. On average they give policymakers around 20 days to act before the outbreak occurs. This solution has good Economic, Environmental and social impacts.

References

[1] Our World in data , Coronavirus (COVID-19) Vaccinations, https://ourworldindata.org/covid-vaccinations?country=OWID$_W RL$