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Partial unlock for COVID-19-like epidemics can save 1-3 million lives worldwide

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Abstract

This paper accounts in lives-saved partial unlock strategies that may be used to facilitate reopening economies that have been shut down due to an epidemic or pandemic. For this purpose it introduces a new approach to simulation using an internal SIR engine with seasonality, and external behavior forcing calibrated with case data to account for initial human behavior under social distancing. The overall method relies on public goal setting and both professional and public feedback behavior. In this way it avoids much of the chaotic sensitivity to parameters and divergence of predictions and behavior which undermine the public image of epidemiology models and create rebounds. We study reducing the total cases by controlling threshold overshoot as economies reopen, controlling medical resource utilization, and reducing economic shutdown duration, all of these across significant scenario variation. We provide a quantitative analysis of overshoot and demonstrate a two-step manual method as well as the feedback method of avoiding it. We show goal-managed partial unlock to manage critical resources has the consequential effects of reducing economic downtime and bringing the cumulative cases down about 9%-27%, thereby saving lives with some degree of certainty. The optimization of overshoot does leave some risk of creating a residual small infection existing on birth rate and migration, and we provide some guidelines for minimizing the risk. Effectiveness is demonstrated using COVID-19 actual data and parameters for other diseases with replication factors up to 15.

Keywords

Epidemic, caseload management, partial unlock, social distancing, overshoot, COVID-19, coronavirus, economic impact, ventilator utilization, SARS-CoV-2

1. Introduction

The goals of global efforts against a pandemic are threefold: (1) reduce the number of infected individuals and therefore deaths, (2) avoid overtaxing the healthcare system (which would restrict all services not just COVID-19), and (3) reduce the social and economic impact of the pandemic [1].

In the case of COVID-19 ballooning case rates have been brought down, but it is generally conceded that the effort is failing on the third count, social and economic impact. The natural cycle of COVID-19 without intervention we will show would have ended by early summer with only one month of effective shutdown while a large percentage of the world population was simultaneously ill. Lockdown-and-wait strategies guarantee a high degree of economic and travel shutdown for one to two years even if vaccine development is successful, which we will also show, along with the wait time and criteria to extinguish or re-contain an infection. Perhaps more troubling for the long run, governments are now considering COVID ID cards to identify those with immunity who will be

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permitted to travel and work, while enforcing a kind of mandatory quarantine on innocent and socially compliant citizens as well as individual monitoring and tracking.

As regards the second goal, the world healthcare system for elective procedures is already shut down. In the U.S. it should be marginally possible to accommodate all anticipated demand for ventilators. This conclusion will be supported by our simulations also. The world at large has ordered 880,000 or more new ventilators, which may or may not be producible in time. We will further show this is about the right number, and that the production rate should be about 1250 units per month.

What is less fully appreciated, and not at all in some circles, is that in regard to the first goal the eventual death toll has not been reduced significantly by recent actions. The primary aim of this paper is to show that while initial flattening unequivocally reduced eventual death toll, with or without a vaccine, the gradual escalation of the policy combined with natural public fear and self-isolation will increase it in either of three cases:

1. An effective vaccine is not available.
2. Social chaos and hardship create unrest that forces unlock any time prior to vaccine deployment.
3. The hoped for supply of ventilators and other medical equipment and personnel is not forthcoming.

In addition to these three purely epidemiological consequences, social unrest may claim lives directly, topple otherwise stable governments, and undermine the long term geopolitical stability of the world.

There are three causes of death in these scenarios: (a) mortality among cases that occur ahead of the development of a vaccine, if a vaccine is developed, but which contribute to herd immunity, slowing further spread; (b) mortality among overshoot cases, which is completely unnecessary; (c) deaths due to social unrest or economic conditions which we do not quantify in this paper.

2. Approach

Our approach would be employed after containment is an opportunity past and a vaccine is a prospect too far in the future to avoid economic catastrophe. Opinions differ as to the effect of severe and prolonged recession on mortality and health. For example, there are fewer motorway deaths due to less driving [2]. During the COVID-19 pandemic there may well be fewer deaths due to pollution. On the other hand, the 2008 financial crisis resulted over the next few years in at least 260,000 additional cancer deaths [3]. Economic losses from pandemics, even without a long term global shutdown, have been estimated at the low end of but within the range of impacts from climate change [4]. These historical analyses are likely to vastly underestimate the impact from the economic and social disruption of COVID-19. While we currently have hostilities on pause in a few regional conflicts, when people are starving because they have no money there is likely to be mass unrest and replacement of governments, even in some very large countries, including countries that have nuclear weapons.

That leaves the approach of curve flattening, which can have one or both of two objectives as they lie on a continuous spectrum:

1. Keep the number of cases extremely low (and in consequence the economy completely shut down) until someone develops a therapy that prevents the disease or dramatically lowers mortality, or until the disease disappears on its own (unlikely if no herd immunity is building).
2. Keep the number of cases moderately low while herd immunity builds more slowly, but the medical system remains operational, the economy is not fully shut down, and the length of shutdown is minimized.

Various governments and regions are currently implementing shutdown (or lockdown) rules or recommendations based on cultural preferences and the number of cases they have. Instead of taking control of the situation from the pathogen as intended, by the implicit dependence of strategy on cases hands control back to the pathogen, and we will show this can assure the survival of the pathogen long into the future. It decays slowly under lockdown as the effective replication factor is near and slightly over 1.0, and the large remaining number of susceptible individuals assures the pathogen has infection targets. Even at current case levels which are well below those anticipated in the near future, fear-based shutdown as evidenced by traffic reductions in cities that have no shutdown is nearly that of cities which are locked down (See https://www.bbc.com/news/world-52103747 and scroll to “Travel declines even without official lockdowns”). Figure 1 shows replication rate of the pathogen R_0 defined in terms of new cases, active cases, and the average length of cases. R_0 appears to correlate well with a damped exponential function given in the figure.

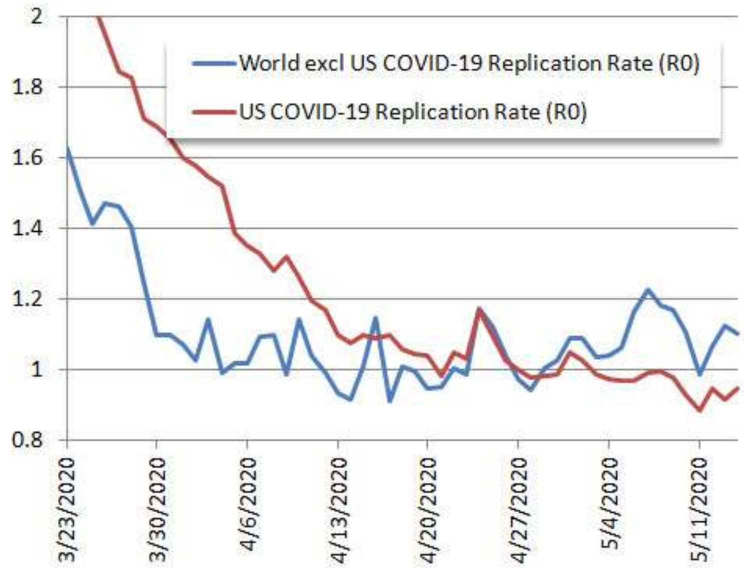

Figure 1. Empirical replication rate R_0 for US and World-excluding-US during phase-in of lockdown and social distancing – 4-day moving average.

While lockdowns began to be enforced outside China from late January, they were initially selective and directed at international travel. By mid-March they were widespread. We would expect a few days delay before a reduction in R_0 would appear in the new cases data (largely taken from the CDC, with supplementary data from https://www.worldometers.info/coronavirus/). Prior to March 21 the US cases were doubling every two days for about a week. This quickly declined following March 21, so that date was chosen as the start date for our tracking and modeling.

Any method of caseload management must affect the replication rate, and act quickly enough to provide control. The chart suggests case data lags from changes in lockdown of a week or slightly less. Lockdowns were mostly in place by the end of March. Effectiveness of lockdown appears to have reached a maximum by mid-April. We believe the downturn in US R_0 in May likely represents seasonal effects which are predicted to be as much as 40% in New York and 20% in Florida [5]. World R_0 reflects mixed seasonality and approaches.

It is possible there would be little response if governments eased lockdown, unless they also declared the environment safe, which isn’t true any time soon. However, as economic distress builds, coupling easing with the ability to work would likely be a powerful motivator. If the initial drop on the left is the response to government recommendations as we speculate, then it may be indicative of the control flexibility over the lockdown replication rate.

The authors of this paper believe that such measures should be voluntary and regional. Those healthy and at low risk and in economic need are likely to be willing to expose themselves to the environment, especially if governments maintain the integrity of the healthcare system and people are not dying from neglect. We take it as an assumption that fear could be overcome to some degree and a partial unlock implemented. Controlling the degree of R_0 rebound is a separate problem. In our simulation we simply establish a percentage of R_0 recovery to the initial level of March 21. An SIR model is unduly sensitive to the exact value of such measures and they are likely to be useful only with some monitoring and adjustment. In an alternative scenario to reduce this sensitivity we allow the activity that results in this R_0 rebound to occur on selected days of the week, along with explicitly modeled feedback and adjustment. We simulate a decision maker who would decide what days of the week would be partially unlocked. This demonstrates that even crude on/off level of control is adequate. Our per-day effectiveness ranges from 20% to 100%, with lower numbers used early on, and larger numbers when herd immunity is reducing R_0 and it needs more of a push to progress toward herd immunity and is not in danger of exploding and overloading the healthcare system. If it happens that partial unlock occurs during the low season, less caution is needed and a 40% unlock is required to counter seasonality.

In a real world implementation, the simulated unlock manager is replaced by humans looking at new cases data, and from that calculating future ventilator utilization. New cases data should in turn lag their decisions by no more than a week. Our simulations will attempt to show that in a variety of scenarios, over a range of disease parameters, whatever happens the managers will have control authority to accomplish their goal. One thing we cannot do with epidemiological "trajectory" models is to plan the whole thing out in advance because tiny changes in R_0, often due to behavior, make large changes in future caseload. What we demonstrate instead is that it is possible by making decisions in the future to accommodate those changes in intrinsic R_0 and counter them, even with measurement lag in the system (which we assume is one week between implementation and an uptick in cases).

At this writing many countries are implementing or considering partial unlock. This might result in a gradual approach to the minimum cases or a dramatic overshoot and unnecessary deaths. Without intention, the authors feel it is likely to result in the latter or to a series of panicked re-locks and unlocks which result in the latter. The intent of such moves is to slowly return to normal. The intent of the easing advocated in this paper is to quantitatively manage caseload, and prevent deadly rebounds later this year or next year. The rebounds approach the herd immunity threshold too fast which causes overshoot [6, 7]. Some investigators refer to rebounds as a second outbreak or second wave, and specifically identify that it is likely to be uncontrolled and cause significant overshoot [8].

2.1. Model parameters and algorithm

Most model parameters are user adjustable. The model is in a spreadsheet to be uploaded with this paper, and also available at http://shulerresearch.org/covid19.htm . A subset of the model with cases projection only is available as an interactive online JavaScript model which can automatically load data for most countries and many regions at the above URL.

The particular parameters for COVID-19 are explained below. Some of the parameters are varied over a range making the results applicable to other similar epidemics. If the R_0 is more than about 5 then it may peak before unprepared governments can respond. Otherwise our general conclusions should apply to some degree.

An initial value of R_0=2.5 was taken from the March 20-21 case data for the US and within range of CDC and other estimates [1, 9]. We also conduct simulations at R_0=3 to check sensitivity to this parameter.

For resource utilization the number of ventilators in the U.S. including reserves, alternatives (anesthesia machines) and older equipment is taken at 200,000 [9] and reduced to 100,000 as likely actually available. The number of ventilators in the world is harder to obtain. About 340,000 were identified at https://en.wikipedia.org/wiki/List_of_countries_by_hospital_beds but a number of large countries were listed as "unknown". A rough estimate of 500,000 was assumed. A parameter for manufacture of additional ventilators accommodates announced intentions or running simulations to determine requirements.

The case ratio of total likely cases including undocumented ones to known reported has varied. Lower numbers are more critical due to the way the model calculates ventilator requirements. Higher numbers imply lower mortality than expected and achieve peaks more quickly. Published numbers began around 14% [10] which is a ratio of 7.1. Numbers eventually reached as high as 50 to 85 from randomized testing in Santa Clara County, California [11]. Unknown cases are likely higher there than elsewhere because it has since been shown cases were introduced there much earlier than realized. Within New York state a range of 7 to 12 was evident from the Governor's announcement on April 23rd on results of tests of shoppers (see https://www.nytimes.com/2020/04/23/nyregion/coronavirus-new-york-update.html). Such testing is surprisingly slow to happen given that antibody testing does not compete with active case testing, the value of the information, and the small number of tests required for statistical samples (as opposed to screening for cases). Testing has been announced in Indiana and Ohio but results are not yet available. This is the most critical parameter in estimating deaths, more critical than mortality among known cases. While we simulate over the range 7 to 80, it is useful to know what to expect. Based on fitting epidemiological models to the April peak in cases, which is very inexact, we are comfortable with a range for the US of 30 to 50, more in line with the Santa Clara data. A value of 12 allows rough matching of deaths predicted by a Wharton model (viewed on May 12, 2020 at https://budgetmodel.wharton.upenn.edu/issues/2020/5/1/coronavirus-reopening-simulator), but while that is reasonable for the New York, New Jersey and Connecticut combined area, which we adopt as a principle sub region NYNJCT, it does not fit the US data excluding that sub region.

A precise number for how long a case of COVID-19 lasts is of course not obtainable due to the wide variation. Data is complicated by regulatory requirements for waiting and testing. For matching public data on active cases 14 days is reasonable. But for matching known values of R_0 and observed case growth rate, an average spreading period of 6 days is used. Quite often R_0 does not actually appear in SIR (Susceptible-Infected-Resistant) models, but instead the product of contact rate, infection rate, and disease period (or case duration). In order to have R_0 directly appear in our model, we use R_0 / spreading-days as the principle propagator coefficient (see next section for model details).

The fraction of cases that require resources such as a ventilator is also important. We used 5.0% of known cases, or about half of critical cases, taken from Meng, et. al. [11]. Lower estimates and wide variety exist. Regionalization is also important as ventilators may not be distributed where needed. In another epidemic it may be some different resource. If no resource is critical, one must invent a "parameter" which is related to mortality. In the case of COVID-19 we assume mortality is percent of patients on vents, and this is a regional parameter. The percentage may be greater than 100% since people not on vents may also die.

Mortality among known cases varies by city or region. The mortality rate is changing and likely to come down a great deal as it has been found patients respond better if just given oxygen not ventilation, various drug therapies are introduces, and there is a general learning curve. The current trend in US data is shown in Figure 2.

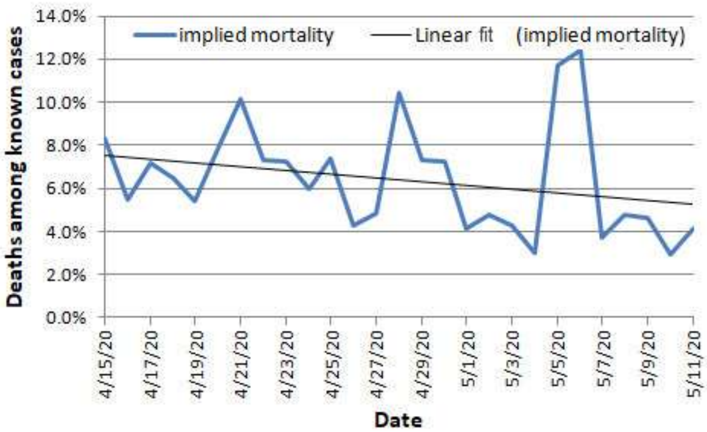

Figure 2. US COVID-19 mortality rate trend with linear fit, estimated from comparing daily reported deaths to new cases one week earlier

We assumed that improvement would taper exponentially amounting to 0.04% per day ending in September. This would produce a 75% improvement and a high advantage to putting cases off until September. Dividing by a case ratio of 12 that gives an initial total cases mortality of 0.67% and a September estimated mortality of 0.16%. This compares with 0.1% often attributed to flu, though with vaccines fewer people may get flu. The reader can

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scale our results to his or her own estimate based on whether more deaths are occurring early or late, or can download the model and simulate their own estimate.

Economic activity is assumed to be proportional to degree of unlock easing (also called reopening). However, as distancing will be greater and personal protective equipment used (masks), the gain in economic activity per unit of contact will be greater than what was lost. We don't have data on this and used an efficiency factor of 1.2 as a kind of minimum expected gain. The parameter can easily be adjusted.

Social networks, location tracking and other massive data mining efforts recommended in research of more persistent (non-pandemic) diseases [12] are specifically not part of our approach. They take time, where we require rapid feedback. They invite abuse for other applications later. But most importantly, social networks change as soon as a pandemic is announced, change again when government policy is announced, and keep changing. An aggregated tracking and feedback method will work better.

Five unlock dates are provided each with its own percentage effectiveness (or degree of unlock). In addition a mode for intermittent daily unlock is provided to control the simulated unlock manager. A target percentage utilization for the critical resource is specified as a parameter. In using this target the model varies each day of the week in a cycle by 2% from the previous day to avoid a hard turn on/off, in other words, to avoid being a bang-bang (on-off) controller like a thermostat which for our purposes has too high a loop gain causing unwanted oscillations.

Inputs are provided for a population annual growth factor and for the number of days immunity is expected to last. These are used for analyzing potential for recurrence or persistence using a 14 year simulation. Our simulations were run with 0.6% population growth for the US and 1.1% for the world, with a 730 day assumed immunity persistence. This has no noticeable effect on the short term simulation, only the recurrence check.

Inputs are provided for seasonality. These are *not* used for school or other cultural patterns which are more appropriately handled with planned unlock percentages. They are only for climate seasonality. A starting month, number of months and reduction factor are specified. The reduction factor can be set to 1.0 if seasonality is not to be used. Based on the previously mentioned 40% and 20% figures for New York and Florida, averaging them to 30% for the US, and cutting in half to 15% in a "guesstimate" of the amount attributable to school, we arrive at a 15% reduction for the US and set default reduction factor to 0.85. Only half the reduction is taken in the first and last months, which are assumed to be May and September. For the world seasons are not synchronized, but as 90% of the world population lives in the northern hemisphere, we use a reduction factor of 0.9.

There are customizing inputs for region name and population. A sub-region option eases simulation where one particular city has substantially more cases than the rest of the country.

2.2. Model dynamics

We use a standard S modeling approach [13]. During "lockdown" the reproductive factor is adjusted according to (a) the ratio of new cases from the previous day, and (b) the increase in herd immunity factor over the previous day. A moving average on this number prevents wild swings from anomalous data. For manually established unlock (easing, or reopening) scenarios we use a 4 day moving average. For intermittent daily unlock, a feedback strategy not as sensitive to the early data that calibrates the model, we use a 2 day moving average and an explicit 6 day delay from infection propagation to observation of new cases.

The model is designed to be instantiated with data prior to any unlock actions so a baseline 0% unlocked R_0 can be established using the average for the previous week. In the case of COVID-19 there appeared to be a weekly pattern which was some kind of data collection artifact of significant magnitude, and this averaging technique removes it.

When an "unlock" policy is established in the predictive model, the reproductive factor is biased toward the initial value and proportioned toward the last data-derived baseline reproductive factor according to the unlock effectiveness. Then it is reduced by the herd immunity factor (which we define below). Calibrating unlock effec-

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tiveness, i.e. what policy will have what percentage unlock effect, is an important activity that is left to the user and local authorities.

Each day actual data was used to replace predicted data. This affects the model's integration base and the effective reproduction rate. The number of total cases, used for the herd immunity calculation, is calculated by the case ratio model parameter described above.

Using the reproductive factor either taken from the data, or for future projections calculated using the last value, the herd immunity, and the unlock percentage, the model calculates the number of new cases. Based on the number of days entered for average case duration it updates the total active and resolved cases and calculates ventilator utilization.

3. Results

Figure 3 compares four world reopening schedules for COVID-19, also applicable to similar epidemics with no prior immunity in the population. The US is excluded and will be addressed separately.

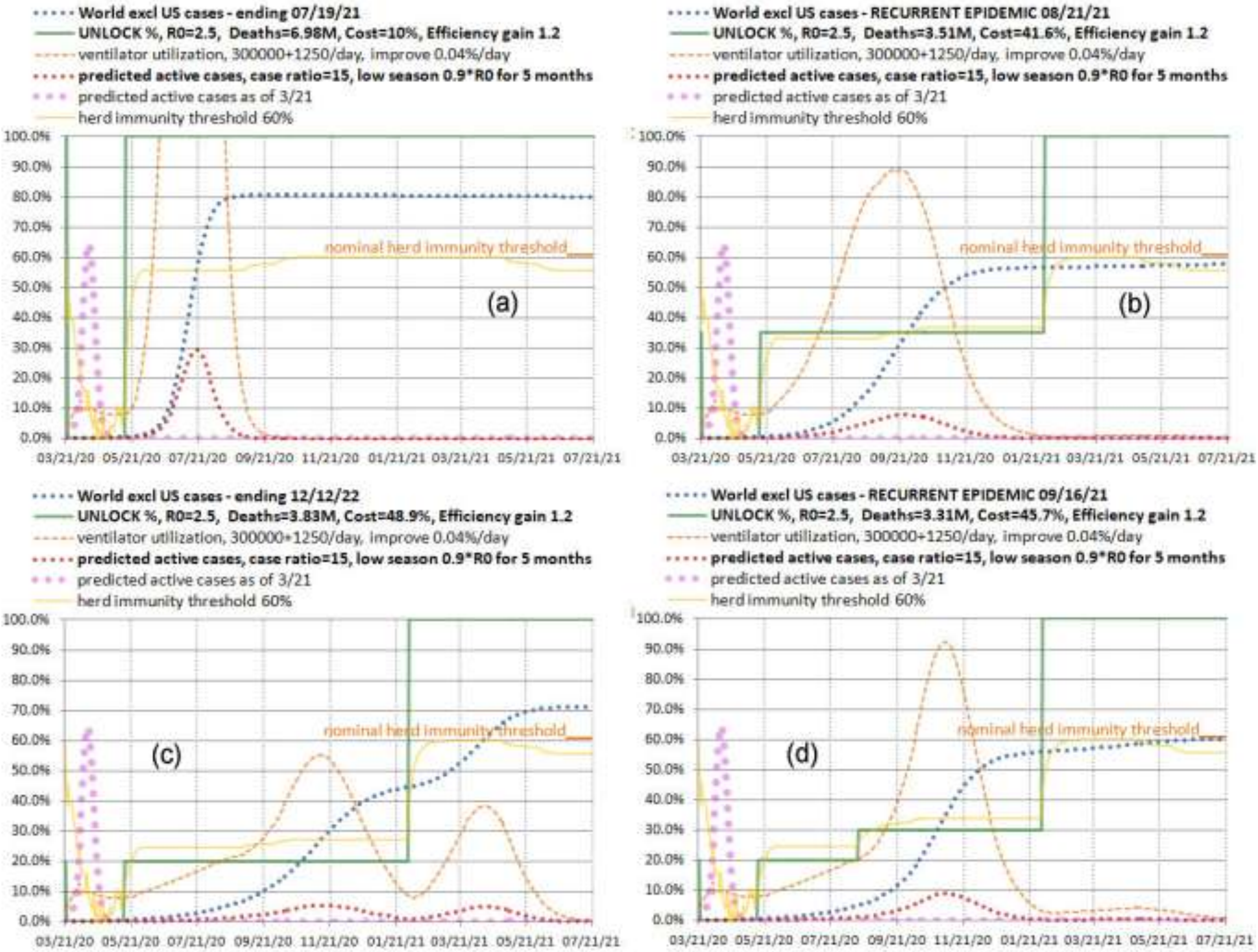

Figure 3. COVID-19 World reopening schedules for R0=2.5 and case ratio=15 (a) immediate full unlock, (b) 35% immediate and 100% in February 2021, (c) 20% immediate and 100% in February, (d) 20-30% multi-step unlock and 100% in February.

All charts in Figure 3 show the effect of never locking down as a spike of large pink dots on the left. This is

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over sometime in May. Total infections are even higher than in 3(a) and deaths are higher. Flattening has to be considered successful. For replication factor R_0 up to about 5 we see similar results. For R_0=6 herd immunity threshold is reached if there is even a two week period before lockdown. All higher replication rates overshoot herd immunity if there is a two week window and replication rates over 10 infect 99% of the population. This assumes homogeneous contact, a characteristic of SIR models, a sort of worst spreading case. Spreading may take longer if it has to reach isolated populations are travel through a geographically constrained region. Equal spreading in all world climates is also assumed. So there are a lot of caveats. It is a general guide.

The deaths and economic cost for the above cases including alternative R_0 and case ratio values are in Table 1 for these values and for alternate values of R_0 and case ratio.

Table 1. SIR-projected world deaths and economic impact for four reopening schedules of Figure 3 Baseline R_0=2.5 and case ratio 15. Alternatives in right two columns.

Schedule	**Deaths** *in millions*	**Economic Impact** *as % of 18 month lockdown*	**Deaths for R_0=3**	**Deaths for case ratio = 50**
(a) immediate	6.98M	10%	9.26M	2.6M
(b) 35% - 100%	3.51M	41.6%	4.4M*	1.28M
(c) 20% - 100%	3.83M	48.9%	4.35M	1.31M
(d) 20-30-100%	3.31M	45.7%	3.74M*	1.16M

* Indicates ventilator capacity may be exceeded

The economic impact is only a function of the unlock degree and schedule. Generally case ratio does not change the trajectory of cases, but if cases are unknown because they are mild then it dilutes both mortality and resource utilization proportionately (e.g. double case ratio and half mortality). Case ratio does not remain constant. This is for some value expected when the simulation is run. A higher replication factor will create more cases and if they have the same mortality (not always true) will result in more deaths, but only slightly more. It is not proportional.

Notice that the total cases (blue dotted line) are about the same in all except (a) which had overshoot of the natural population (herd) immunity level (yellow line). This is because we assume a vaccine is not available until about the end of this simulation. Partial lockdown in (b) and (d) is not sufficient to keep everyone from becoming infected before then. Only the 20% unlock prevents full infection but only by 15 percentage points as it overshoots its reduced immunity threshold badly. The immunity threshold is drawn to show the theoretical stopping point for total cases at each level of lockdown, based on the value of R_0 associated with that level. Thus you can see overshoot is a problem even for very modest amounts of reopening.

There are two reasons for variation in the level of deaths. All schedules except (a) move the bulk of cases into the September time frame or later when we assume mortality is reduced. This affects both mortality and critical medical resources in our model (the dashed orange line for medical resources will get closer to the active cases line later in the year). That is not the subject of this paper. We merely have tried to make a realistic model which does not overstate our main point, and to assume no reduction of mortality would definitely overstate it.

The remaining reduction is from elimination of overshoot. The difference between comparable schedules (with cases in the September time frame) of overshoot for 20% then 100% unlock (c) and the best targeting of population immunity (d) is 0.52 million deaths avoided. If we remain fully locked down until an August 15 100% unlock (not in the figure, date chosen to support school in the fall) the overshoot will be to the 93% level and 4.8 million deaths, with 1.49 million avoided by using a partial unlock approach with overshoot avoidance. The reason an overshoot in the fall is higher than an overshoot immediately is because we are already into the low season for the virus in May, and in the world model reducing its R_0 by 10%. In the fall it is full strength.

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If the anticipated mortality reduction is more modest, a quarter of that projected here, the worst case deaths at a case ratio of 15 becomes 13.91 million, and overshoot reduction of schedule (d) reduces that to 10.14 million, a 27% reduction. For case ratio of 7 which was initially supposed the numbers would be 29.86 million with full overshoot and 21.15 million with schedule (d).

3.1 Overshoot Analysis

Handel et. al. [8] say that to avoid overshoot, cases should vanish as one approaches the herd immunity threshold. This assumes we know what that threshold is, and have very fine control over cases. They suggest “adaptive” control. We’ll discuss some ways of putting bounds on R0 and thus knowing the threshold in the section on case ratio, though it is not really accurate enough for to avoid recurrences as we will see later. And our intermittent daily unlock method is a kind of adaptive control. In this section we discuss where overshoot comes from and provide some guidelines about case magnitudes that translate into overshoot.

The simplest method of avoiding overshoot is evident from Figure 3. It is to use at least one partial step before unlocking to your intended destination level. Whether this should be a half, a third or two thirds of the final level depends on R_0 and the number of susceptibles (which effectively reduces R_0). The question is best answered in simulation. With a high R_0 the first step will overshoot its own threshold by more, and so a smaller first step is required.

At the threshold effective R_0 is 1.0. If 1% of your population is sick, they will still sicken another 1% and you have overshoot 1%. Then R_0 is reduced a little more but some additional people get sick, and so forth. Figure 4 gives a rough idea of how much overshoot to expect from a certain number of cases at the threshold for different values of raw R_0. The overshoot is less for high R_0 because they have such a high threshold there is not much room for overshoot.

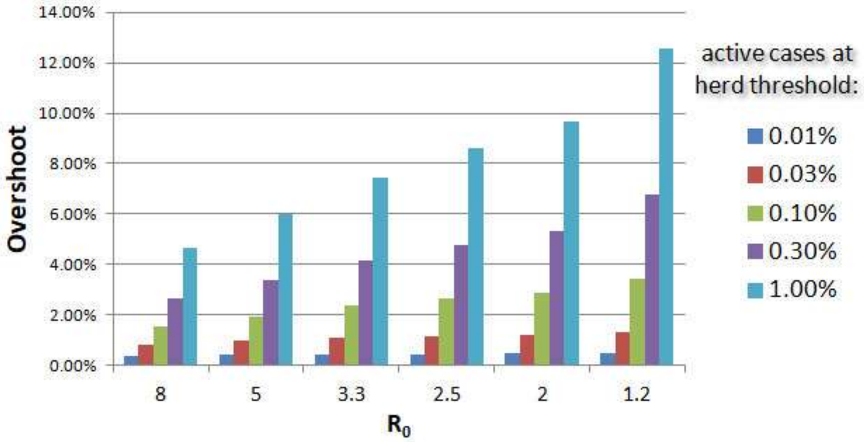

Figure 4. Expected overshoot from cases-at-threshold and R_0

Undershoot is a bad idea. That’s what went wrong in Figure 3(c). Even if one has very few cases, as long as they are not zero they start up on the next unlock because then there are again enough susceptible targets for the infection to grow.

In the section on recurrences we will discuss why hitting the threshold exactly is also a bad idea unless one is sure there will be a follow up vaccine.

Targeting a little beyond the threshold, based on the margin of uncertainty to which it is known, and to which control can be exerted, will in the long run produce the least suffering by bringing a definitive end to residual infections. Then efforts can focus on identification and containment of re-introductions from either travelers or animal reservoirs. If the primary transmission is using an animal vector some of this discussion does not apply.

3.2 Reconciling case ratio with actual case data

Case ratio is infinite when the epidemic begins as no cases are yet known, and it decreases constantly to the annoyance of modelers. Randomly sampled antibody tests are one of the few ways to ascertain the case ratio without changing it and are extremely important in ascertaining the shape of the problem, yet in the case of COVID-19 few have been done. When a disease transmits asymptomatically, case tracking methods eventually come to dead ends. What is the true mortality? How many people will die? How long before cases peak? None of these questions can be answered without case ratio. We have seen it creates more variance in predictions than replication factor.

In theory, if one knows replication factor then case ratio can be inferred from where the cases peak and how fast they decline. However, when data from regions at different stages of the epidemic are added together such shape criteria are lost. It is particularly pointless to look at world data in this regard. Until recently we felt it was pointless to look at US data also, but then the authors learned that the combined New York (state), New Jersey and Connecticut region (hereafter NYNJCT) was exhibiting a nicely shaped SIR curve turning down with declining cases, while the rest of the US was still increasing cases. When added together they make a choppy, nearly-flat shape that doesn't fit any SIR curves. Figure 5 shows separate plots for NYJNCT and the US without NYNJCT.

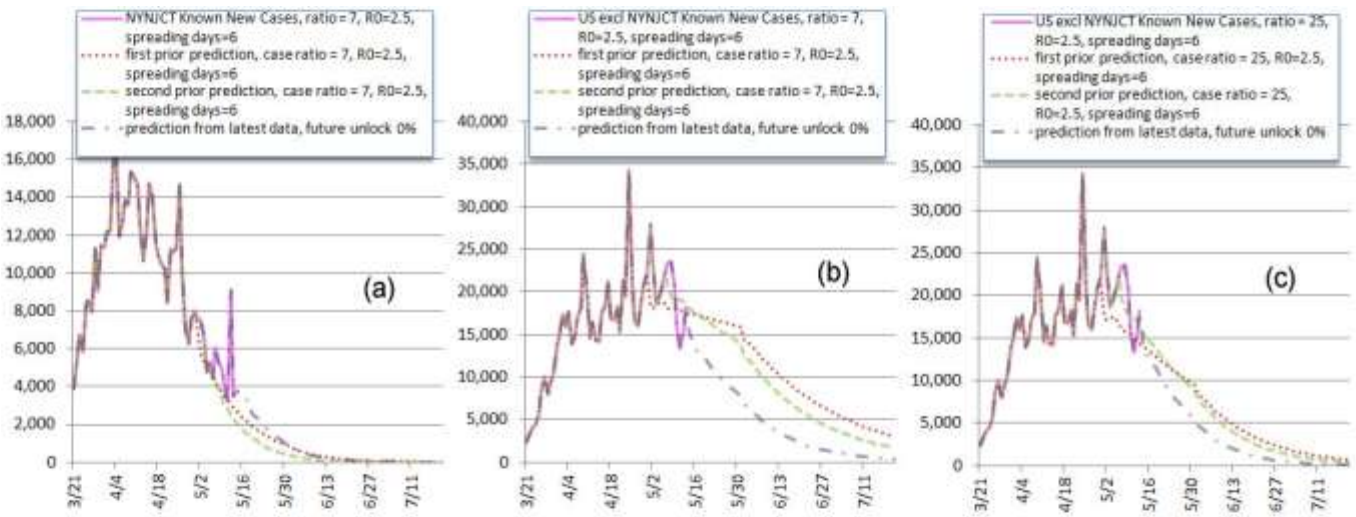

Figure 5. Comparison of new cases data vs prior predictions for the New York, New Jersey, Connecticut sub-region of the US, and the US without the sub-region: (a) case ratio 7 for NYNJCT, (b) case ratio 7 for US without sub-region, (c) case ratio 25 for US without the sub-region.

There are two principal ways case ratio changes: There is testing of people who aren't showing symptoms to discover the unknown cases. And before that enough test kits are available to test everyone who suspects they have symptoms, and thus all new cases are discovered and therefore known except the asymptomatic ones who have no suspicion they are making people sick.

In Figure 5 new cases data is compared with predictions made from one week and two weeks prior to the end of data. In 5(a) for NYNJCT a ratio of 7 provides a reasonable fit. Higher ratios drop below the data trend. This number is within the range of numbers that have come out of New York mentioned earlier. In 5(b) we see the 7 case ratio does not follow the sort of falling cases curve we would expect if lockdown were not lifted at all, which was the simulation scenario for comparison. The lowest case ratio that gives the expected decline is 25 shown in Figure 5(c). This is below the only numbers available at this writing, the range of 50-85 from Santa Clara County, California. The graphical analysis is just a reasonableness check and not reliable for determining the case ratio. The value of R_0 is constantly changing in the early part of the data due to social distancing, and

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case ratio changes throughout as outlined above, forcing us to compare only a short period of time (two weeks) which undermines statistical validity. Soon data will be available from Ohio and Indiana. For current purposes, we take a case ratio of 25 to be a reasonable if pessimistic estimate of "likely" case ratio and continue to simulate over a range.

3.3 Intermittent Daily "Adaptive" Control

Figure 3 (c) and (d) illustrate that a 10% change in a reopening schedule has a dramatic effect on outcomes. It is unlikely we can plan levels to within 10%, and even a couple of percent can in fact have such effects. So can changed in dates by even a week or two, if too many cases from the tail of a previous peak are caught in a new higher unlock level for example. Planners will have to constantly monitor and adjust, what Handel et. al. call "adaptive" control. We show here it is possible to formalize that. Figure 6 gives a "4-corners" simulation of intermittent daily unlock over the range of case ratio from 7 to 40 and initial unlock level from 20% to 60%.

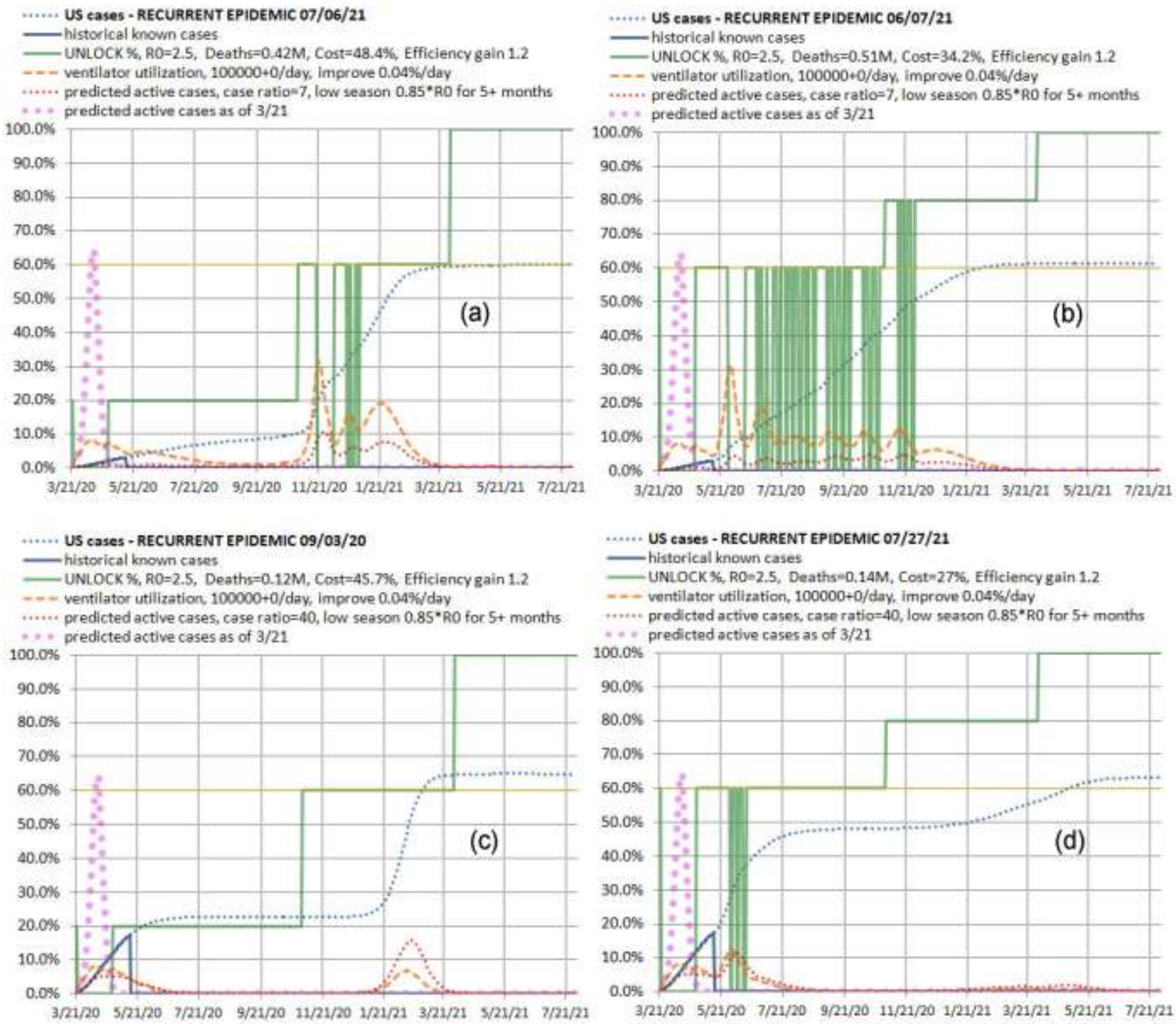

Figure 6. Intermittent daily unlock, US, 20% vent target, case ratio 7 to 40 (top to bottom), first unlock 20-60% (left to right).

There are some countries already scheduling activities by days, but there are issues with constantly changing it. How does one schedule an appointment or buy transportation in advance? The advantages are so great that it might be worth looking into how to solve these problems. A phone app could schedule appointments and transportation schedules based on unlocked business days, for example.

We follow a two-level unlock approach on top of the intermittent unlock in keeping with minimization of overshoot. The second step is half way from the first step to 100%. A 20% critical resource (ventilator utilization) target is used for the feedback control, with a one week delay to demonstrate stability. The slight difference between the 20% and 60% death totals is due to whether cases are put off until fall or not. There is only a modest difference in cost between 20% and 60% as the feedback is regulating what goes on. The big difference in cost is whether the case ratio is high (low cost, low mortality, low critical resource usage) or low (high everything else).

Notice that by using a critical medical resource for the feedback, rather than controlling to cases, that cases are automatically shifted into periods of lower mortality. This is most evident in Figure 6 (b). The cases rise toward fall while medical resource utilization is level or falling.

The 60% case works well only because in this simulation the epidemic is entering a low season with R_0 reduced by 30%. If not, the 20% case is preferable, and one might have to ban certain days altogether in the first two months so that the infection does not explode before the lag in the feedback notices and responds to the increase. Our model only simulates human controllers, who may be able to better handle this situation.

3.4 Recurrence, Persistence and Extinction

Notice that of the eight simulations presented only Figure 5 (a) and (c) give an infection ending date. This is because they have overshoot. The larger and earlier the overshoot, the sooner the infection collapses to zero and can only return by re-introduction. In all the other cases our overshoot targeting was so good that an infection persisted by means of population growth and lapsing immunity (two years in these simulations). Figure 7 shows the recurrent infection for 14 years following the schedule of Figure 5 (b).

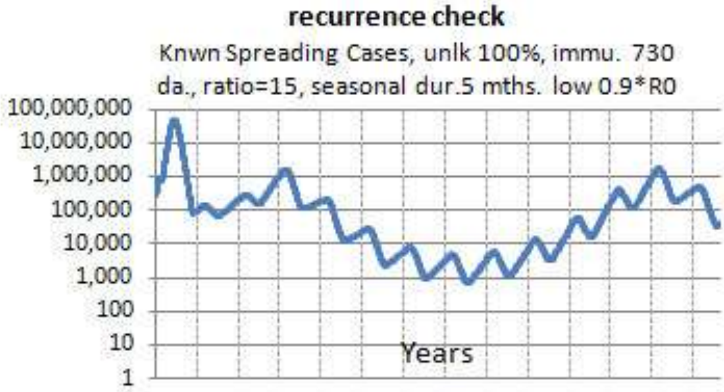

Figure 7. Recurring or persistent infection associated with scenario from Figure 5 (b).

This is typical of the recurring ones. They scale in the following way with population: the curve maintains its exact shape but descends toward “1” and below that disappears from view, existing among unknown cases because of the case ratio. When it descends so that the number of unknown cases is 0.5, which we consider to be a “probability” of a case, the model declares the infection terminated and sets the value to zero. It is easy to see from Figure 7 that if a persistent infection varies over 5 orders of magnitude as this one does, including the invisible portion due to the case ratio, then it requires a population of a few hundred thousand to persist. This is a classic result of epidemiological modeling of diseases such as measles.

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Usually one must end up within 1% to 2% of the herd immunity threshold to get this effect. The trouble is, one is targeting the immunity threshold, so the probability of hitting this window is substantial. In simulation we have hit it every time we have avoided overshoot without any other special effort to do so.

Seasonality diminishes the chance of creating such a condition. The variation driven by seasonality tends to drive the infection to zero during a low season.

Epidemiologists differ on whether this is significant. For the world it really is not, since the world is very heterogeneous and conditions differ enough that avoiding the condition in most areas will not prevent it occurring in another, from which it can spread. However, given the logistics of case discovery and tracking, the authors feel the process of containment is much easier when addressing only re-introductions, as opposed to an unidentified pool of mostly invisible cases. So on a region by region basis, depending on what strategy is available (vaccine, herd immunity, suppression of the virus within the region), it may be desirable to consider recurrence and persistence. Also, in simulation we found a typical recurrence of COVID-19 near the persistence threshold would kill up to 60,000 people over a two year period, which is magnified if it keeps repeating.

The more overshoot, the faster this is suppressed. That has a cost, of course. With undershoot, the infection tends to rebound in one to three years (in the case of COVID-19) at which time it exceeds the threshold and extinguishes itself.

3.5 Applicability to more transmissive epidemics

Figure 8 shows that the same scenario as above for intermittent daily unlock handles an R_0=4 epidemic.

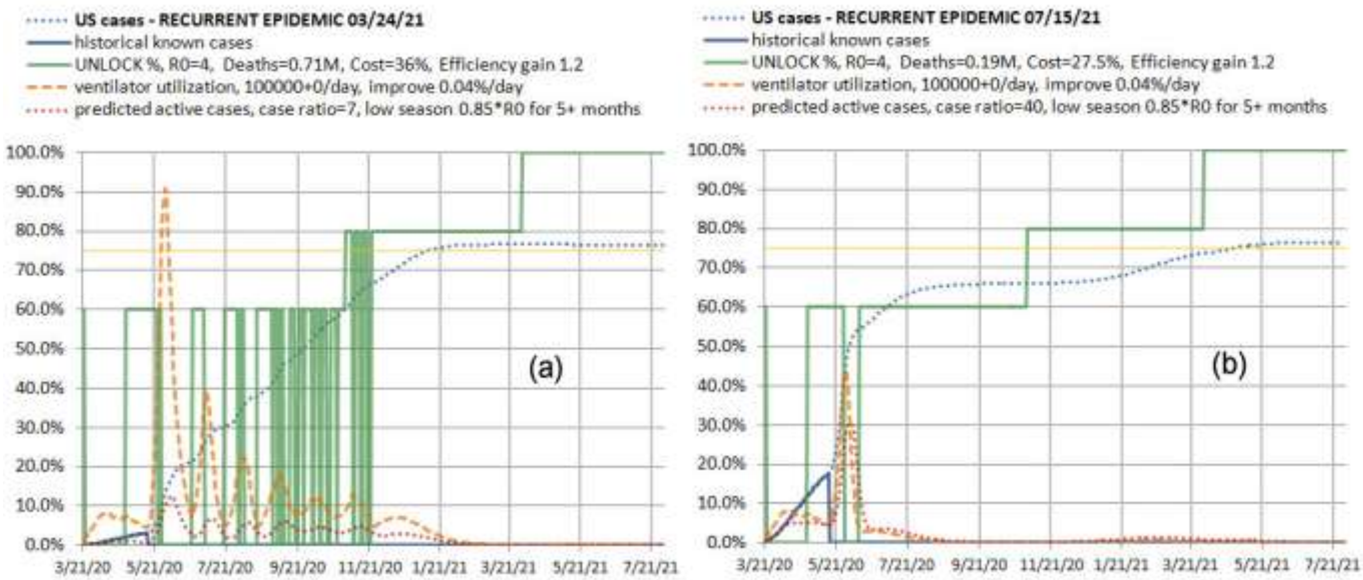

Figure 8. Intermittent daily management of R0=4 epidemic for case ratios of 7 (a) and 40 (b).

How far can we take this? A lot depends on whether it is at the beginning of the low season, and whether citizens have protective masks and food on hand and businesses have rehearsed procedures like fire drills or civil defense drills, because very high R_0 pathogens move seemingly with the speed of an air raid.

As a test of the method Figure 9 shows, with case ratios of 5 and 80, that at least theoretically the method can handle R_0=15, e.g. measles. Mortality numbers are based on COVID-19. For the case ratio of 50 dates are adjusted to minimize economic damage. We assume that there exist, on the shelf and ready to use, social distancing measures that can throttle the R_0 of 15 down to levels just below 1.0 for the zero unlocked case, and from there everything proceeds as before.

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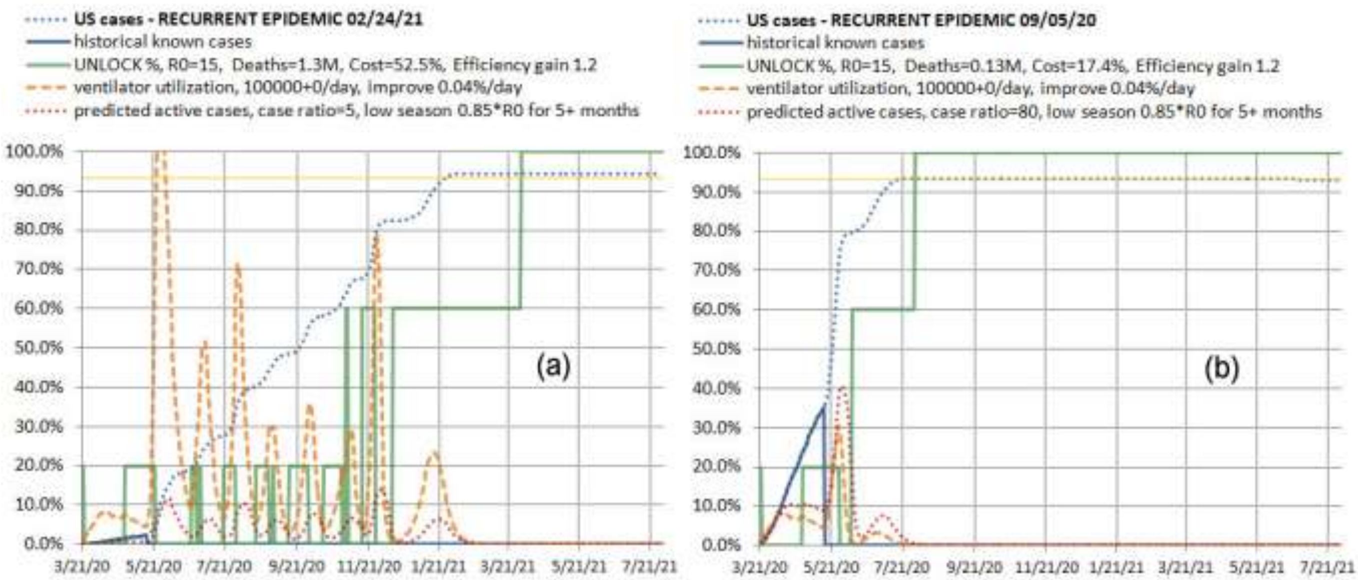

Figure 9. Intermittent daily management of R_0=15 epidemic for case ratio 5 (a) and 80 (b).

4. Discussion

We leave more detailed regional and local analysis to the many regions and locations of the world, but with the suggestion that perhaps each locality should independently assure that any thresholds are approached slowly or using the two-step method. Each region can also best devise and measure its partial unlock strategy based on culture and responsiveness, geography, types of industry and so forth.

Without active management, our simulations suggest epidemics like COVID-19 will produce a badly broken world economy and medical equipment supply. Applying partial unlock with feedback control to efficiently use medical equipment, and using economic unlock to effect this control, provides relief from not only the medical resource problem, but some relief from economic shutdown, and a significant improvement in deaths due to total cases.

While virus evolution is not a certain science, there is reason to believe viruses are rapidly selected for increased transmission (R_0) [14]. A long delay in building immunity to the virus and driving it mostly out of the human population leaves a large number of active cases present in which the virus is being selected to overcome the near-1.0 R_0 condition of social distancing, eventually making the virus more difficult to control by this method. The authors tried one simulation of measles (R_0≈15) and immediately realized it was not controllable by the methods in this paper. A long period of persistence or multiple recurrences, though involving a smaller number of cases, also provides the opportunity for virus evolution.

If we have one request of public health authorities it is that more effort be put into determining case ratio, and re-determining it periodically. This type of testing must be random samples. For a new disease antibody testing can be used and compared with cumulative known cases. If there is existing immunity a test for active illness will have to be used and compared with active known cases.

If we have something to ask of government officials it is to be utterly straightforward about the goals and likely length of lockdowns, and to consider freezing financial obligations and employment status while such measures are in place. We do not expect people to be fired or loans foreclosed because of other civil emergency response actions. It has been suggested that COVID-19 and its related cousins (SARS, MERS) do not kill directly, as the virus count has already passed the peak when death occurs, but the *coup de grâce* is delivered by the immune system fighting back too hard [15, 16]. Is that how our society and civilization is going to die, by fighting too hard? Given the current data and direction, it appears likely – if not now, then eventually on some other crisis.

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It is important to establish a level-headed precedent.

While we did not calculate economic impact in detail, only giving a fractional allocation of an undefined 18 month full lockdown, the idea of comparing this impact to an ordinary recession is off the mark. One of the author's was traveling overseas following the 2008-9 financial crisis. It was felt very hard in Ukraine and North Africa as the US curtailed buying from Europe and Europe curtailed both employment and buying from those regions. The result of that was a color revolution in Ukraine, tensions with Russia, economic impact on Russia, the Arab Spring revolutions (begin by a Tunisian man immolating himself because he was not allowed to work), and resulting in still continuing wars in Libya, Yemen and Syria, and massive migration problems in Europe. The world COVID-19 lockdown is potentially bigger, depending on what strategy is followed on reopening economies. The UN is predicting the number facing starvation will double to 250 million (see https://www.bbc.com/news/world-52373888). The economic costs and their consequences are not conditional. They occur whether a strategy works against a pandemic or not. In 2018 three economists published a paper suggesting the impact of pandemics be accounted in lives rather than economic costs [4]. This unbalances the equation if effort to control pandemics is not accounted in lives also.

We had neither the knowledge nor cooperation level to fight the 1918 flu epidemic by shutting down our world. But we survived it. It may have had some effect on the WWI armistice some think, keeping the American President Woodrow Wilson away and imposing harsher terms on Germany that may have contributed to WWII. It is possible that despite the warning shots of SARS and MERS and urging from influential scientists and wealthy activists that we just don't have the medical technology to shut down this pandemic out of hand.

However, we have the ability to shut not only our economy, but so throttle the progress of the disease that it doesn't run its course and remains in the wings, forcing us to continue locked down for so long that social order will be called into question, and countless lives will be economically ruined. Not every country can afford trillion-dollar-a-month compensation for losses due to lockdowns. Those that can, will not manage to distribute it equitably. Those that receive it will be demoralized by the loss of their life's work. It may be intellectually uncomfortable to compare social and economic losses, however large, to a medical body count.

Complicated things like stopping and starting an economy, much like controlling an R_0=15 outbreak, do not happen without rehearsal, involving both the officials who must coordinate response, and ordinary citizens. *Planning is not nearly sufficient*. Ordinary disasters like storms and fires require rehearsal. Military operations require war games. Already in direct government outlays the US has spent more than double the cost of the Iraq war, longest in its history, on COVID-19 response. Preparation for future disasters of such high probability require no less attention.

5. Conclusion

We have shown a method in this paper that provides predictable control as long as the public responds to increases and decreases in social distancing, and the amount of social distancing is able to moderate the replication factor above and below 1.0. This should help maintain public calm as cases build in a planned way, rather than just shooting up as COVID-19 and similar epidemics clearly have the potential to do. It allows planning and requires no improbable knowledge of either pathogen characteristics or human behavior, while shifting cases toward lower mortality periods automatically if mortality rates are changing.

This paper provides a medical body count associated with following a less than optimal unlock strategy, and specific tools and theoretical understanding for finding and following a near-optimal strategy, whatever goal society adopts.

Managing a partial unlock strategy is always a feedback process. If the expectation is to establish periods of weeks or months of a certain regime, it will have too much lag to respond to an increase in infections, and too much uncertainty to make timely adjustments. Setting the expectation to a fast notice of a daily schedule change could potentially make an order of magnitude improvement in epidemic management. In any case, use of partial unlock consciously to avoid overshoot results in fewer deaths than simple one-step easing strategies, even if the goal is only moderate easing while still basically waiting on a vaccine.

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