# HOW CONTROL THEORY CAN HELP US CONTROL COVID-19

Using feedback, a standard tool in control engineering, we can manage our response to the novel coronavirus pandemic for maximum survival while containing the damage to our economies

**BY GREG STEWART, KLASKE VAN HEUSDEN & GUY A. DUMONT**

**CLOSED FOR BUSINESS:** The streets of Manhattan are quiet on 10 April as most people comply with the city’s self-quarantine rules.

**As we write these words, countless people, perhaps the majority of the world's population, are subject to physical-distancing policies or confined to their homes in an attempt to contain one of the worst pandemics of modern times. Economic activity has plummeted, hundreds of millions of people are out of work, and entire industries have ground to a halt.**

**Quite understandably, a couple of questions are on everyone's mind: What is the exit strategy? How will we know when it's safe to implement it?**

Around the globe, epidemiologists, statisticians, biologists, and health officials are grappling with these questions. Though engineering perspectives are uncommon in epidemiological modeling, we believe that in this case public officials could greatly benefit from one. Of course, the COVID-19 pandemic isn't an obvious or typical engineering problem. But in its basic behavior it is an unstable, open-loop system. Left alone, it grows exponentially. However, there's good news, too: Like many such systems, it can be stabilized effectively and efficiently by applying the principles of control theory, most notably the use of feedback.

Inspired by the important work of epidemiologists and others on the front lines of this global crisis, we have explored how feedback can help stabilize and diminish the rate of propagation of this deadly virus that now literally plagues us. We relied on feedback-based mechanisms to devise a system that would bring the outbreak under control and then adeptly manage the longer-term caseload.

It is during this longer-term phase, the inevitable relaxing of physical distancing that is required for a functioning society, that the strengths of a response grounded in control theory are most crucial. Using one of the widely available computer models of the disease, we tested our proposal and found that it could help officials manage the enormous complexity of trade-offs and unknowns that they will face, while saving perhaps hundreds of thousands of lives.

Our goal here is to share some of our key findings and to engage a community of control experts in this vital and fascinating problem. Together, we can contribute vitally to the international efforts to manage this outbreak.

THE COVID-19 PANDEMIC is unlike any other recent disease outbreak for several reasons. One is that its basic reproduction number, or R0 ("R naught"), is relatively high. R0 is an indication of how many people, on average, an infected person will infect during the course of her

PREVIOUS PAGES: SPENCER PLATT/GETTY IMAGES illness. R0 is not a fixed number, depending as it does on such factors as the density of a community, the general health of its populace, its medical infrastructure and resources, and countless details of the community's response. But a commonly cited R0 figure for ordinary seasonal influenza is 1.3, whereas a figure calculated for the experience in Wuhan, China, where COVID-19 is understood to have originated, is 2.6. Figures for some outbreaks in Italy range from 2.76 to 3.25.

The goal of infectious-disease intervention is reducing the R0 to below 1, because such a value means that new infections are in decline and will eventually reach zero. But with the COVID-19 outbreak, the level of urgency is quite high due to the disease's relatively high fatality rate. Fatality rates, too, are quite variable and depend on such factors as age, physical fitness, present pathologies, region, and access to health care. But in general they are much higher for COVID-19 than for ordinary influenza. A surprisingly large percentage of people who contract the disease develop a form of viral pneumonia that sometimes proves fatal. Many of those patients require artificial ventilation, and if their number exceeds the capacity of intensive care units to accommodate them, some number of them, perhaps a majority, will die.

For that reason, enormous worldwide efforts have focused on "flattening the curve" of infections against time. A high, sharp curve indicating a surge of infections in a short time period, as occurred in China, Italy, Spain, and elsewhere, means that the number of serious cases will swamp the ability of hospitals to treat them and result in mass fatalities. So to reduce the peak demand on health care, the first priority must be to bring the caseload under control. Once that's done, the emphasis shifts to managing a long-term return to normalcy while minimizing both death rates and economic impact.

The two basic approaches to controlling the spread of disease are mitigation, which focuses on slowing but not necessarily stopping the spread, and suppression, which aims to reverse epidemic growth. For mitigation, R0 is reduced but remains greater than 1, while for suppression, R0 is smaller than 1. Both obviously require changing R0. Officials accomplish that by introducing social measures such as restricted travel, home confinement, social distancing, and so on. These restrictions are referred to as nonpharmaceutical interventions, or NPIs. What we are proposing is a systematically designed strategy, based on feedback, to change R0 through modulation of NPIs. In effect, the strategy alternates between suppression and mitigation in order to maintain the spread at a desired level.

It may sound straightforward, but there are many challenges. Some of them arise from the fact that COVID-19 is a very peculiar disease. Despite enormous efforts to characterize the virus, biologists still do not understand why some people experience fairly mild symptoms while others spiral into a massive, uncontrolled immune response and death. And no one can explain why, among fatalities, men predominate. Other mysteries include the disease's long incubation period—up to 14 days between infection and symptoms—and even the question of whether a person can get re-infected.

These perplexities have helped bog down efforts to deal with the pandemic. As a recent Imperial College London research paper notes: "There are very large uncertainties around the transmission of this virus, the likely effectiveness of different policies, and the extent to which the population spontaneously adopts risk reducing behaviours." Consider the long incubation time and apparent spreading of the virus before symptoms are experienced. These undoubtedly contributed to the relatively high R0 values, because people who were infectious continued to interact with others and transmitted the virus without being aware that they were doing so.

This lag before the onset of symptoms corresponds to time delay in control-system theory. It is notorious for introducing oscillations into closed-loop systems, particularly when combined with substantial uncertainty in the model itself.

In addition to delays, there are very significant uncertainties. Testing, for example, has been spotty in some countries, and that inconsistency has obscured the number of actual cases. Even NPIs are not immutable. The extent to which the public is complying with policies is never 100 percent.

The point is, a pandemic is a dynamic, fast-moving situation, and inadequate local attempts to monitor and control it can be disastrous. In the Spanish flu pandemic of 1918, cities took widely varying approaches to the lockdown and release of their citizens, with wildly varying results. Some recovered straightforwardly, others had rebound spikes larger than the initial outbreak, and still others had multiple outbreaks after the initial lockdown.

**IN THE ABSENCE** of widespread immunity or vaccination, the only way to suppress the disease is total confinement—obviously not a viable long-term solution. A reasonable middle ground is to implement a policy that makes extensive use of feedback to keep R0 close to 1, with perhaps small oscillations on either side. In so doing we could maintain the critical caseload within the capacity of health care institutions while slowly and safely building immunity in our communities, and returning to normal social and economic conditions as quickly as is safely possible.

What exactly do we mean by "feedback" here? Consider what's already happening now: Public officials are now taking hospital caseloads into account before imposing or lifting restrictions. This is an example of the use of feedback, where the feedback variable is the number of cases in local hospitals. However, the use of feedback now is typically relatively coarse, and its results less satisfactory, in comparison with what could be achieved if control principles were more finely and systematically applied.

Here's an obvious way that coarseness would cause problems. If the tuning mechanism is too aggressive—for example, switching between full and zero social distancing—it would lead to severe oscillations and overwhelmed hospitals. On the other hand, tuning that is too timid also courts fiasco. An example of such tuning might be a policy requiring a full month in which no new cases are recorded before officials relax restrictions. Such a hypercautious approach risks needlessly prolonging the pandemic's economic devastation, creating a catastrophe of a different sort.

But a properly designed feedback-based policy that takes into account both dynamics and uncertainty can deliver a stable result while keeping the hospitalization rate within a desired approximate range. Furthermore, keeping the rate within such a range for a prolonged period allows a society to slowly and safely increase the percentage of people who have some sort of antibodies to the disease because they have either suffered it or they have been vaccinated—preferably the latter.

Clearly, tried-and-true principles of control theory, particularly feedback, can help officials plot more robust and optimal strategies as they attempt to safely ease the social distancing that has helped mitigate the COVID-19 pandemic. But how to make officials aware of these powerful tools?

Imagine an online interactive tool offering detailed, specific guidance in plain language and aimed at public officials and others charged with mounting a response to the pandemic in their communities. The guidance would be based on strategies developed by a small group of control theorists, epidemiologists, and people with policy experience. The site could review the now-familiar initial response, in which nonessential workers are confined to their homes except for essential needs. Then the site could go on to give some guidance on how and when the tightest restrictions could be lifted.

The biggest challenge to the designers of such a Web-based tool will be enabling nonspecialists to visualize how the various components of the epidemiological model interact with the various feedback policy options and model uncertainty. How exactly should the main feedback measure—likely some aspect of hospital or intensive care occupancy—be implemented? Which restrictions should be lifted in the first round of easing? How should they be eased in the first round? In the second round? While monitoring the feedback measure, how frequently should officials consider whether to implement another round of easing? Feedback will help officials determine when to time various phases of interventions.

Such an interactive tool that could assess different policy approaches, vividly illustrating what conditions must be in place to lessen the effects of uncertainty and shrink the projected caseload, would be of incalculable value. It could save untold lives.

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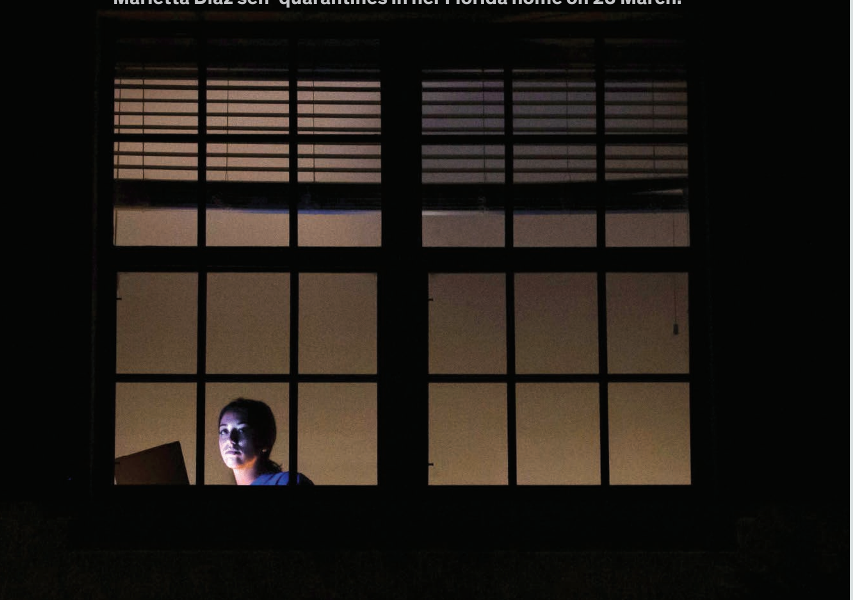
*Material in this article originally appeared as a post on Medium, "Coronavirus: Policy Design for Stable Population Recovery," and in several other outlets.*

**THE WOMAN IN THE WINDOW: Having tested positive for the novel coronavirus, Marietta Diaz self-quarantines in her Florida home on 23 March.**



ZAK BENNET/AFP/GETTY IMAGES

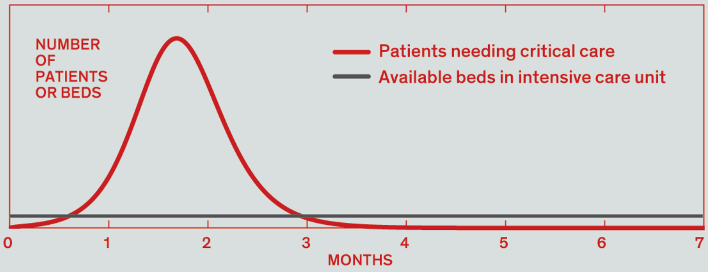
# Five Scenarios

**To explore how feedback can save lives,** we devised a series of scenarios, each indicative of a recovery strategy with a different level of feedback, and simulated the resulting policies against a commonly used infectious-disease computer model. We plotted the results in a series of graphs showing COVID-19 hospital cases as a function of time. Hospital occupancy is probably a more reliable and tangible measure than total case count, which depends on extensive testing that many countries (such as the United States) do not have at the moment. Furthermore, hospital ICU bed occupancy or ventilator availability is arguably an important measure of the ability of the local health care system to treat those who are suffering from respiratory distress acute enough to require intensive care and perhaps assisted breathing.

The model we used was created by Jeffrey Kantor, professor of chemical engineering at the University of Notre Dame (Kantor's model is available on GitHub). The model assumes we can suppress disease transmission to a very low level by choosing appropriate policy levers. Although worldwide experience with COVID-19 is still limited, at the time of this writing this assumption appears to be a realistic one.

To make the model more reflective of our current understanding of COVID-19, we added two types of uncertainty. We assumed different values of R0 to see how they affected outcomes. To consider how noncompliance with nonpharmaceutical interventions would affect results, we programmed for a range of effectiveness of these NPIs.

Our first, simplest simulation confirms what we all know by now, which is that not doing anything was not an option [Figure 1, below].




## 1. CURVE OF DEATH

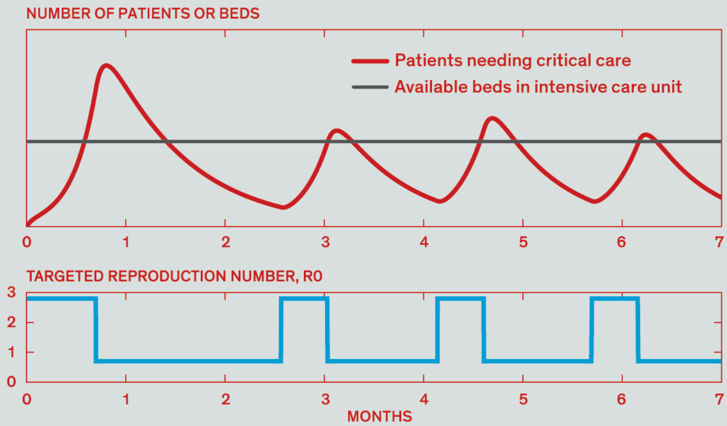
Failing to respond to the outbreak of a deadly and highly contagious illness results in a sharp spike of serious cases that overwhelms the capacity of local hospitals.

The large and lengthy peak well above the available bed capacity in the intensive care unit indicates a huge number of cases that will likely result in death. This is why, of course, most countries have put aggressive measures in place to flatten the curve.

So what do we do when the number of infections comes down? We considered one possibility: relaxing all restrictions when the number of infections has come down. We simulated such a tactic and confirmed what epidemiologists have long known: It would only lead to a second surge in infections. Not only could this second surge overwhelm our hospitals, it could also lead to an even higher mortality rate than the first surge, as occurred repeatedly in several U.S. cities during the Spanish flu epidemic of 1918.

# 2.
## AN ON-OFF APPROACH

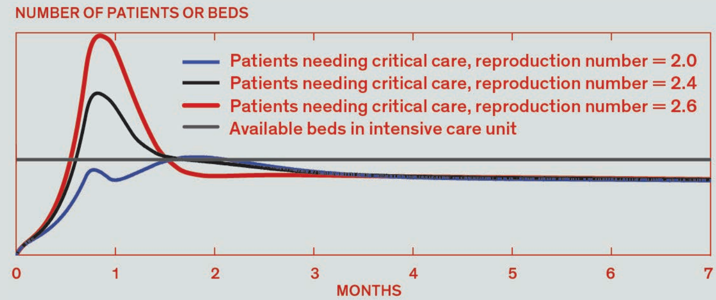
Imposing and lifting strong social restrictions causes abrupt swings in the reproduction number, R0 [in blue]. Those swings in turn lead to oscillations in the caseload [red, upper graph], which can exceed the capacity of local hospitals [black].




In the simple on-off approach to confinement, most of the usual restrictions on gatherings, travel, and social interaction are lifted entirely when the number of new ICU cases drops below a lower threshold, and then are put back into place when this number exceeds a higher threshold. In this case, the R0 swings sharply between two levels, a high above 2 and a low below 1, as shown in blue in the graph. This approach leads to oscillations, and if it is applied too aggressively, the high points of these oscillations will exceed the health care system's capacity to treat patients. Another likely problem with this approach has been labeled "social distancing fatigue." People become weary of the repeated changes to their routine—going back to work for a couple of weeks, then being told to stay at home for a few weeks, then being given the all-clear to go back to work, and so on.

# 3.
## THE BEAUTY OF FEEDBACK

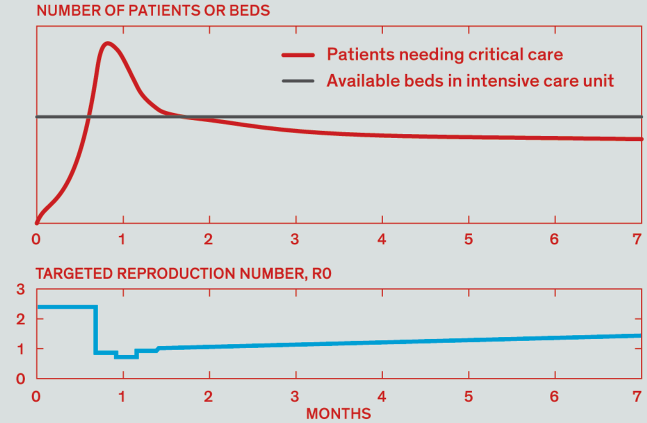
In real-world scenarios, officials will typically have only an approximate value for the basic reproduction number, R0. However, with appropriately applied feedback, this uncertainty won't matter. For R0s between 2.0 [blue] and 2.6 [red], the caseload stabilizes at an acceptable level within a couple of months as a result of feedback from actual hospital conditions.




Using feedback to finely and systematically modulate the restrictions imposed on a population to modify R0 leads to a policy that is robust. For example, early on in the outbreak, there will be a great deal of uncertainty about R0 because testing will still be spotty, and because an unknown number of people will likely have the disease without realizing it. That uncertainty will inevitably fuel a surge in initial cases. However, once the case count is stabilized by the initial restrictive regime, a policy based on feedback will prove very tolerant of variations in the base-level R0, which is the R0 that prevailed before the restrictions were put in place. As the graph shows, after a few months it doesn't matter whether the base-level R0 is 2.0 or 2.6 because the total case count stays well below the number of available hospital beds due to the use of feedback.

# 4.
## SYSTEMATIC APPROACH

A response based on control-theory principles strives to maintain the reproduction number, R0, at close to 1 [shown in blue]. As the caseload comes down, officials use feedback painstakingly to ease restrictions and control R0 so that it very gradually approaches 1, perhaps slightly and briefly exceeding it from time to time. As shown in the upper graph, this strategy keeps the caseload within the capacity of the local health care system to accommodate it indefinitely.



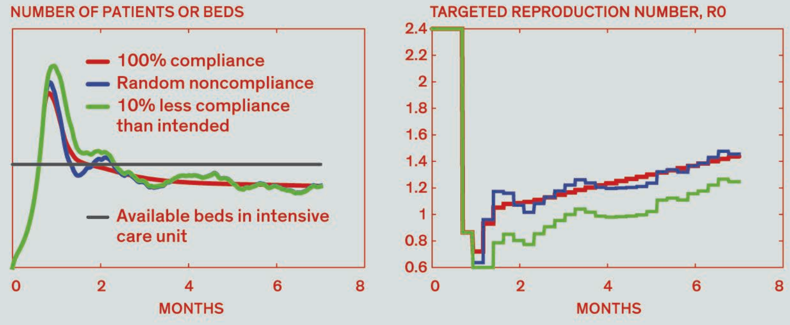

For our third experiment, we developed a scenario in which we targeted 90 percent occupancy of hospital intensive care units. To achieve this, we designed a simple feedback-based policy using the principles of control systems theory.

When R0 is high, many restrictions are put into place. People are largely confined to their homes, and services are limited to the bare minimum needed for society to function—utilities, police, sanitation, and food distribution, for example. Then, as conditions begin to improve, as revealed by our feedback measure of hospital-bed occupancy, other services are gradually phased in. Recovered people are allowed to move freely as they can no longer contract, or transmit, the virus. Perhaps people are allowed to visit restaurants within walking distance, some small businesses are allowed to reopen under certain conditions, or certain age groups are subject to less-stringent restrictions. Then geographical mobility might be loosened in other ways. The point is that restrictions are eased gradually, with each new gradation based carefully on feedback.

This strategy results in a stable response that maximizes the rate of recovery. Furthermore, the demand for hospital ICU beds never exceeds a threshold, thanks to a "set point" target below that threshold. The health care capacity limit is never breached. In addition, note the general upward trend for the release of restrictions, as the number of recovered and immune people grows and nonpharmaceutical interventions are gradually phased out.

# 5.
## COMPLIANCE CONUNDRUM

Officials can never know the exact extent to which people are disregarding their restrictions. But if their policies are based closely on feedback, realistic levels of noncompliance won't cause anything more than minor deviations from the expected levels of illness.




Using feedback creates a policy that restricts social interaction effectively even in the face of likely degrees of noncompliance.

In practice, what noncompliance means is that a given level of restrictions will result in an R0 that is slightly higher than expected, which in turn causes fluctuations in the number of people who are infected. Noncompliance might, for instance, result in the restrictions being 10 percent less effective than intended. However, through feedback, the policy will automatically tighten to compensate.