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TESTING-BASED INTERVENTIONS FOR COVID PANDEMIC POLICIES

Eva Regnier
Susan M. Sanchez
Paul J. Sanchez

Naval Postgraduate School
1 University Circle
Monterey, CA 93943, USA

ABSTRACT

Testing and test-based interventions are critically important in managing the virus that causes COVID-19 because people who are infected can transmit the virus when they have no symptoms. We develop simulation-based tools to help assess testing-based interventions for COVID management.

1 INTRODUCTION

The United States Marine Corps, the National Basketball Association, colleges, universities, and other organizations have tried to manage and limit the spread of SARS-CoV-2 virus that causes COVID-19 (hereafter, COVID) by various interventions. These include creating "clean bubbles" and closed cohorts of people believed to be non-infected, isolating known infected and potentially infected people, testing, and tracing contacts to identify potentially infected people. To support leaders setting policies for testing and test-based interventions, we developed two models. The first captures the impact of COVID's characteristic time-varying viral load on secondary infections, false negative and false positive test results. The second simulates the potential spread of COVID through a cohort in the presence of test-based intervention policies.

2 INDIVIDUAL TESTING POLICIES

The biggest reason COVID is so deadly is that people who have no symptoms can have high viral loads and spread the disease. This also means that *when* an individual is tested affects the test's clinical sensitivity—the probability an infected person receives a positive test result.

We built an interactive decision tool that can be used to compare policies regarding when and how often to test infected or potentially infected individuals. The current version of the tool evaluates policies for individuals suspected to be infected, and estimates the probability that a person receiving all negative tests is nevertheless infected (Regnier 2020).

A user inputs a testing policy, and the tool estimates results including the probability that an individual who tests negative is actually infected (a false negative). The user also inputs parameters regarding the potential infection, such as the infection date or range of dates, as well as the probability of infection, which could be based on individual risk, prevalence, or local test positivity. For example, the tool supports decisions regarding how long to isolate and when to test individuals prior to integrating them into an existing clean population, such as a work group, dormitory, or military squadron. It also supports decisions regarding how long to self-isolate after a potential exposure, such as traveling to visit a sick loved one.

A simulation model takes into account the impact of uncertainty regarding the time-profile of detectability and individual variability in the time profile; *when* the infection occurred—or, for a group, a distribution of infection dates; and incorrect test results due to imperfect test accuracy.

3 GROUP-LEVEL INTERVENTION POLICIES

We have enhanced an earlier model of disease progression by Sanchez and Sanchez (2015) to create the NPS Pandemic Model (Sanchez and Sanchez 2020). This agent-based stochastic model tracks individual outcomes, but without creating connectivity graphs for all members of the population. This makes it scalable to much larger populations than traditional agent-based models. Unlike conventional SEIR (Susceptible, Exposed, Infectious, and Recovered) models that use deterministic transition rates between compartments, the NPS Pandemic model preserves the impact of variability that is so important during the critical early stages of an outbreak, where a "flare" may occur due to a super-spreader event, or an outbreak can "fizzle" as the infected individual(s) do not pass on the disease.

To reflect the characteristic time-profile of infectiousness and detectability of COVID, the NPS Pandemic Model includes separate compartments based on individuals' test results and to support contact tracing capability, and the possibility of infections introduced from outside the cohort. Policies that combine test choice (sensitivity and processing delays), isolation and contract tracing policies, testing policies for symptomatic individuals and contacts, and surveillance testing can be evaluated. Many important characteristics of the disease, test performance, and the cohort and community environment are not well known and may change over time. Some of the distributions and parameters are estimated from available data, others use assumed distributional shapes and parameter values or ranges that are deemed reasonable. If the results are very sensitive to some of these estimates or assumptions, then the insights obtained from these results may be fragile (i.e., not robust).

We mitigate this uncertainty—in terms of its impact on decision making—by using a data farming approach, rather than scenario-based analysis. The pandemic model has been constructed to facilitate this type of experimentation and assessment. Using a data farming approach for the pandemic model allows analysts and decision makers to seek robust policies in the face of this uncertainty. It also facilitates trade-off analyses concerning the number of infected individuals, the number of quarantined individuals, the number of tests required, and the probabilities of an epidemic fizzling or flaring within the cohort.

4 DISCUSSION

This work demonstrates the value of conducting model-based assessment of COVID testing and intervention policies. Assessing risk and outcome uncertainty associated with the policies is important, since there are tradeoffs among disease risk, readiness, and resource use.

Rapid but less-sensitive antigen tests are becoming more widely available. Our models can be used to evaluate the performance of policies using tests with difference performance characteristics, or using multiple test types. As universities have reopened for some in-person activities this fall, they have followed very diverse policies which can also be compared using this model.

As more information regarding the relationship between detectable viral load, time since infection, and infectiousness emerges, a related tool that evaluates testing policies for individuals who have been infected in terms of screening for infectiousness is planned.

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