

[COVID Information Commons \(CIC\) Research Lightning Talk](#)

Transcript of a Presentation by Babatunde Ogunnaike (University of Delaware), July 2021



Title: [Predictive Modeling & Optimal Control Framework for Model-Based Epidemic Response in Delaware](#)

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[YouTube Recording with Slides](#)

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Transcript

Lauren Close:

So now I'd like to introduce everyone to today's fantastic speakers. This afternoon we'll be hearing from some researchers whose work focuses on a wide range of topics from human mobility tracking to predicting Covid immune responses and possible decontamination processes.

First I'd like to invite Professor Ogunnaike of the University of Delaware to kick us off so I will stop sharing my screen and professor if you'd like to get started you're up.

Babatunde Ogunnaike:

Slide 1

Let me share my screen. Alright good afternoon everybody thanks for coming. I'm going to be talking about the work that we are doing with the Nemours Children's Hospital on predictive modelling and optimal control - a framework for model based epidemic response in Delaware.

Slide 2

By definition of a lightning talk things will go by very quickly and if you have any questions please feel free to ask them at the end. Our objective is to develop and evaluate a predictive modeling approach

that can be applied to the spread of SARS-CoV-2 but able to adapt it to emergent infectious diseases later on, especially for children we're focusing on the state of Delaware right now and we talk a little bit about the optimal model based mitigation strategy toward the end.

Slide 3

I don't need to tell this audience about mathematical modeling and how it has become a standard tool in the arsenal of practitioners and there have been various approaches to COVID-19 modeling which we don't have time to go through but I will then motivate why we're taking the approach that we're taking.

Slide 4

We're using the concept of chemical reaction kinetics. When a species comes in contact with another species they react, but by using this framework it allows us to do several things that we may not be able to do otherwise. So for example we have this concept of residence time distribution which helps us characterize how much time a molecule spends inside of a reactor, which is somewhat similar to the time it takes for a person who's been infected to recover or to die.

Slide 5

So it's those kinds of things that we use. This is probably the most important slide at this point - to give you an idea of the mechanism. So if A in red represents someone who's infected comes in contact with someone who is not infected, you get two infected people at the rate of transmission is $k_{sub t}$ and then that person can recover but goes through an intermediate stage where you're still infectious and then you become completely recovered. Same thing unfortunately for death intermediate stage where you can still infect people and so on and so forth. The secondary transmission is somebody who's on the way to recovery or someone on the way to death can still infect other people and then if you imagine that everybody who's been infected and who's on the way to getting well or on the way to dying is in some reactor they take some time before they escape to recovery, completely or to death, completely. By doing it this way we can characterize this with a set of state equations that chemical engineers will recognize. But the most important thing from this framework is we recognize that not every person that has been infected, has been identified as such. So when we take a measurement, measurement intake is only a fraction of the people that have actually been infected.

Slide 6

So by incorporating this into this model it allows us to be able to develop a model. I'm not going to go into a lot of the details but from the model how do we determine the parameters? We take data, training data and we use least squares optimization to obtain these parameters, this rate constant and we reserve the most recent week of data for validation. In other words, if we had three weeks of data we used the first two weeks of data to fit the models, and then we tried to predict what would have happened the third week as if we didn't have that and use that to do validation and then we repeat this every week, moving the origin of the validation data for a moving horizon situation.

Slide 7

So here is what happened for us at May 23rd. The blue line - the solid blue line is the seven day moving average. The data has a lot of noise obviously, this daily recorded cases is all over the place. Our model prediction at the time is this classic curve that people are familiar with and so this is what we were thinking of on May 23rd and we were really feeling good that maybe things would be finishing by the end of July.

Slide 8

This is the cumulative data. You can see what we used to fit and what we used to validate.

Slide 9

This is the percent of uninfected people.

Slide 10

These are the results that we obtained at that time and the prediction of the final population of uninfected and so on and so forth.

Slide 11

The most important result at the time was that we estimated a total infected percent infected that was unidentified as 30 percent and actually that has been, since it was since confirmed that only about that much at that time was identified as infected, which meant that 70 percent were asymptomatic or presymptomatic or symptomatic but untested. And all of that started to argue strongly for random sampling to be able to detect the asymptomatic and then do something about it.

Slide 12

Let me just jump real quickly to what happened on September 27th and as you can see we did some pretty stupid things in the sense that we didn't pay attention and we had a second wave then we had the third wave and our model was able to adapt and keep up.

Slide 13

And since then we've actually had a fourth wave and I'm just going to show you how a model was keeping up. Again keep your mind, keep your eye on the curve itself. The solid blue line is the seven day moving average and so we've been tracking it fairly well and all of the things that are going on

Slide 14

And it's probably important to show you some estimates of the rate of transmission and so this is what's happened over the last nine weeks by the last time that we checked you can see that the rate of transmission was starting to go down and it's starting to eke back up again and so I hope we don't have some really serious issues again.

Slide 15

Now the, the part that you may not have seen before is the fact that we can actually do active intervention. When we do random sampling and contact tracing and we find people that are infected we quarantine and we treat them. This is the mathematical equivalent of introducing this function $u(t)$ - which unfortunately I don't have the time to explain to you how we obtain this - but if you give me a fraction of infected, a start date for going out to sample people, and the sampling period, and the total population, and the fraction of the population, we can determine what to do to meet some objective that you can say let me just show you some results that's the equation you will see.

Slide 16

So, for example, if at the very beginning in the state of Delaware, at the very beginning - 30 days after if we had sampled every week and we took a 0.02% of the population of the state of Delaware that is the number of people that we sample and we test and for an initial fraction of infected people of 0.01 here is what we would have seen.

We could have shortened - this is not flattening the curve, this is changing the curve completely. We would have brought things back by about 15 days and about a 50% reduction if we had done this in 30 days. Now why are we doing this now we're saying the next time something happens, we will know what to do, how to do it, and things that look like [inaudible] the record is what would have seen instead of the blue curve would have handled things.

Slide 17

Now I don't want to spend too much time on this but there are many many parameters that we can select so there are different ways of achieving the same objective, and so that's typical. You show a contour curve so for example if we wanted to bring the COVID infection down to a less detectable value in a hundred days, we can achieve that by doing a sample size of 0.15, sampling seven every week, and so anyway these, these are some of the results that we've obtained.

Slide 18

I'm gonna skip this because it's really not this is just to show us that if you don't start early it becomes more difficult to be able to get things done.

Slide 19

So let me summarize and conclude we've used the chemical engineering reaction kinetics-based model for COVID-19 spread. We've applied it to the state of Delaware but we haven't shown you the other data

sets that we've applied it to. We've used the model to study the effect of active intervention. We're now developing a recursive approach for children and that we're going to develop a platform that decision makers can use.

Slide 20

I'd like to acknowledge my post doc Yu Luo who now has a real job with GlaxoSmithKline and we have two grad students working with us: Rob Akins and with me Neha and Jonathan and Julie Carrick is the computer scientist working with us. That's it.