

CORONA VIRUS SIRD MODELING & OPTIMAZATION

Dayan Parker
Wahsington Univeristy Electrical and
Systems engineering
St. Louis Missouri
d.b.parker@wustl.edu

Lesly Zelaya
Wahsington Univeristy Electrical and
Systems engineering
St. Louis Missouri
l.m.zelaya@wustl.edu

Xiaohai Yang
Wahsington Univeristy Electrical and
Systems engineering
St. Louis Missouri
xiaohai@wustl.edu

Abstract- Through linear dynamical systems we were able to create a model which predicted the spread of a Corona virus with a high degree of accuracy. Using this modeling technique, we split the data into multiple time periods based on changes in virus propagation over those intervals of time. After separating that data, we created a linear dynamical system for a “what if” scenario in which a policy increasing the effectiveness of masking, vaccination, and isolation during the delta wave were implemented. Such a policy would have had a drastic effect upon the spread of Covid. If the policy made masks were 20% more effective, isolation was 40% more effective, and vaccination was 50% more effective the total number of cases would have been reduced from 383116 cases in the ST. Louis area to 287337 cases. Fatalities would have also been reduced 6128 deaths to 4596 deaths.

1. INTRODUCTION

This project is intended to expand upon the idea of linear dynamical systems as a modeling methodology by using it to model the propagation of Corona Virus in the ST. Louis metropolitan area. Through the creation and analyzation of linear dynamical systems we gained a more fundamental understanding of their benefits and limitations, namely the ability to quickly model complex scenarios and the difficulty to account for all of the possible variables present in reality. It also shed light on the extent to which policies would have needed to be enforced to create a significant change in the propagation of Corona Virus. Modeling Corona virus through a linear dynamical SIRD system provides a deeper understanding of the system itself and the spread of pandemics.

I. METHODS

Formulate your project goals. Describe the methods you used to complete the project. Define any relevant terminology. Include any equations that contributed to your work.

A. Creating an SIRD Model

The first step in our exploration of SIRD Models was to make one for ourselves without using the built in *MatLab* functions. We created and update matrix A, which was defined

using the SIRD percentages specified in Applied Linear Algebra textbook [1].

We then set up an initial state where 100% of the population was susceptible and none were infected, recovered, or dead. By multiplying the update matrix by our entail state, we were able to generate all other states we wished to model shown in Figure 1. We then implanted reinfection by allowing a percentage of recovered people to become susceptible again, the plot is shown in Figure 2.

B. Fitting the Model to COVID-19 Data

Once a thorough understanding of the function and creation of SIRD models had been established we began making a model to accurately represent the spread of corona virus. We first wrote a function called “*siroutput_full*” to create SIRD models given, and input vector contains the infection, recovery, and fatality rates desired along with an initialization state.

To find actual the specific rates needed from the Corona Virus data by hand was impossible an impossible task, so we decided to use digital optimization through the “*fmincon*” [2] function in MatLab. Fmincon optimizes using many different algorithms, but to understand the efficacies of its result a cost function must be created which fmincon would try to minimize must. Our cost function, named “*siroutput*” compared the predicted number of cases and deaths to the actual amount specified in the Corona Virus data. To find the total number of predict cases we added the number of the number of infected, recovered, and deceased individuals into one vector. Next, we changed the percent values in the actual numbers of cases for easier conceptual comparison. We then found the error between then predicted number of cases and deaths and the actual number of cases and deaths. Fmincon then tried to minimize that error.

To further shape the output of fmincon we gave it several restrictions to what values it could guess for the infection, recovery, and death rates and initial values. Since the rates are percentages, they should never be more than 1, i.e. 100% and less than zero. The infection, recovery, and death rates be non-zero values because a pandemic did take place.

After this process we used the “*siroutput_full*” function to simulate the pandemic based on our values. The simulation we achieved is shown in figure 3.

C. What if Policy

To create a COVID-19 relief policy which we would have put given the chance we multiplied the infection rate from the actual COVID data by the percentage which we believe would have changed with an increase in masking, isolation, and vaccination. This section specifically highlights the power of this form of modeling as we were easily able to understand how changing introduction in a policy could have clear changed the course of the pandemic. This is show in figure 4.

D. Seperation of COVID waves

By visualizing our “Figure3: optimized model” on the curve of measured cases, we separate the covid data into 5 phases. The separation of the covid data into multiple waves allowed us to use `fmincon()` to find different rates for the different parts of the pandemic.

By using multiple rates instead of a single rate for the entire pandemic we were able to model the data more closely over each wave This caused spikes in the model which we mitigated by only allowing minion to select values that we within the range of the previous two values.

E. Vaccinated Model Generalization

The real word COVID situation might not be as simple as a SIRD model. For example, those who are vaccinated will have a different rate for getting infected. Additionally, we are interested in how SIRD model varies with the vaccinated groups. We have mock data describing the fraction of a population that is infected and the fraction of a population that is deceased over 365 simulated days. And we want to simulate a model that can tell us:

1. Fraction of population that is vaccinated over time
2. Portion of the population experiencing a breakthrough infection over time

A SIRD model is not sufficient at this point, we need to track more states. So, we are using what we called “SIRDVN” model to help finding the results, where V stand for vaccinated population, and N stand for daily new infections. We assume only susceptible people will go get vaccinated, and vaccinated people will have a different rate of get infected. We used very similar approach we did when fit the model that we first wrote the function “`vaccine_sir`” to simulate the SIRDVN model in the 365 days as a linear dynamic system, then use another funtion “`vaccine_sirfun`” to calculate the cost of the SIRDVN model. The cost is evaluated as the weighted square difference between the model’s predicted daily new infections and cumulative deaths, and the given mocked data. We use the matlab function `fmincon()` to find the input that minimizes the cost. We have six inputs this time: rate of susceptible people gets infected; rate of infected people dies; rate of infected people recovers; rate of susceptible people gets vaccinated; rate of vaccinated people gets infect; and rate of infected people go to susceptible (people who are recovered but still didn’t get immune to COVID). Then

we use this optimized input to simulate the model again and make plots.

F. Figures and Tables

FIGURE 1 ORINGAL SIRD MODEL

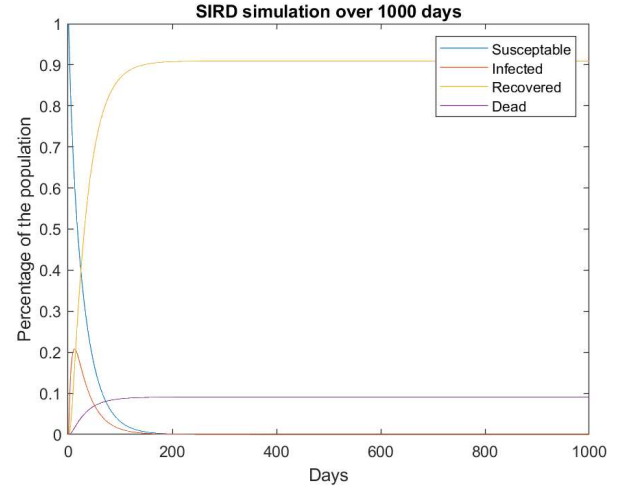


Fig. 1. SIRD model created by hand using the textbook’s [1] SIRD rates.

FIGURE 2 SIRD MODEL WITH REINFECTION

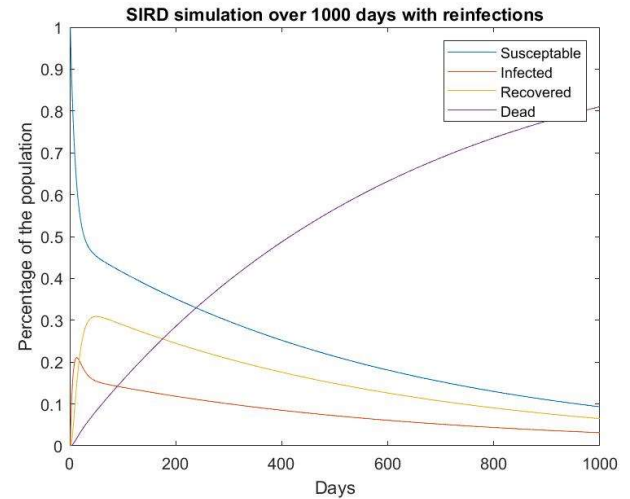


Fig. 2. The SIRD model using the textbook’s [1] rates with possible retionetions

FIGURE 3 OPTIMIZED MODEL

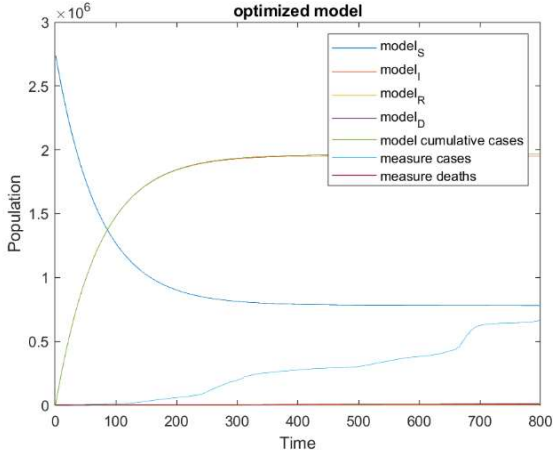


Fig. 3. The SIRD model of the optimized rates using fmincon. The cumulative cases measured from STL metro area COVID data was also plotted for comparison.

FIGURE 4 DISTINC WAVES MODEL

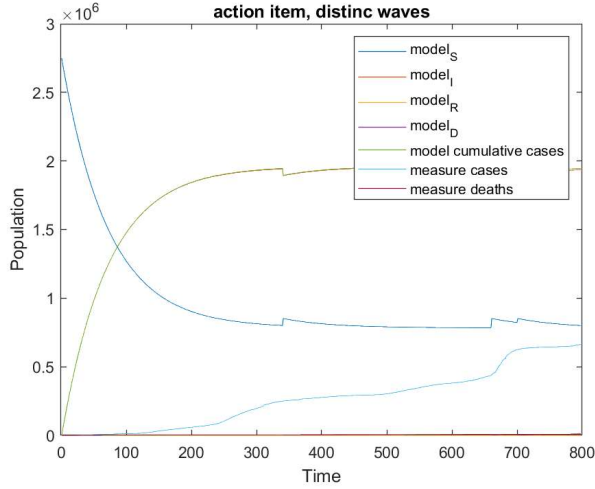


Fig. 4. The SIRD model of the optimized rates using fmincon over distinc waves.

FIGURE 5 POLICY CHANGE

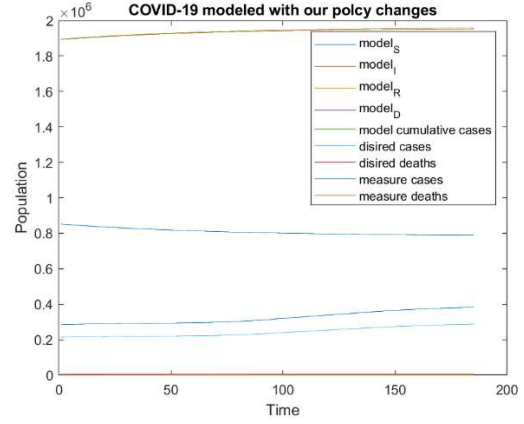


Fig. 5. SIRD model of the actual COVID rates if our polciy had lowered infection rate during the delta wave.

II. RESULTS AND DISCUSSION

A. Optimizing the SIRD Model

The optimized model for the propagation of corona virus over the course of the pandemic very closely modeled the actual data we were provided. From visual inspection of the figure 3 there a negligible difference between our model and the actual cumulative cases. However, when we spilt the data into smaller subgroups for each of the waves, I became more clear that our model was not able to cover all the nuisances of the pandemic as there were spikes at nearly every wave in figure 4. Even with those challenges our model was accurate enough to be a useful representation of the pandemic.

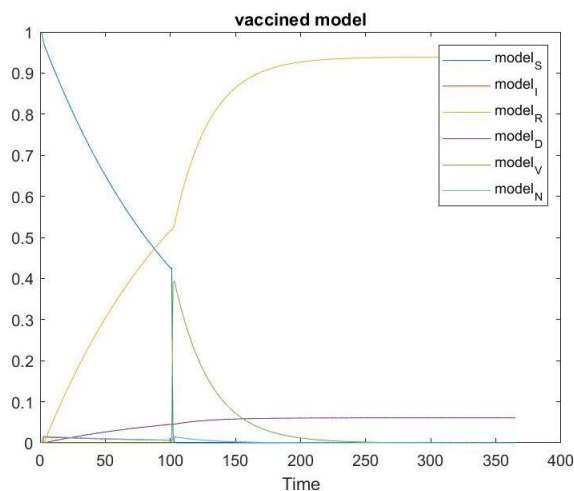
B. Policy Influence

Our policies are feasible. Mask, lockdown and vaccine are the best weapons to fight with infectious virus, and they are not too expensive for people. In Figure 5, our model's output matches the desired cases and deaths.

C. Vaccinated Model Generalization

We know that in the given year of mock data, vaccine is not offered in the first 100 days. So, we slightly modified the SIRDVN model that force the vaccination rate being zero for the first 100 days. We then use the 100th day's prediction data as the initial condition and fit the rest 265 days. Then we concatenated them and got the model shown below:

FIGURE 6 VACCINATED MODEL



The rates for our model are:

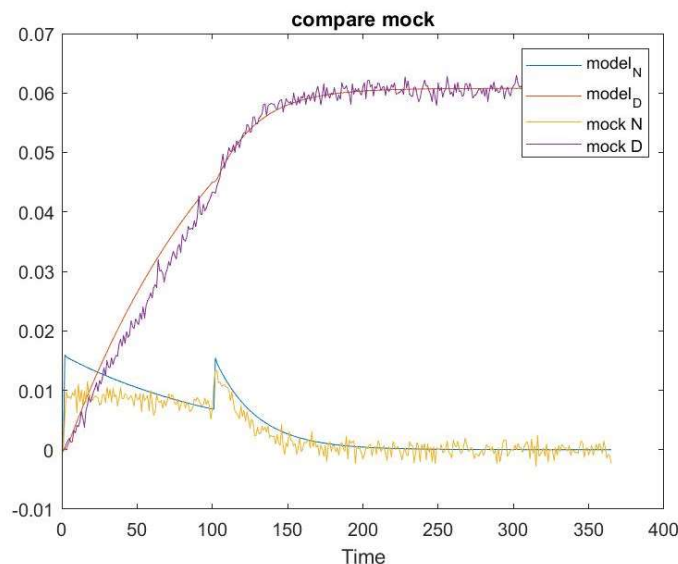
TABLE 1 VACCINATED MODEL

Dates/ Rate of	susce ptible gets infect ed	infect ed dies	infect ed recov ers	susce ptible gets vacci nated	vacci nated gets infect	infect ed go to susce ptible
First 100 days	0. 0159	0. 0487	0.559 3	0		0. 5203
Rest 265 days	0. 0364	0. 0367	0. 9820	0. 9092	0. 0355	0. 0002

It's easy to observe the spikes around $x = 102$, which is the point vaccines released. Also notice we have a 0.9092 rate of susceptible gets vaccinated, indicate that within the first three days vaccine released, most people have taken it.

We compared our fit model with the given mock data, the algorithm did a very good job and the cost returned by `fmincon()` is a very small number: $7.3329e-04$.

FIGURE 7 COMPARED TO MOCKED

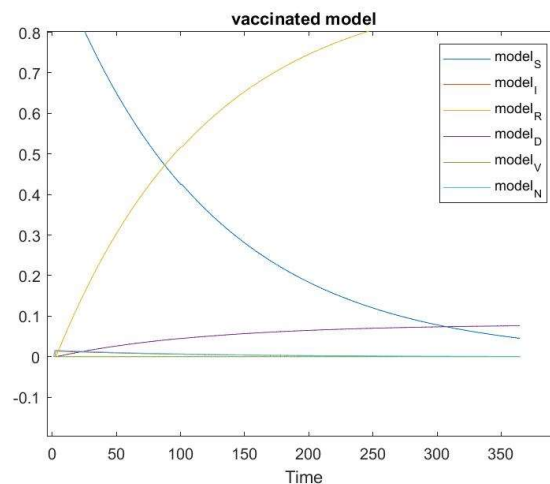


However, the spikes on the model still don't look appropriate enough, they are too sharp and can not be perfectly explained in real world, especially the over high speed of people get vaccinated.

We take back and look at our optimized rates and notice `fmincon()` not only change the rates relate to vaccinated, but also the rates for unvaccinated people get infected and recover, which indicate there's a virus variation like "Delta" or "Omicron" happened right at vaccines released. That is not a given condition and can not have a high chance of it happening.

So, we use the rates optimized in the first 100 days and force them to be constant when we use `fmincon()` to optimize the model of the rest 265 days. Then we got the model shown below:

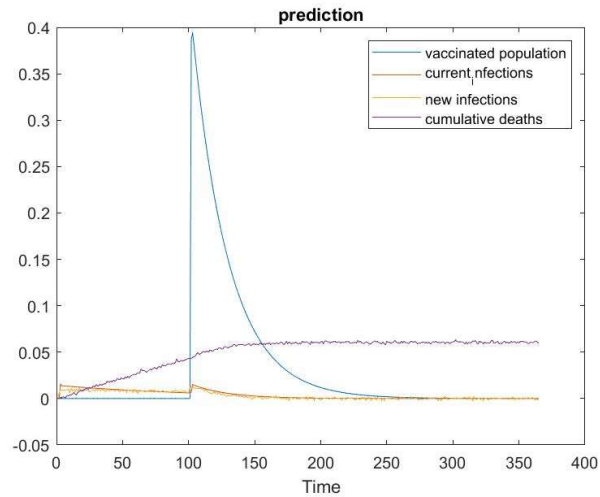
FIGURE 8 FORCE RATES



The plot doesn't look bad at first glance, but when look deeper in the graph and displayed rates value, we find out the vaccine

rate is still 0 in the 265 days after vaccine come out, and that is obviously not the result we want, also don't make sense in the real world.

The nice and smooth model happened on our first draft of unpervised model. I.E., we didn't tell `fmincon()` there's no vaccines in the first 100 days.



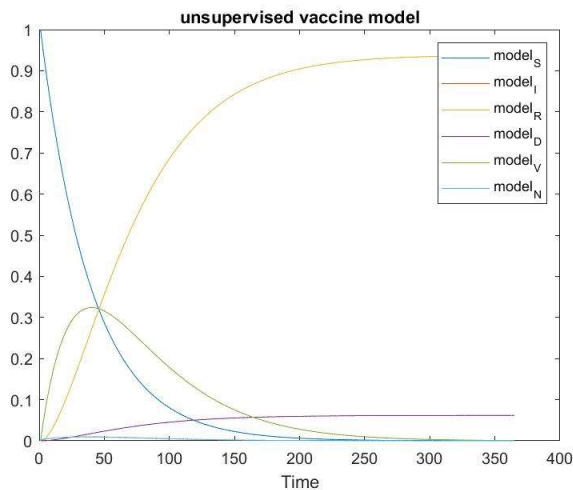
III. CONCLUSION

The key findings that were found in the process is that vaccination is the best method to reduce the number of the cases producing each day, month, and year. Analyzing and modifying the mock data to fit in to the question of what if vaccines were offered for the first 100 days or what happens to the number of cases the first 100 days that the vaccine is not being offered shows us a model of susceptible people gets infected; rate of infected people dies; rate of infected people recovers; rate of susceptible people gets vaccinated; rate of vaccinated people gets infected; and rate of infected people go to susceptible. Observing the trend and align it to unsupervised vaccine model shows a big change of rate of the amount of people recovering or the infected becoming susceptible in a rapid growth. The benefit of studying the patterns of the population when something affects it: is that it gives an idea of how an effective policy is the solution to the challenge. The statistics and the visualization of models that represent the “What if” is a good way to see it in another perspective and do calculations based on what has been observed through the evolution of time.

Throughout this process, not everything came smoothly. We ran into a few challenging problems where the models would not give the result that looked plausible enough to fit reality. For instance, when constructing the vaccination and the compare mock model, the models would not give a result with the correct data and the models looked unrealistic with unexpected spikes. Despite the shortcomings, the models were still used to make a related connection with the prediction that was made initially.

This experiment has given the inspiration to explore the rapid development of technology and science within 100 years from now. Use the same concept that was studied in this experiment but analyze how long it will take for humanity to develop an innovative technology that would impact socially, politically, or economically using today's data. It would be an experiment that would eventually tell us where humanity is heading in terms of science, math, and technology that could potentially affect our living styles in this universe.

FIGURE 9 UNSUPERVISED



However, we cannot ignore the condition we are given, so we will keep using the concatenated model as our result. And there exists a spike of new infected people near day 100 on the given mock data, which increases the chance of a virus variance around day 100. To better visualize the more complete breakdown of the population over time we are focusing on, we also generate the graph below:

FIGURE 10 MODEL PREDICTION

REFERENCES

- [1] Boyd, S., & Vandenberghe, L. (2019). Introduction to applied linear algebra: Vectors, matrices, and least squares. Cambridge University Press
- J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.
- [2] *fmincon*. Find minimum of constrained nonlinear multivariable function - MATLAB. (n.d.). Retrieved November 4, 2022, from https://www.mathworks.com/help/optim/ug/fmincon.html?s_tid=doc_ta#d124e94144