Epidemic Modelling and Simulation

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Abstract

This simulation project's goal was to use AnyLogic simulation software to model and examine the propagation of a virus throughout a population. The simulation sought to offer insights into the dynamics of virus transmission and the potential outcomes for the population under various scenarios. It did this by using probability laws and taking into account a variety of epidemiological factors. The effectiveness of various intervention tactics, such as social isolation, mask use, and quarantine measures, as well as differences in population density and vaccine coverage were all included in the many scenarios that were simulated. To determine how these elements would affect the rate of infection, the height of the epidemic, and the total length of the outbreak, the simulation outputs were examined.

1 Introduction

Infectious diseases have a terrible effect on communities all around the world, as seen in recent years. Understanding the dynamics of disease dissemination and assessing the efficiency of intervention efforts are essential, from the emergence of novel viruses like SARS-CoV-2 to recurring seasonal influenza. A potent method for simulating and analyzing the spread of viruses within a population, simulation modeling offers insightful information about possible outcomes and aids in decision-making. In this report we detail a simulation exercise that was carried out with the AnyLogic program to examine the viral propagation throughout a population. The goal of this study was to build a model that captures the essential dynamics of virus transmission using epidemiological characteristics and probability principles. Despite the simplicity of the model and it being not the most realistic, it still offers an overview of the general dynamics of virus transmission. We will first see the model's structure, then the underlying probability distributions we used and finally the results of the simulation.

2 Model Structure

The model structure is straighforward. Every day healthy people can become exposed to the virus, at this point they are either already immune or they become infected. People are first `InfectedHidden` and then `InfectedShow` after a certain number of

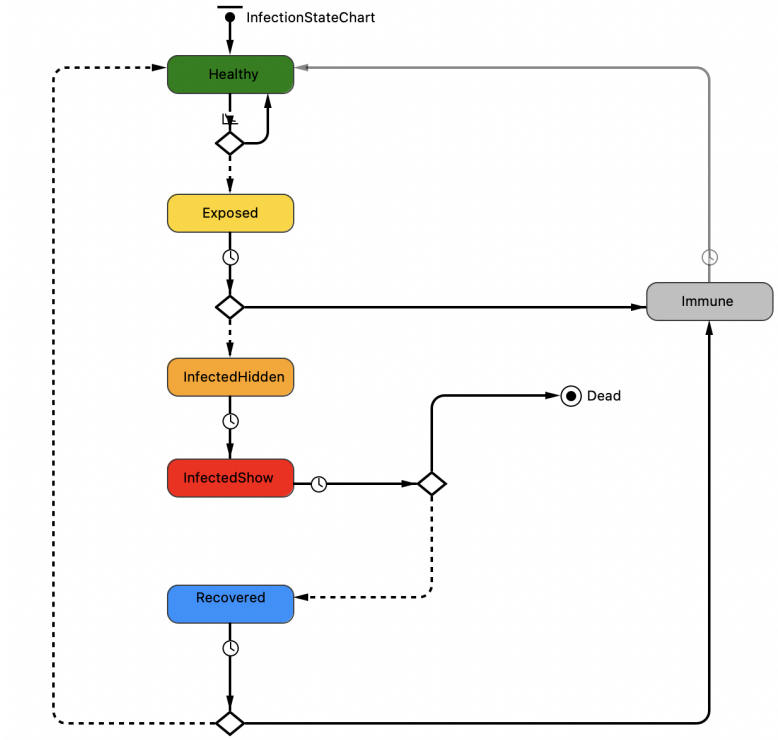

Fig. 1 Model Structure

days. They can then either recover or die. If they recover, they can either become immune or susceptible again. Also, people immune to the virus can become susceptible again after a certain number of days. This transition is disabled at first but we enabled it for later testings.

3 Statistical modeling

3.1 Being exposed

Every day, a rate of the population of agents is susceptible to be exposed, this rate is given by a `lognormal(1, 0.3, 1)` distribution. We then do a Bernoulli test for each agent to see if they'll become exposed or not.

3.2 Being infected

When an agent is exposed, it has a probability of being immune to the virus, this is done by a Bernoulli test with a probability of 0.1. If the agent is not immune, it becomes infected.

3.3 Dead or recovered

Once an agent is infected, it remains infected for a certain period of time, following an exponential law with $\lambda = \frac{1}{5}$, after this period, the agent becomes either dead or recovered, this step is again done by a Bernoulli test with a probability of 0.02 for the agent to die.

3.4 Recovered

If the agent did not die, it becomes recovered and stays in this state for a period of time following a uniform law between $[25, 30]$ days, after this period, the agent becomes either immune or susceptible again.

4 Results

For our testings, we used a population of 1000 agents and the following hyperparameters in general. Some of them were tweaked for specific testings.

Infection time	Recovered time	Incidence
5	$\mathcal{U}_{[25,30]}$	Log-$\mathcal{N}(1, 0.3, 1)$

Table 1 General parameters

4.1 Base case

In the base case, we used the following parameters:

Initial immunity	Death rate	Immune
0.07	0.1	0.1

Table 2 Base case parameters

We can see in the base case that the epidemic reaches its peak at around 10 days and then starts to decrease in waves. In parallel, the immune population increases until it reaches a plateau at around 0.6 of the population. The death rate is also increasing and reaches a plateau at around 0.4 of the population.

4.2 Immunity changes

4.2.1 High immunity after infection

We then tested the effect of the initial immunity rate and the immunity after infection rate on the epidemic. This was done to simulate a reaction by the population to the virus. We tested the following parameters:

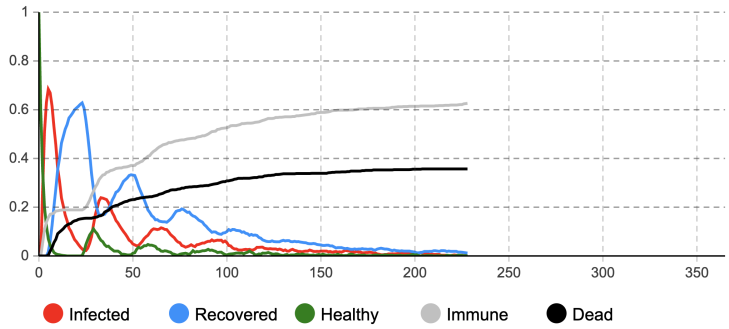

Fig. 2 Base case

Initial immunity	Death rate	Immune
0.07	0.02	0.3

Table 3 High Immunity parameters

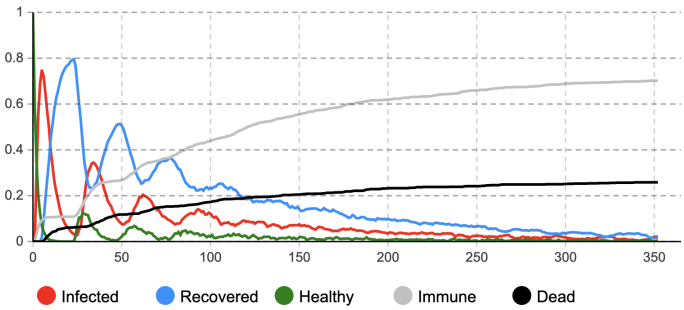

Fig. 3 High Immunity

We can see that the epidemic is much less severe than in the base case, the peak is much lower and the death rate is also much lower. This is due to the fact that the population is much more immune to the virus.

4.2.2 High initial immunity

We then tested the effect of an initial high immunity with a chosen 60% of the population immune to the virus.

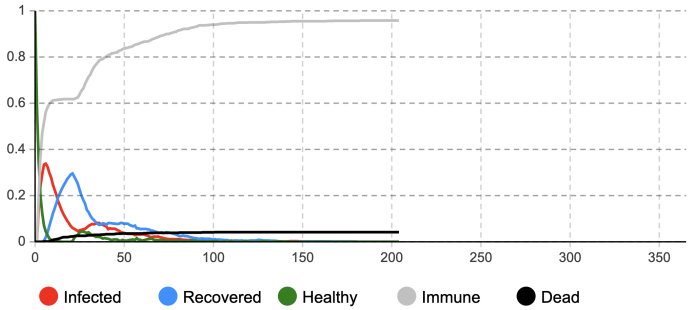

Fig. 4 High Initial Immunity

4.2.3 No Initial immunity

We also tested the effect of low immunity rate and no initial immunity.

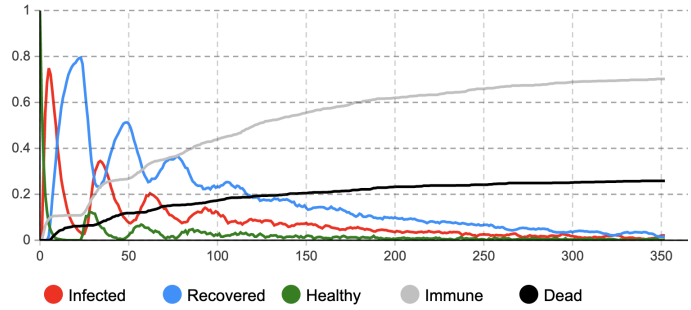

Fig. 5 No initial immunity

4.2.4 Limited time immunity

All the models we saw before were such as `Immune` is a final state, but in real life, we know that immunity is only temporary due to the body or mutations of the virus. That's why in this simulation, we changed the behaviour of the model: the time an agent spends in the immune state follows a normal law $\mathcal{N}(60, 5)$. This adds more realism to the model.

We can see that despite a high initial immunity, wave after wave, it drops slowly.

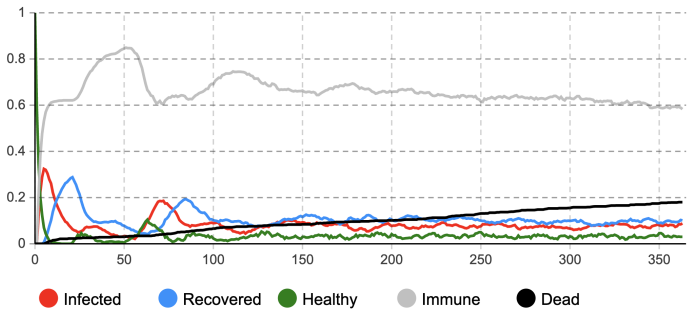

Fig. 6 Limited time immunity

4.3 High Death Rate

Unfortunally, some virus can be very deadly, to simulate this we did a parameter change with a death rate at 30%.

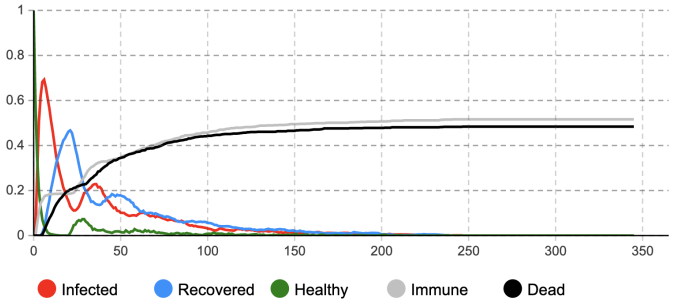

Fig. 7 High death rate

Over a year, the proportion of the population that is dead is 45% and is going up and up with time. If the immunity was also temporary, 100% of the population would be dead in 900 days. Naturally, all the population end up in one of the two final states, either dead or immune.

5 Conclusion

In conclusion, we saw that despite the parameter changes, the epidemic has the same shape, a spike of infected followed by a spike of recovered. And then again a spike of infected then recovered but much smaller. All this while the immunity rate and the death rate augment and stabilise.