# A Study of Disease Propagation using a C++ Model

SDS322

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## I. Introduction

In order to study infectious diseases and their rates of infection, computer programming tools can be leveraged to model a closed population and simulate the spread of a disease through probability and interactions within the population. This paper examines the statistical distribution of disease as well as the factors of vaccination and minimizing contact through social distancing. In addition, herd immunity is analyzed as well as effects on disease duration.

## II. C++ Model Setup

In this experiment, a person's status can be described as sick (infectious), susceptible (healthy but can be infected), and inoculated (recovered and cannot be infected again). The C++ model is created using a set of classes and methods that enable disease propagation and measure the amount of sick people over time. First, a *Person{}* class is created with private variables to store the condition of each person as well as their number of sick days. In this model, an infected person will be sick for 5 days upon infection before recovering. The *Person{}* class also holds public methods to update the number of sick days, infect a person by setting their sick days to 5 and iterating until the number of sick days reaches -1 and the person has recovered.

A second *Population{}* class is created that builds a vector of people upon integer input. For this experiment, the population number is set to 40,000 to model the population of a large public university. A *random_infection()* method is used to create a patient zero, or choose a random person in the population vector and infect them immediately. A *set_probability_of_transfer()* method is used to define the statistical threshold for infection; this probability is set to 95% for this model and a random number is generated for each person in the interaction segment of the program. If the random number falls above 0.95 and the person is not already infected or vaccinated, they immediately become sick. The disease propagation is handled through the *random_interaction()* method which iterates through the entire population vector and selects *n* amount of other people to interact with. If either party is infected, the method calls *set_probability_of_transfer()* and determines if the person will get infected. This experiment explores various interaction amounts in order to study the effects of social distancing. Finally, an *inoculation()* method is used to immediately vaccinate a portion of the population at the beginning. Instead of assigning a set amount of vaccinated people, the method uses a vaccination percent and compares random numbers to determine if a person will be vaccinated or not. For example, if the vaccination percent is set to 0.2, roughly 20% of the population is expected to be vaccinated in the beginning.

The *main()* function calls these methods and outputs the number of vaccinated people as well as the number of sick people each day. A sample output is shown below:

```
5504 people are vaccinated at the start
On day 1: people infected 1
On day 2: people infected 3
On day 3: people infected 33
On day 4: people infected 166
On day 5: people infected 1052
On day 6: people infected 5295
On day 7: people infected 16955
On day 8: people infected 28567
On day 9: people infected 32700
On day 10: people infected 32958
On day 11: people infected 28997
On day 12: people infected 17415
On day 13: people infected 5796
On day 14: people infected 1535
On day 15: people infected 392
On day 16: people infected 109
On day 17: people infected 29
On day 18: people infected 6
On day 19: people infected 1
On day 20: people infected 0
39906 people are inoculated at the end
```

## **III.** Results and Discussion

After running the program for various vaccination and interaction input for a closed population of 40,000 people, the data was exported to MATLAB and analyzed. The following plots examine the statistical distribution of the number of infected people over time.

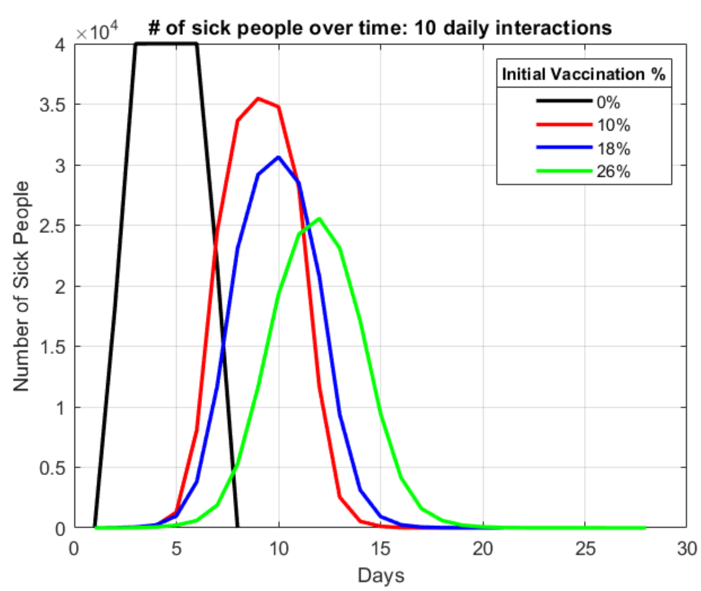


Figure 1: Number of People Sick over Time for 10 interactions

Based on the plot, disease propagation follows a normal distribution and is symmetric about the day with the maximum number of sick people. The effect of increasing initial vaccination rate is illustrated through progressively lower peaks in the distribution. As more people are vaccinated, the infection rate is also slowed down because the slope of each successive distribution becomes less steep. For a vaccine rate of 10%, the maximum number of people sick on a single day is around 35,000 while a rate of 26% brings the maximum down to nearly 25,000. In a real world scenario, a higher vaccine rate would be very beneficial to populations with limited hospital capacity by lowering the amount of sick people on any given day. The vaccine rate effectively flattens the distribution, bringing down the number of cases while also postponing the day with maximum cases. As a result, the vaccine rate also prolongs the duration of the disease, lasting around 20 days for 26% vaccination and 15 days for 10% vaccination. If hospital capacity is limited, prolonging the disease is necessary in order to control the infection rate and reduce the maximum number of cases. In addition to vaccination rate, the number of daily interactions per person also plays an important role in weakening the rate of infection.

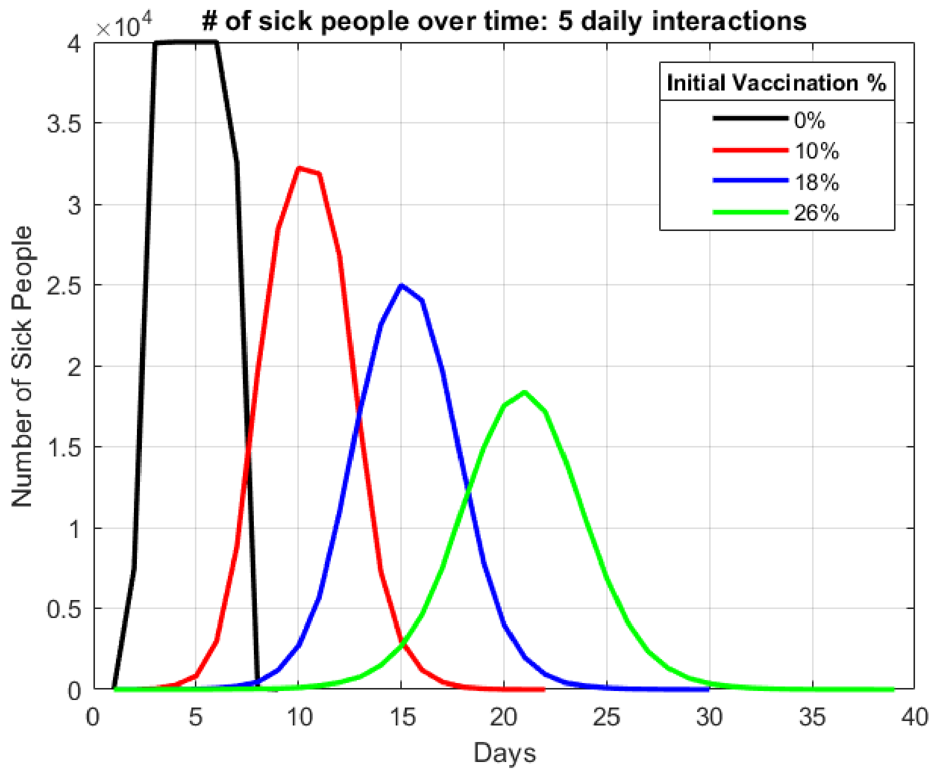

Figure 2: Number of People Sick over Time for 5 interactions

In these examples, the number of daily interactions is reduced by half in order to simulate the effect of stronger social distancing. Overall, this reduction in interactions results in vaccine rate having a much stronger effect on limiting the rate of infection. Unlike the previous plot, each succesive distribution is spaced much furher apart from the previous and the distributions have been flattened even more. The jump from 10% vaccination to 26% now results in lowering maximum cases by nearly 50% or about 15,000 people. As a result, disease duration is also prolonged significantly and lasts an entire month for a rate of 26%. The effect of social distancing shows that lowering interactions to only 5 people per day results in a significant difference in the peaks of the disease, even for lower vaccination rates. As a result, communities with limited numbers of vaccine samples can promote stronger social distancing protocols in order to overcome the lack of vaccines and keep hospitals below capacity.

The following table examines the concept of herd immunity, or the amount of people in a population who cannot get vaccinated but will also never contract the disease due to vaccination of others. In this experiment, disease contagiousness is defined as the percent of total unvaccinated population that contracted the disease. The simulations are conducted for 10 interactions per person and varying initial vaccination rate.

| Initial Vaccination % | Disease Contagiousness % | Herd Immune # of people | Disease Duration |
|---|---|---|---|
| 0 | 100 | 0 | 11 |
| 5 | 99.98 | 8 | 16 |
| 10 | 99.89 | 39 | 19 |
| 14 | 99.74 | 90 | 18 |
| 18 | 99.38 | 203 | 22 |
| 22 | 98.89 | 346 | 22 |
| 26 | 98.58 | 423 | 24 |
| 33 | 96.87 | 838 | 28 |
| 39 | 94.78 | 1269 | 33 |
| 45 | 91.37 | 1892 | 44 |

Table I: Herd Immunity vs. Vaccination Rate

As the percent of vaccinated people grows, disease contagiousness lowers and less total people are infected. As contagiousness decreases, the herd immunity rate rises as suddenly there is a portion of the population that never got vaccinated but also never got infected. The herd immunity rate does not grow proportionally to the vaccination rate. While vaccination rate is below 26%, the rise in the number of herd immune people is slow and steady and disease contagiousness does not drop below 98%. However, after the vaccination rate increases from 26% and grows up to 45%, the contagiousness immediately drops to nearly 91% and the amount of herd immune people grows to the thousands and nearly reaches 2,000 people incredibly fast. As a result, a vaccine rate above 45% can produce a herd immunity rate of nearly 5% of the total population. The model's results show that a population can achieve really high rates of herd immunity by vaccination rates above 50% of the population. This raises the issue of cost and resource allocation as many populations will not have access to such high rates of vaccination due to lack of supplies. In these cases, social distancing and limiting interactions must continue to play a role in preventing people from getting infected. The following plots will now examine the large-scale effects of interactions for a fixed vaccine rate.

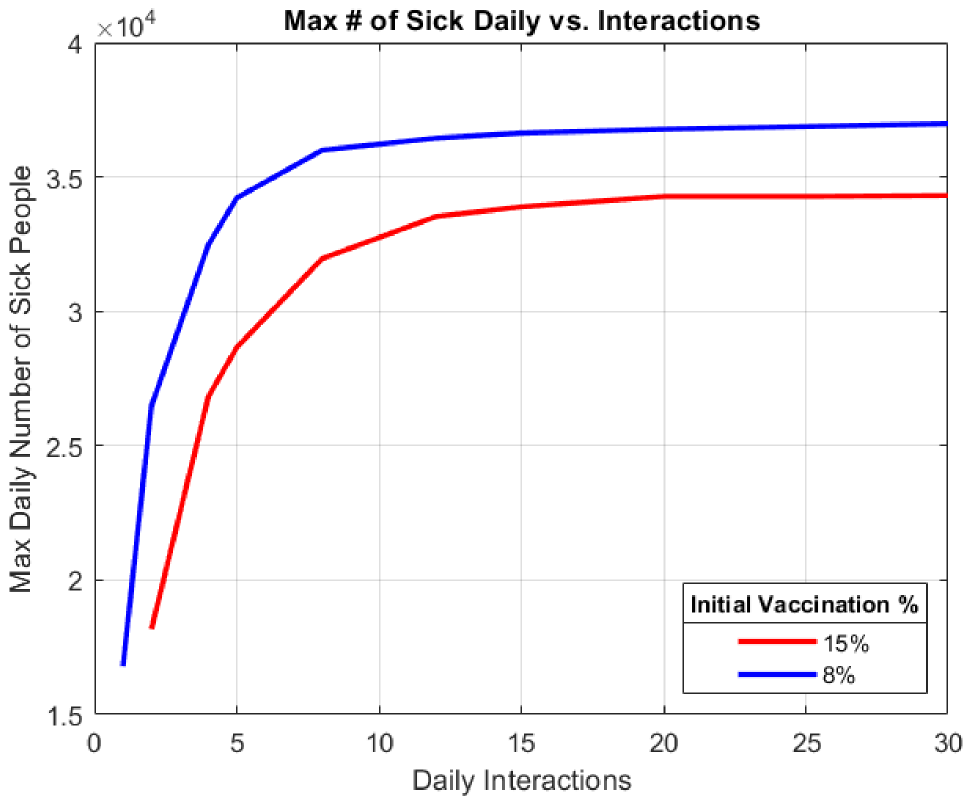


Figure 3: Max No. of Sick People vs. Interactions

According to the plot, limiting daily interactions below 10 provides exponential decreases to the maximum number of sick people at the peak. Reducing interactions from 10 to 2 results in over 10,000 less people being sick at the peak for both vaccine rates. In the case of lower vaccine rates such as the 8% example, stronger social distancing is required in order to achieve comparable peak reductions which supports earlier evidence that showed social distancing is paramount for populations with lower vaccine rates. In both cases, the peak number of sick people appears to flat-line after 15 daily interactions, showing that limiting interactions to any number above 15 per day will have little to no effect on the rate of infection as the number of interactions is already too high.

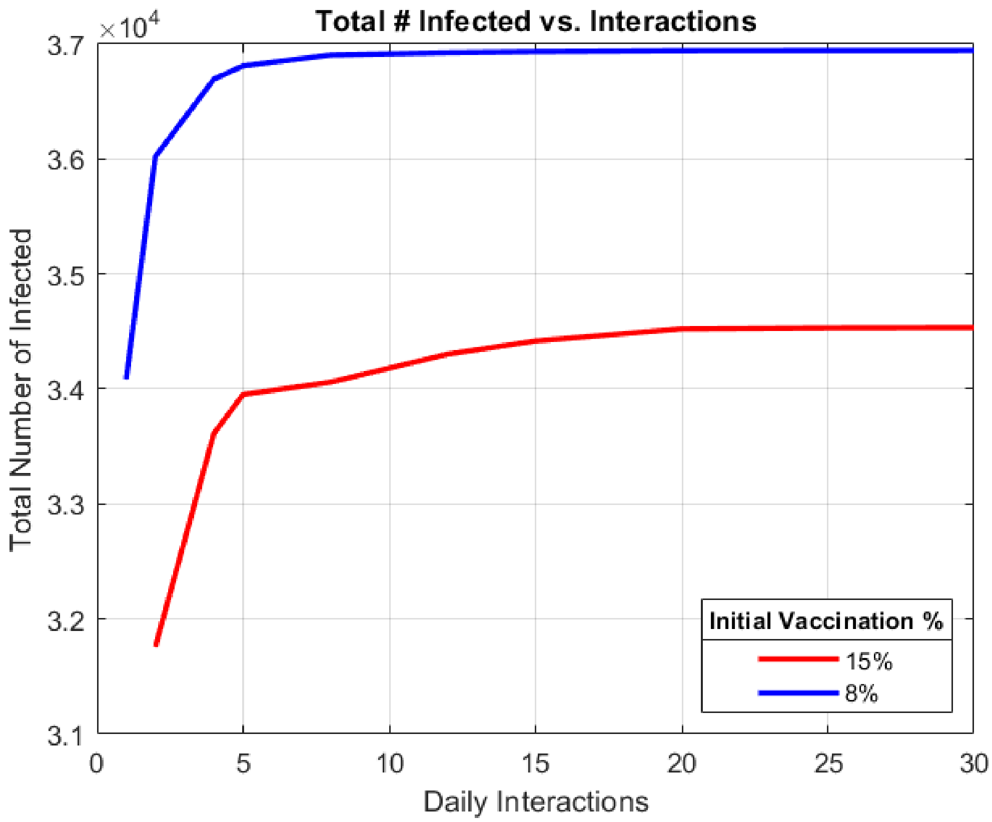


Figure 4: Total No. of Sick People vs. Interactions

This example follows the same behavior as the previous one, where the total number of infected people starts to drop off exponentially as the number of daily interactions is reduced below 5. For a higher vaccine rate, the total number of infected individuals will always be lower which is seen by the cushion of 2,500 people once the plot reaches a plateau. Similar to peak number of cases, social distancing is shown to be a powerful tool for managing the rate of infection and reducing the total number of cases in order to keep hospitals below capacity. The following plot examines the effect of interactions on the disease's duration itself.

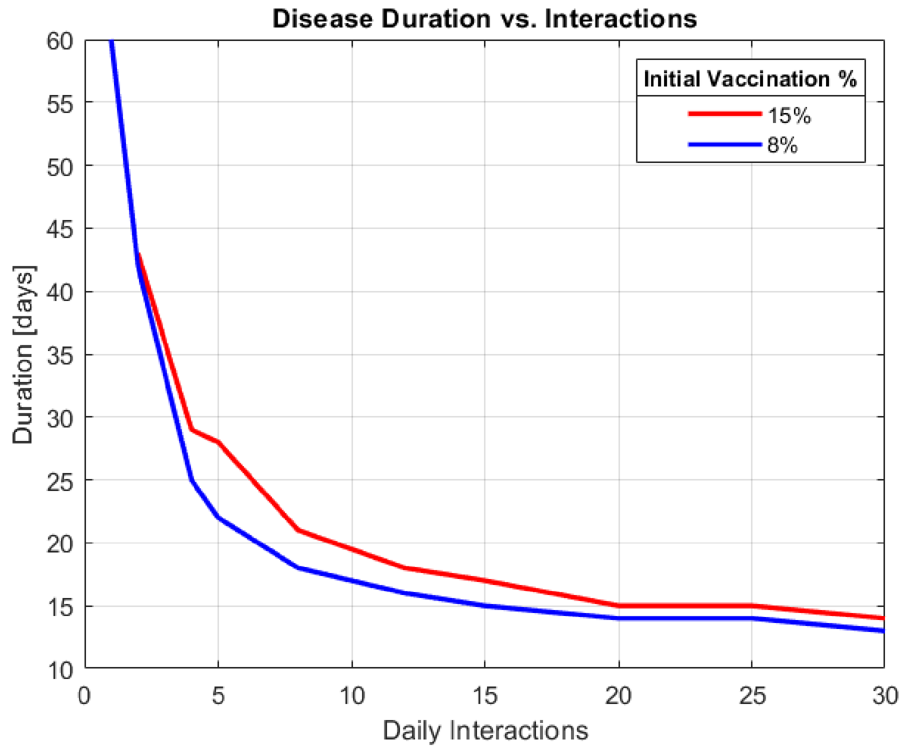


Figure 5: Disease Duration vs. Interactions

According to the figure, an increase in daily interactions results in an exponential decay of disease duration as the rate of infection grows and the disease spreads faster. As a result, the disease runs its course quicker but will impact hospitals and medical supplies by raising the peak and total number of cases. A higher vaccine rate is shown to provide a very slight increase in disease duration which is consistent with earlier results depicting how a rising vaccine rate will flatten the disease's normal distribution.

## **IV.** Conclusion

The effects of higher vaccination rate and increased social distancing result in slower infection rate, lowered contagiousness, and increased herd immunity. In the case of social distancing, lowering daily interactions has shown to decrease the peak and total amounts of sick people while flattening the normal distribution and lengthening the disease's duration. Populations that lack access to higher vaccination rates and rely on strict social distancing in order to mitigate the spread of the disease until more vaccines arrive. If no vaccination or social distancing measures are taken, the disease will reach its peak very early and more people will be infected, putting substantial strain on hospitals and families. If these measures are successfully executed, herd immunity numbers will start to rise and people unable to take the vaccine will become protected from ever contracting the disease.