The Effectiveness of the Coronavirus Rapid Antigen Tests Based on the Usage Frequency

Agent Technology Practical - Final Report

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1 Introduction

1.1 Topic

In December 2019, severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) infection cases were reported in Wuhan, China, causing daily case changes due to increased respiratory distress and high mortality [23, 16]. This rapidly spread to first, neighboring cities within China, and then to neighboring countries [4]. It was observed that human-to-human contact played a crucial role in the transmission of the disease caused by a virus, named as the coronavirus disease 19 (COVID-19) [23]. Just after a month, the World Health Organization (WHO) declared a worldwide pandemic [17]. Many variants have become dominant since. The Alpha, Beta and Delta strain all had a higher transmission rate and were discovered to lead to more severe cases and deaths than the previous variants [10]. However, with Omicron being dominant in the Netherlands and most of the world at this moment, the transmission rates and severity have changed. The Omicron variant is more contagious than all previous variants, however, the severity is significantly less [15].

Since the very beginning, due to uncontrollable increase in death tolls, several governments have put various prevention and control measures in force such as social distancing and lockdown [22], as well as wearing face masks [7], hand disinfectants [5] and (optional) vaccinations [11]. In order to detect the active virus in infected individuals and prevent further infections with quarantine [13], various tests have been made available. For example, the PCR is the most used direct diagnostic test for active SARS-CoV-2 infections [21]. Another example to detect infection is the rapid antigen detection tests. These tests, however, are recognized for their low sensitivity, and increased likelihood of false-negative results. Hence, they are generally used as a supplement to PCR tests [21]. Rapid antigen tests have also been provided in various countries for self-testing. This development has enabled rapid results and detection of people with suspected virus in society via frequent large-scale testing [18].

In a world where there is still very much need for data and modeling, the field of agent technology, a fast emerging sub-discipline of computer science and artificial intelligence, could be used to explore the effects of such phenomena via creation of intelligent systems revolved around agents with a certain goal. This could allow for predictions to be made for future outcomes, and relevant policies to be put in force. Therefore, agent-based modeling serves as a tool to model properties of the real-world as close as possible. Hence, the aim of this study is to use agent technology modeling to simulate the spread of the coronavirus.

The motivation behind choosing this topic involves the relevance it has in the pandemic era where data and modeling of the COVID-19 virus is much-needed. This is because recently, most countries have decided to abolish the restrictions put in place against the virus, yet are still dealing with high infection rates [19]. Therefore there needs to be some way to predict how those changes could impact the welfare of the society. The virus COVID-19 hit in early 2020 and has triggered lots of advancements in technology, including models and programs that model how viruses spread and infect people in different settings and environments [1].

1.2 Innovation

There are many aspects of the spread of COVID-19 that we could focus on. For this study, we decided to focus on the effectiveness of regular rapid tests in maintaining a relatively low number of infection rates. This was a particularly interesting question to ask because most models tend to focus on vaccinations or the usage of masks, or simply modeling the virus itself. Inspired by the current developments, such as the recent lifting of the mandatory face-mask regulations in almost all public indoor spaces in the Netherlands [2], the focus of this study has been set to study the effects of rapid testing on the spread of the virus. Nowadays, most people are encouraged to conduct frequent rapid antigen tests (self-tests) at home, and to quarantine if they get a positive result[15]. Therefore, the idea for this study is to investigate how frequent the self-tests should be conducted so that overall number of infections would not increase via a simulation in NetLogo, a multi-agent modeling program [20].

2 Methods

2.1 Conceptual model

The current project aims to test the effectiveness of the Coronavirus rapid tests in a city where most spreading would occur in an indoor environment based on the frequency of the usage of the tests. We decided to extend an existing NetLogo model which implements the spread of COVID-19 [12]. This model has implemented many aspects of the spread of COVID-19 in the beginning of the pandemic. Next to basic elements such as population size, number of infected people, transmission rates and deaths, certain specific parameters can be set such as the health care capacity and quarantine effort. After trying the model ourselves, we decided to simplify it by removing some properties that will not be relevant in our model. This existing model was published when the original strain of the coronavirus was dominant in the beginning of 2020. Because of the changes in severity with new variants mentioned previously, such as the Omicron variant, we have decided to remove the health care capacity and mortality from the original model.

Next to this, the original model has implemented agents in the world that are stationary, representing the people who are socially distancing. Since all social distancing rules have been lifted at this moment (March 2022) in the Netherlands, we decided to remove this element as well to accurately represent the current situation. The final element we removed is the quarantine effort. This models the ability of infected individuals to infect other people by setting the degree to which they isolate themselves. We will be implementing a different version of this that connects with testing results, so we removed the original way this was implemented.

The current model represents a simplified version of the real world, where we assume ideal conditions. The population consists of a number of reflexive agents. Each agent of the model has a few properties that define it, namely whether it is infected or not, the last test result, the number of days spent in quarantine and the immunity level. The agents test regularly, based on the frequency set. When a test result is positive, the agent immediately goes into quarantine, in order to avoid infecting other agents. The agent's immunity level decreases over time, and a higher immunity decreases the chance of getting infected when having contact with other positive turtles. The infected agents can spread the virus to others based on the transmission rate. Lastly, the agents move around in a continuous space.

2.2 Implementation details

We implemented the model in NetLogo. We decided to set the world to a wrap. This is because although we are researching the spreading of the virus in mainly indoor settings, we wanted to use a wrapped world to somewhat simulate the effect of infections from external environments where there are many access points and people are highly in contact with one another. Using a wrapped world simply increases the chances of contact with other people from other areas of the world, which better simulates the spread of the virus. Having a wrapped world in NetLogo is the most representative of the real-world situation we are trying to model.

Certain parameters need to be fixed before we experiment with the model, in order to get the most accurate results that represent the current situation. First is transmission rate, which models how contagious the virus is. The higher this value, the easier people get infected. In the original model, this value is to be set between 0.50 and 0.70. However, the current Omicron variant is more contagious than the original coronavirus strain. Even though Omicron is not as severe as previous strains and causes less symptoms, even asymptomatic people can still infect others [6]. Additionally, we are modeling the spread of the virus where most infections happen in an indoor setting, which increases the risk of getting infected compared to an outdoor setting. Because of these factors, we have decided to set the transmission rate higher than the originally recommended 0.50-0.70, namely at 0.85.

Moreover, we also need to set the value of the recovery rate that dictates the likelihood of a turtle recovering at a certain tick. Since the virus is still relatively new, there are no fixed rates of recovery that is available in various sources. However, several sources have stated that with the Omicron variant, most people tend to heal much faster than previous versions of the virus. Most people who do not have any underlying condition recover after 5-7 days [9]. Therefore, we have decided to increase the recovery rate from the original model's preset value of 0.11 to 0.13, giving a higher chance of recovery during each tick.

Since we are modeling the effect of using rapid tests on the spread of the coronavirus, it is important to know the accuracy of those tests. We will be focusing on rapid antigen tests for COVID-19. Different studies have found that these rapid antigen tests almost always correctly identify a negative case (near 100 %). This means that someone who does not have the coronavirus, will almost 100% certain receive a negative test result. However, positive cases are not always correctly identified. Depending on whether the person has symptoms or not, the virus will not always be detected by the rapid antigen tests. It is showed that the rapid antigen tests accurately identify a positive person in 72% of the cases when a person has symptoms, and 58% of the cases when someone does not have symptoms [8]. Since we want to simplify our model and not make a distinction between people with or without symptoms, we decided to average this number and set the accuracy of the rapid tests to 65%.

Another parameter we need to set is the initial immunity of the population, which includes everyone who is fully vaccinated or who has had the virus before. This will depend on the situation we are trying to model. If we are to look at an indoor space at a University in the Netherlands, approximately 74% of people will be fully vaccinated (ages 18-30). If we are looking at an indoor office space, about 80% of people will be fully vaccinated (ages 31-60) [14]. However, this parameter does not only refer to the vaccinated population, but also to the ones who were previously infected. The value of this parameter therefore also needs to include people who are not vaccinated but only recovered from the virus. Since we want to model the spreading of COVID-19 in a more general setting, we have decided to set the initial immunity to around 70%. This is because of the combination of different ages that have different immunity levels, such as children and elderly people.

Each agent has an immunity level, which can be either gained from the vaccine or after recovering from the virus. The immunity decreases over time, and our model uses a decay of 0.985 that was selected in order to fit certain immunity decrease values. Figure 1 shows the graph line of the immunity decrease with decay in one year. The coloured points represent the immunity level after certain periods of time according to [3], namely 65.5% after 30 days (green), 16% after 105 days (orange), and 8% after 180 days (red). It can be observed that the graph line mostly overlaps with the points, meaning that the decayed immunity fits the actual data.

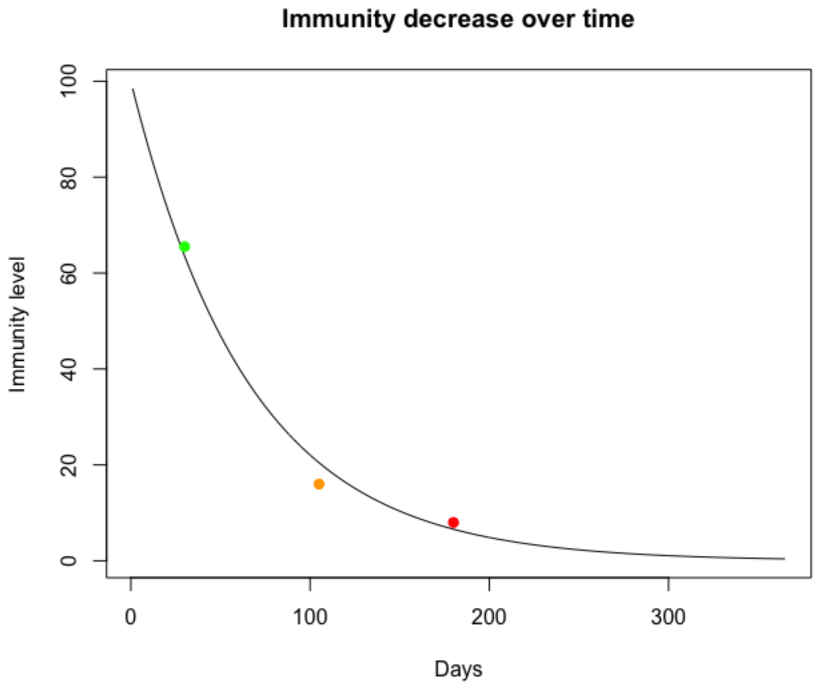

Figure 1: Immunity decay

The chance of getting infected in the real world depends on several factors. However, since this model is a simplified version aimed to analyze the frequency the rapid tests should be used, it only takes into consideration a few factors: the immunity level, the transmission rate of the virus and the number of infected agents in their radius. The immunity level slowly decreases over time, as it is decayed at each tick by multiplying the current level by 0.985, such that it represents the real world. The procedure in which the susceptible turtles are infected is shown below:

```
ask turtles with [not hidden?] [
    let infected-neighbors (count other turtles with [color = red] in-radius 1)
    if (random-float 1 < 1 - (((1 - transmission.rate) ^ infected-neighbors) +
        immunity)) [
      set infected? true
    ]
  ]
```

For each turtle that is not in quarantine, the number of infected turtles in their radius is counted. Then, their chance of getting infected is calculated; a higher transmission rate increases the probability of getting infected, the number of positive neighbors increases it exponentially and the immunity level plays an important role, as high immunity values drastically decrease the probability of getting infected, while low ones do not keep the agent from being infected much.

Finally, the mobility rate needs to be set in the model. In the original model, the mobility was set to 2.0, representing how much agents move around in the world. Since the original model was made at the start of the pandemic, the mobility of people is different at this stage of the pandemic. All facilities like shops and clubs have opened up so people come into contact with more people. Therefore, we have set the mobility to 3.0 in our model.

2.3 Experimental setup

We decided to model the setting of the experiment according to how people move around in their daily life, specifically during colder times when infections mostly happen indoors. Because of this, we ran the experiment in a wrapped world, with both horizontal and vertical wrapping. We set the population size to 500 and the initial immunity to 350. The transmission rate and recovery rate are set to 0.85 and 0.13 respectively, as mentioned in the implementation details. The initial infected people are set to 30 (out of the 500 agents in the setup). Finally, quarantine time is set to 7 days, test accuracy to 65% and mobility to 3.0.

After 365 ticks, we measure the total number of agents that were infected in that time and the total number of agents that were infected and not in quarantine. We kept all variables constant, except for the testing frequency. This variable was set to 1, 2, 3, 4, 5, 6, 7, 10 and 14 in different runs. The experiment was repeated 50 times to ensure more reliable results.

3 Results

After running the simulations and collecting the data, we evaluate them based on two main variables, namely, total number of infections, and total number of infected people who are not quarantining. We segment this data based on the frequency of rapid tests and plot them in Figure 3 and Figure 4. It is clearly seen that doing a rapid test everyday would lead to the lowest number of infection rates. However, it is seen that the box-plot of each testing frequency somewhat overlaps with each other.

The distribution of data within each testing frequency was found to be normal by performing Shapiro-Wilk normality tests. Therefore, to test the significance of the differences, we decided to conduct a one-way ANOVA test. An ANOVA test with self-testing frequency as a factor found a significant effect of self-testing frequency to the number of total infections, $F(8,436)=38.47$, $p <$ 2e-16. Another ANOVA test with self-testing frequency as a factor found a significant effect of self-testing frequency to the number of infected agents who are not in quarantine, $F(8,436)=1660$, $p <$2e-16. Since both tests produce significant results, we conducted a post-hoc Tukey's HSD test to test the significance of the differences between each testing frequency.

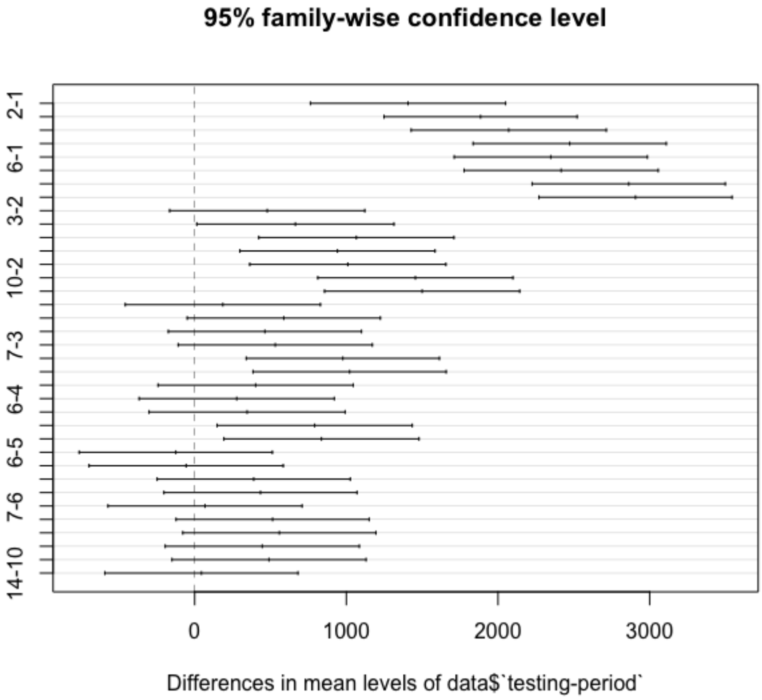

Figure 2: Confidence intervals from post-hoc Tukey's hsd

As seen from Figure 2, it was found that the total cases resulting from testing every day was significantly different from the total cases resulting from all the other testing frequencies. Moreover, it was found that there was no significant difference between testing every 2 days and testing every 3 days. But there was a significant difference between testing every 2 days and every 4 days $p < 0.05$. Overall, the post-hoc test shows us that with a testing frequency of 1, there was a significant difference with higher frequencies, but as the number of testing frequency increases, the difference between the means of total infections of each frequency decreases and becomes less significant. This is consistent with the box plot in Figure 3 and 4, where the slope of the graph is much steeper in the beginning, and gradually stagnates as the number of self-testing frequency increases.

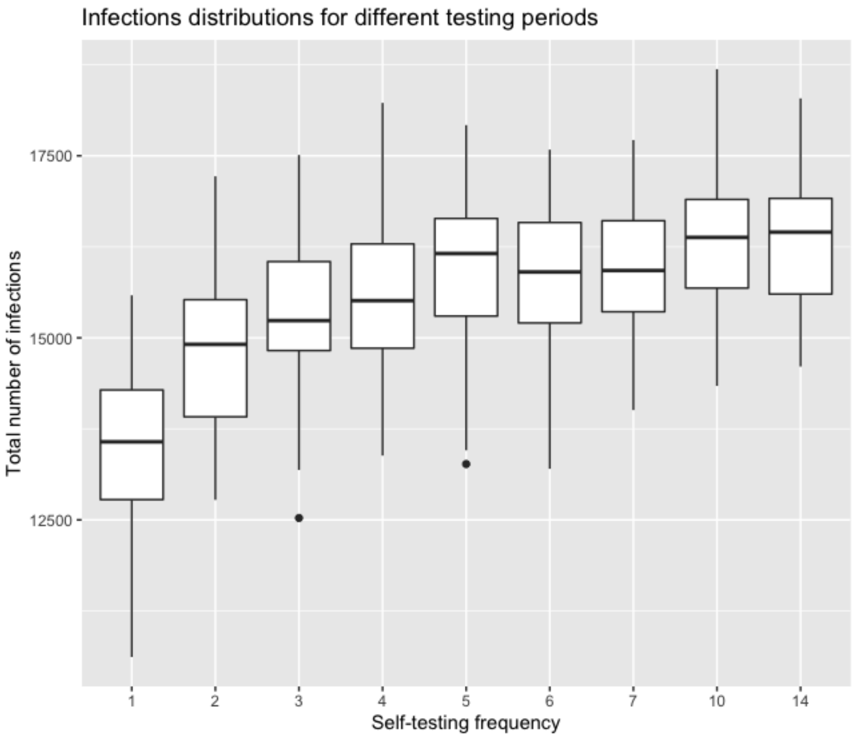

Figure 3: Infections distribution for different testing periods

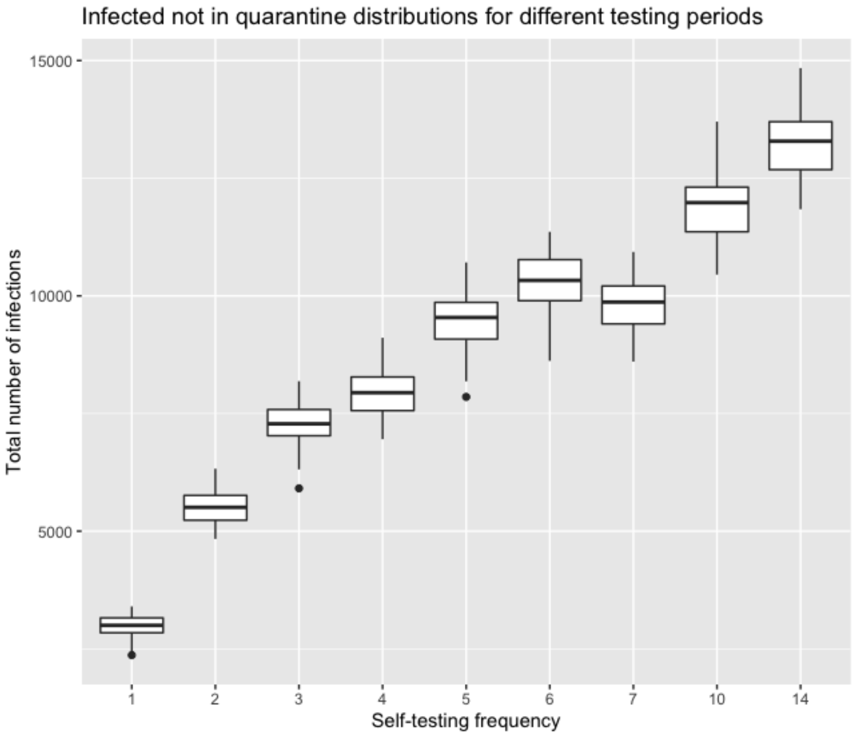

Figure 4: distribution of infected people not in quarantine for different testing periods

4 Discussion

4.1 Implementation

Even though our model is able to simulate the effects of rapid testing frequency, the overall pattern of findings cannot be completely generalized to real-life situations.

For example, one of the most noticeable differences is that the recovery rate is not constant in real life, instead there is an exponential growth day by day leading to more speedy recovery. Moreover, regardless of the decay rate, individuals may have different immunity against COVID-19 due to either their vaccination history or previous infection.

Furthermore, in real-life, the quarantine period is advised as 5-10 days depending on the severity of the infection and recovery speed. However, in our simulation we assume the recovery period to be 7 seven days. Therefore, the quarantine period setting overestimates the count for 'infected' individuals compared to real-life since there could also be individuals recovering in less than 7 days. However, this may also be balanced out by those that stay in quarantine for more than 7 days due to slow recovery.

Also, different world settings could represent different indoor spaces. For example, a box world could better represent a room or an office environment compared to a wrapping world setting. We realized that using a wrapping world setting would better represent the real world where people move in and out of the room and get in contact with people outside of a single room in their daily life.

Moreover, we assume that everyone takes a rapid test on the same day. However, in real life, people could test themselves on different days while still keeping the same frequency, this would most likely depend on symptoms and severity of infection. Furthermore, we assume that everybody takes a self-test as if it is a mandatory task. However, in real-life people may actually be discouraged to take a test when they don't show symptoms since it is just a recommendation. One downside of frequent rapid testing is that since rapid-tests are costly, people may be discouraged to test frequently.

This study could be extended to further research the effects of frequency of rapid testing with different policy changes. For example, depending on the severity of the virus, an initial policy of testing every 2 days could be set. And later on this policy could be changed to testing every 5 days. Furthermore, the world could be changed to consider only strictly indoor spaces with limited mobility such as an office environment.

4.2 Results

Based on the Results section, we found that there were significant differences to the number of infections based on the frequency of self-tests being done. The post-hoc tests showed us that the differences between the testing frequencies were only significant for lower testing frequencies. For higher frequencies, the differences is not very significant. This is seen in the Figure 3, where it is observed that the changes in mean generally stagnates after a testing frequency of every 4 days.

Based on these tests and observations, we would generally recommend a testing frequency of once every three days. This is because even though having everyone conduct a test everyday would be the most ideal since it would lead to the fewest cases, this is not realistic. Not only would people not want to do it everyday, we also need to take into account the resources that it would require. Testing every 3 days instead of every 2 days is optimal because the post-hoc test shows that there is only a small, not significant, difference in total cases, and again, people would prefer to conduct the test less frequently. However, the total infections when testing every 2 and every 4 days does have a significant difference, so increasing the testing frequency from 3 to 4 is not desired since total infections would rise much more.

5 Division of labor

5.1 Andreea Tudor

'Conceptual model' and 'Implementation details' (Section 2), the implementation of the model code, and organization of design choices for the model-code, as well as implementation of statistical tests.

5.2 Charlotte Mennema

'Experimental setup' and 'Implementation details' (Section 2), preparing the original model-code, organization of design choices for the model-code, and implementation of statistical tests.

5.3 Ekin Fergan

'Introduction', 'Innovation' and 'Discussion' (Section 1. 4), general parameter settings for the model-code, organization of design choices for the model-code, as well as statistical test selection.

5.4 Izzi Kampono

'Introduction', 'Results', 'Discussion of Results' (Section 1, 3, 4) immunity formulae for the model-code, organization of design choices for the model-code, as well as statistical test selection.

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