

Using Agent-Based Simulator to Assess Interventions Against COVID-19 in a Small Community Generated from Map Data

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ABSTRACT

During the COVID-19 pandemic, governments have struggled to devise strategies to slow down the spread of the virus. This struggle happens because pandemics are complex scenarios with many unknown variables. In this context, simulated models are used to evaluate strategies for mitigating this and future pandemics. This paper proposes a simulator that analyses small communities by using real geographical data to model the road interactions and the agent's behaviors. Our simulator consists of three different modules: Environment, Mobility, and Infection module. The environment module recreates an area based on map data, including houses, restaurants, and roads. The mobility module determines the agents' movement in the map based on their work schedule and needs, such as eating at restaurants, doing groceries, and going to work. The infection module simulates four cases of infection: on the road, at home, at a building, and off the map. We simulate the surrounding areas of the University of Tsukuba and design three intervention strategies, comparing them to a scenario without any intervention. The interventions are: 1) PCR testing and self-isolation if positive; 2) applying lockdown measures to restaurants and barbershops 3) closing grocery stores and restaurants and providing delivery instead. For all scenarios, we observe two areas where most infection happens: hubs, where people from different occupations can meet (e.g., restaurants), and non-hubs, where people with the same occupation meet (e.g., offices). The simulations show that most interventions reduce the total number of infected agents by a large margin. We observed that interventions targeting hubs (2-4) did not impact the infection at non-hubs. In addition, the intervention targeting people's behavior (1) ended up creating a cluster at the testing center.

KEYWORDS

Pandemic, Agent-based simulation, Covid19, Computational Epidemiology

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1 INTRODUCTION

The virus SARS-CoV2 (Covid-19)[14], first detected in late 2019, started spreading worldwide in early 2020, causing a disease outbreak. As of September 2021, the pandemic is ongoing and has reached 219 million cases and over 4.5 million deaths worldwide.

To contain the spread of the virus, governments all over the world tried different actions to reduce the infection[5]. Some examples of measures adopted were: social distancing, limiting the occupancy of buildings, mass testing, temporarily closing non-essential business, reducing work hours, incentivizing companies to allow employees to work from home, etc. These measures had different degrees of success and varied a lot depending on the country.

These mixed results highlight the difficulty of choosing which actions to take in a pandemic. Not only do many variables have to be considered, such as social and economic impact, but also, governments have to reflect on aspects specific to their regions, such as population distribution, culture, and others.

A key technology that can help tackle this issue is using a simulator to investigate the spread of the disease. While no simulation can reproduce all the complexities of a real-world situation, its results can give decision-makers many insights and help them make more informed decisions.

Although epidemic simulators already exist, most of them simulate a fictional city or do not use precise geolocation of the agents. In the real world, the transmission of airborne diseases usually depends directly on the interaction between people in the same location. Hence, it is important to consider their movement, where they passed through, and which areas can become crowded under certain conditions. Another factor not usually accounted for is the differences in mobility in different regions; a big city will be more crowded and have its agents having much more interactions than a small city.

In this context, this research proposes a simulator¹ that attempts to model more realistic communities based on geographic data.

¹All the code and data for this paper, including experimental scripts, are open and available at <https://github.com/rithgroove/Epidemicon>.

In our simulation, agents move independently around the map according to their work schedule and needs. These features make it possible to capture particular characteristics of a community, such as the movement of agents in the map and commonly crowded areas. Additionally, our simulator is flexible to be adapted to different regions. It also enables the comparison of various interventions against the spread of disease and can give insights into what is best for a specific community.

In this paper, we simulated three different interventions: 1) PCR testing and self-isolation if positive; 2) applying lockdown measures to restaurants and barbershops 3) closing grocery stores and restaurants and providing delivery instead. Intervention 1 targets the agent's behavior, while interventions 2 and 3 target hubs - where people from different occupations can meet.

These experiments showed that most measures targeting hubs, such as restaurants and supermarkets, can reduce the total number of infections but do not decrease infections at non-hubs like workplaces. In addition, measures such as doing mass PCR testing should be taken with care since they might cause more infections or new clusters if not applied properly. Finally, by comparing the results of our experiments with real-world data, we can see that they follow the same trend and that our simulator is indeed capable of reproducing real-world situations.

The remainder of this paper is organized as follows: Section 2 discusses other simulations and in which aspect our simulations differ from them. Section 3 explains the implementation of the model. Section 4 describes the experiments of all three scenarios, then show their results and analyzes them. Section 5 discusses the results from the previous section. Finally, Section 6 presents the conclusion, limitations, and directions for future work.

2 RELATED WORKS

There are various ways to model an epidemic, each with its advantages and disadvantages. One common method is to use a combination of compartmental models with mathematical models. The most common compartmental model for an epidemic is SEIR (Susceptible - Exposed - Infectious - Recovered). In the compartmental model, individuals are grouped into compartments representing their health status, and each individual can transition from one compartment to another. The mathematical model provides a transition probability for the individual to move from one compartment to another. Abrams et al. [3] expand SEIR by separating the infectious compartment into asymptomatic, symptomatic, mildly symptomatic, and severe for the Belgian Covid-19 epidemic. Similarly, He et al. [9] use a modified SEIR that includes Quarantined and Hospitalized to simulate the Hubei province pandemic.

While mathematical compartmental models are useful to study the epidemic's growth, this model only considers which compartments the individuals are in. We cannot analyze information such as the source of infection or where the infection happened.

Another type of model that can mitigate the problems of mathematical compartmental models is an agent-based model. In this group, each agent represents a person, having a chance to transmit diseases while interacting with other agents. These models better capture complex behavior and interaction at a level of detail that

could help us track the origins of each infection case. This information provides insights into how the disease spreads. Dignum et al. [7] creates an agent-based model to simulate the epidemic that considers the health, economic and social needs of each agent. One interesting point in this study is how the agent's needs are modeled. Each agent has needs such as autonomy, self-esteem, belonging, safety, and survival that will slowly decrease as the simulation progress. When these needs decrease to a certain threshold (hunger), the agent performs activities to replenish them (eat). Our simulator uses a needs-based mobility model inspired by this study, simulating needs such as hunger, food supply at home, and hair length.

Other agent-based simulators have similarities with ours. "Anytown" [8], which is a part of the Delineo project by Johns Hopkins University, simulates a fictional Midwestern town with 6000 agents. Another agent-based model is "PANDEMICSIMULATOR" by Sony AI, is used in two studies. The first is a study in using reinforcement learning to modify the timing for starting covid regulation [10]. The second study infers the likelihood of infecting an individual through real-time contact tracing [13]. While both models can simulate the spread of the disease, both simulations use generic activities. This means that the activities of the agents might not consider the local behavior of the people that live in such areas. One example of this is the high outflow of people from suburbs during working hours.

Another agent-based model is "PANSIM" [4, 6]. This simulator uses anonymized cell phone data to generate agents' schedules. This simulator uses a large-scale distributed system to simulate a large number (more than 100,000) of agents to simulate the spread of Covid-19. This creates a more realistic behavior of the agents, but it was not clear if they used the geo-location of the agent for the infection model.

We use these works as inspiration to develop a simulator that simulates more detailed agent's mobility using real map data. This allows us to simulate the interaction between agents on the road, enabling the transmission of diseases between them. We also adapted the SEIR structure dividing the infectious compartment into asymptomatic, symptomatic, and severe.

3 PROPOSED MODEL

Our model simulates how a virus spreads in small communities. In the simulation, each step represents 5 minutes. The agent may update its location during each step, check for infection, and update its needs according to the modules explained below. Figure 1 illustrates a run of the simulator, where we can see how the agent is placed on the map and their infection status.

The simulation has three modules that are explained below: environment, mobility, and infection.

3.1 Environment

The environment module loads a defined region's geodata from Open Street Map². The geodata contains information about roads and buildings. The building's data includes building types (residential, restaurants, offices, and others) as seen in the Table 1. This tag is used to later assign home, workplace, and leisure to the agents.

²Open Street Map web page: <https://www.openstreetmap.org/copyright>

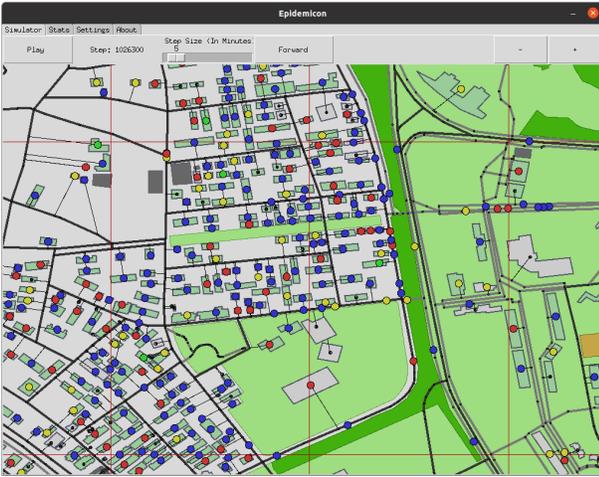


Figure 1: An example of rendered view from our simulator. The blue circles represent susceptible agent, yellow represent exposed agent, red represent an infectious agent, and green represent recovered agent. Green buildings represent a residential building. In contrast, white buildings represent workplaces or facilities.

Map data: ©OpenStreetMap Contributors

Table 1: Buildings available in the map

<i>Building Type</i>	<i>Type</i>	<i>Count</i>
Apartments	hub	867
House	hub	188
Residential	hub	166
Restaurant	hub	36
Retail	hub	68
Train station	special-case	1
Office	non-hub	52
Laboratory	non-hub	80
Hospital	hub	5
School	non-hub	25
University	non-hub	104
Barbershop	hub	8

Most buildings had their tag missing, so we implemented a grid-based tagging technique to give random tags to untagged buildings. In this technique, we split the map into 10×10 cells. For each cell, we specify how many types of buildings are in that specific square. For example, one of the cells can have five restaurants, two retails, and the rest of the buildings are apartments. We created this specification by observing the area on the map using a different online map service. Based on this specification, we randomly gave tags to the buildings within that cell.

After loading the buildings and roads data, the environment module creates connections between buildings and roads. Since this connection is not available on Open Street Map, we connect the centroid of the building to the closest road using the shortest path.

3.2 Mobility

The mobility module determines the agents' movement around the map depending on their occupation, needs, and health.

3.2.1 Occupation. The agents have an occupation, which provides them with a schedule of when to go to work or school. The occupation is a parameter in the simulation. This parameter defines the proportion of the population that has a particular occupation, the building type to perform their occupation, and working hours. The building is chosen randomly among all buildings with the specified tag. For example, we may define students as 30% of the population; students go to a random building with type "school" and stay there from 9 to 5 during weekdays. In this parameter, we also may define agents that work outside the simulated area. These agents go to a train station and stay idle until their work shift finishes. These agents have a different infection behavior, which is explained in the infection module.

3.2.2 Needs. The agents have needs, which define their behavior outside the working time. The agents need to eat, buy groceries, and get their hair cut. They can eat at home or available restaurant when hungry at random based on their preference. When they eat at home, they consume a unit of groceries. If the groceries at home reduces to a certain threshold, the agent goes to a supermarket. The agents also go to the barbershop after their hair grows longer than their preference.

3.2.3 Health. The agents have a health condition that may change their usual behavior. Currently, the health status depends only on one infectious disease according to the SEIR model. Symptomatic agents stay at home and only go out if they need to buy groceries. Agents in severe condition remain in a hospital until they recover. Asymptomatic agents follow their schedule as usual.

3.3 Infection

The infection module provides the logic for disease transmission. We use a modified SEIR model adapted to our simulator, as shown in Figure 2. There are four compartments in this model: susceptible, exposed, infectious, and recovered. The infectious compartment is divided into asymptomatic, symptomatic, and severe symptomatic. The transition from Susceptible to Exposed happens after contact with an Infectious agent, following four different logic depending on where the contact occurred:

- **at residential building:** there is a chance of infection based on time of contact for every infected agent in the same household;
- **at facility:** there is a chance of infection based on time of contact for every infected agent inside the building;
- **on the road:** the chance of infection drops the farther the distance between agents;
- **off-map infection:** we use a different infection logic where each agent has a fixed chance of getting infected.

The transition from Exposed to Infectious has an incubation time of 1 to 3 days. After the incubation time, the agent becomes asymptomatic and can transition to symptomatic or severe based on a random risk factor. They can then transition to recovered after a period of 3 to 14 days after the agent became infectious.

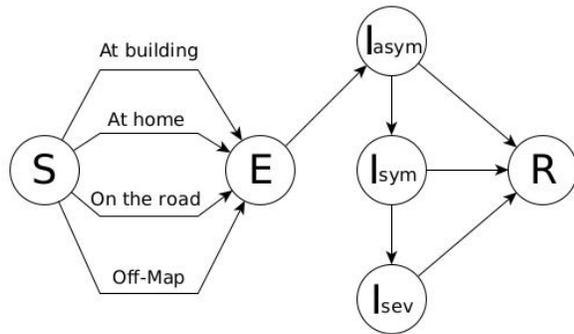


Figure 2: Our modified SEIR structure has four different ways to be exposed to the virus and three different stages of infection

Table 2: Agent’s profession distribution

Profession	Workplace	Count
Office worker	Office	1000
Off map office worker	Train station	800
University student	University	1600
University professor	University	200
Restaurant worker	Restaurant	140
Teacher	School	100
Scientist	Laboratory	150
Medical doctor	Hospital	100
Retailer	Retail	450
Student	School	450
Barber	Barbershop	10

4 EXPERIMENT

We carried out several simulation experiments to investigate promising strategies that can be further investigated and implemented in real scenarios to reduce the spread of the virus. We simulate the University of Tsukuba and its neighborhood with 5,000 agents during 49 days. Table 2 shows the agents’ job distribution. This distribution was selected based on the types of buildings on the map.

We use the infection rate inside buildings as 20% per 24 hours of contact per infected agent, 10% for off-map infection, and 30% for on-the-road infection, where it reduces linearly to 5% once the agents are 2 meters away from the infected agent. It is important to note that this infection rate is not the same as COVID-19; we chose a higher value to produce a surge of infection given the number of simulations days and number of agents.

We implement a baseline scenario where no action to contain the virus is taken and compare it to three other scenarios: 1) applying lockdown measures to restaurants and barbershops; 2) PCR testing and self-isolation if positive; 3) closing grocery stores and restaurants and providing delivery instead.

We record the daily active cases, cumulative cases, and location of infection happened. Daily active cases show the number of people

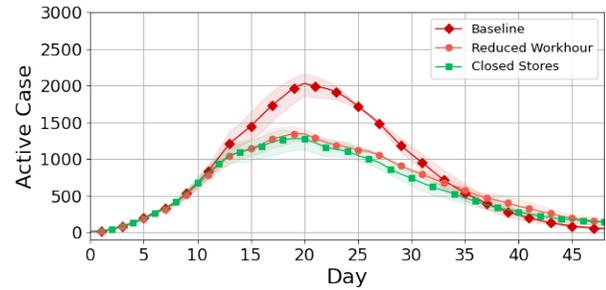


Figure 3: Daily active cases for Baseline, Reduced Workhours, and Closed Stores. Both interventions show a similar reduction in active cases.

that are infectious per day. The cumulative case shows the total number of cases since the beginning of the simulation. Lastly, the location of infection indicates the number of infections per building type.

4.1 Lockdown / State of Emergency

In this scenario, we simulate two different restriction policies for businesses with different degrees of severity. The first policy, which we called Reduced Work Hours, is inspired by the measures adopted by Japan government during the COVID-19 pandemic; it consists of limiting the business hours of certain store types to a limited time frame. The second policy, called Closed Stores, is a stricter restriction; the chosen business types do not open when the policy is in effect.

The period that these restrictions are implemented is called a lockdown period, and we opted to simulate it when the spread of the disease is already in course. The lockdown period starts when at least 150 agents are in severe or symptomatic conditions, and it ends when this same number is reduced below 150. The reason asymptomatic agents do not count for the policy is that, in a real-life scenario, these cases would likely go undetected.

For both policies, we chose to target restaurants and barbershops because they are non-essential businesses. In the case of policy Reduced Work Hours, similarly to Japan, they are only allowed to open between 11:00 and 20:00.

4.1.1 Results. For the lockdown scenario, the simulation results and the comparison between the baseline and the two lockdown policies, Reduced Work Hours and Closed Stores, can be found below.

Before analyzing the data, it is important to note that the lockdown period starts when at least 150 agents are in severe or symptomatic conditions and ends when this same number is reduced below 150. For that reason, the lockdown began on day 8 or 9 and finished after day 40 in all repetitions. Consequently, the number of infection cases on all results only starts to differ some days after the lockdown begins.

Figure 3 compares the active cases (agents that are asymptomatic, symptomatic, or severe) between the baseline, Reduced Work Hours, and Closed Stores policies. As can be seen, the number of cases decreased after the policies were in effect. Then, all scenarios peaked



Figure 4: Infection by location in the simulated scenarios. The graph shows a massive reduction of infection in restaurants, but infections at non-hubs do not show any changes.

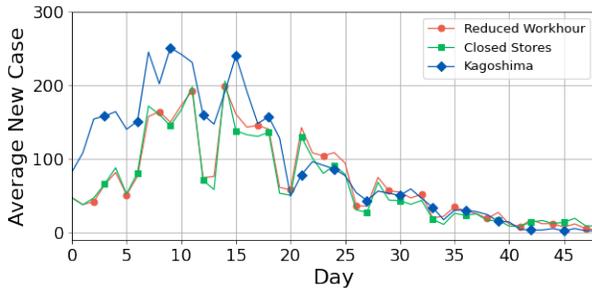


Figure 5: Average new cases per day for the two simulated lockdown scenarios (Reduced Work Hours and Closed Stores) compared with reported cases in Kagoshima.

by the same day, but the number of cases in the Reduced Work Hours and Closed Stores were much lower. By analyzing these results, it is possible to conclude that although all scenarios followed the same trend, both policies successfully reduced the number of cases in total.

Following this, figure 4 shows the locations where the agents got infected. Not surprisingly, the number of cases in the restaurant was significantly reduced when the lockdown measures were applied, and the stricter the measure, the more significant the reduction is. Additionally, the number of infections on the road also lowered since people dislocated less since they did not go to restaurants or barbershops as often. In contrast, the number of cases in retail increased with more restrictive policies. The possible explanation for this is that people ate more at home and, as a consequence, had to visit retail more often to buy food.

4.1.2 Discussion. By analyzing all of these results, it is possible to conclude that both lockdown policies were effective in reducing the total number of cases by a significant margin. After being applied on day 8 or 9, they started reducing the number of cases just a few days after.

Interestingly, the difference of the accumulative cases between reducing work hours and closing stores was not very high, suggesting that more rigorous measures do not necessarily reflect a much bigger reduction of infection. This result shows the importance of considering alternative lockdown measures depending on the situation. A strict policy usually is accompanied by a substantial economic impact for both governments and businesses. Still, its results may not differ much from a moderate approach that could lessen the financial burden.

However, it is important to keep in mind that one limitation these tests had was that agents do not change their schedules to adapt to the measures. This means that if an agent usually eats at 20:10, but the restaurants close at 20:00, it would eat at home instead of eating earlier at a restaurant. As a result, the Reduced Work Hours measure would be the same as closing down the stores for these agents.

Lastly, we compare the number of new cases between our simulation and the real data from the Japanese prefecture of Kagoshima [1]. We chose this prefecture because it adopted restrictions measures similar to the ones on the Reduced Work Hours scenario [2]; likewise, their lockdown period was similar to ours. To have an accurate comparison, we selected a period that starts from 9 days prior to the prefecture applying their lockdown measures (August 11th) and lasts for 49 days. By doing that, both the simulation and Kagoshima cover the same length of days and start their lockdown at similar times.

Figure 5 presents a similar trend between the simulated and the real scenarios, showing that our simulation is able to produce results that are similar to the ones observed in the real world, displaying the reliability of our model.

4.2 PCR and Early Self Isolation

This scenario evaluates the use of PCR and early self-isolation. This scenario is inspired by the early intervention done by countries such as South Korea [11] which do a massive number of PCR-testing. The idea of this scenario is to simulate early self-isolation when the agent has not shown any symptoms. We expect this method to reduce infection, especially infection caused by asymptomatic agents.

There are three variants of this scenario that have different validity periods of the PCR results. The variants are 3-days expiry, 7-days expiry, and no expiry. We chose these configurations because our simulated disease has 1 to 3 days of incubation period. On the 3-days expiry configuration, at worst, the agent will have two days to infect other agents because they think they are healthy. The 7-days expiry is selected to simulate a more prolonged period where the agent behaves as healthy while being infectious. Lastly, the no-expiry scenario was selected to simulate the worse condition that could happen if we were not careful with the PCR results.

For the PCR and self-isolating experiment, we changed the agent behavior to change their movement based on the PCR results instead of their symptoms. In this experiment, agents will take a PCR test at the hospital if they start to show symptoms, and if tested positive, will inform any agents that live in the same building as them or visit their workplace within the last three days to take the PCR test. Once the agents test positive, they will start self-isolation and

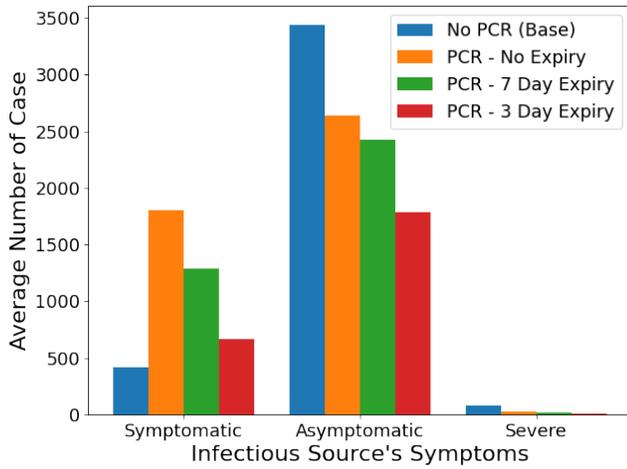


Figure 6: Infection by symptoms for PCR interventions. The graph shows that PCR interventions reduce the asymptomatic infections, but increase the symptomatic infections.

only go out to buy groceries if their food supply at home runs out. Agents that in severe condition will have the same activities as the baseline experiment, which is to go to the hospital and stay there until recovered.

Another change we made in this experiment is that agents in severe conditions will not infect any agents in the hospital. This was designed because the testing area for PCR and the isolation area for Covid-19 patients are usually in different places inside the hospital.

4.2.1 Results. This subsection compares the baseline and three PCR variants (3-days expiry, 7-days expiry, and no expiry). We start analyzing the infection by the health status of the source, proceed to the number of cases per location, compare the active case, then discuss the insights obtained.

Figure 6 shows the number of infections by the health status of the source. The X-axis shows which health status infectious stage of the agent infects other agents, while the Y-axis shows the number of cases. Each color represents the different configuration for this experiment. From this image, we could see that the infection from severe sources was reduced. This reduction is caused by the removal of infection from severe patients in the hospital.

Figure 7 shows the number of cases based on the location where the infection happened. In this figure, we removed the barbershop because it has less than ten infection cases. We also merged School, University, Office, and Laboratory into non-hub. This was done because each non-hub building has similar infection increment trends for the no expiry setting and reduction for the scenarios with 3-days and 7-days expiry dates.

Figure 8 shows the active case for each day. In this figure, we can see that the scenario where the PCR never expires has more active cases than the base. The 7-days expiry scenario has almost the same number of active-case as the baseline. Lastly, the 3-days expiry scenario is the only scenario where we could reduce the number of active-case.

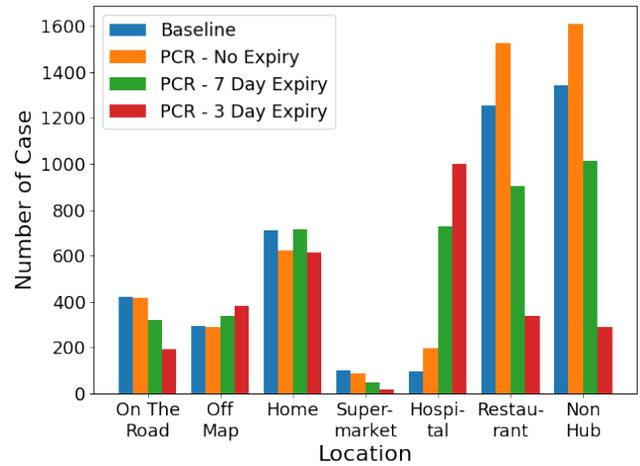


Figure 7: infection by location for PCR interventions. The graph shows that PCR intervention caused a massive number of infections at the hospital.

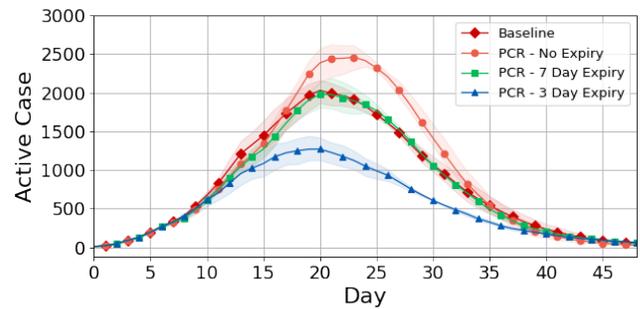


Figure 8: Active case per day for Baseline and three PCR strategies (no expiry, 7-days expiry, and 3-days expiry).

One interesting point from figure 6 is that PCR testing interventions reduced the asymptomatic infections while the symptomatic infections increased. Another interesting point shown in figure 8 is that the longer validity of the PCR results caused higher active cases. This increase of active cases can be attributed to the fact that agents within the PCR scenario act based on their test results rather than their health. In this scenario, agents infected after getting negative results still behave as if they are healthy despite having symptoms. This behavior caused them to move around the map, infecting other agents.

4.2.2 Discussion. In this scenario, we also observed a higher number of infections at the hospital due to the surge of people taking PCR tests. This is similar to what happened in Malaysia, where the vaccination center has to be closed after the workers got infected [12]. During the simulation time (49 Days), agents will take 10 PCR for the 3-day validity scenario, 3 PCR tests for the 7-day validity scenario, and 1 PCR test for the no expiry scenario. This surge of agents taking PCR cause the hospital became a cluster of infections. But in this scenario, hospitals have the same chance of infection

as places like a restaurant. In reality, hospitals are likely to have better safety measures that reduce the infection rate.

These results show that while a massive number of PCR-testing can reduce the spread of infection, it must be noted that, in the 3-day expiry scenario, agents will need to take PCR once every 4 to 5 days, which is not realistic because PCR tests are expensive. The other option is to take a PCR test once every two weeks, represented by the 7-days validity scenario. In this scenario, we could see that we have a similar number of cases with the baseline. Lastly, if we are not careful, we could have more infections than the baseline, as shown in the no expiry scenario. The 7-day expiry and no expiry scenarios indicate that this policy can be dangerous if not implemented correctly. For example, an agent that shows mild symptoms and would otherwise self-isolate out of caution, will instead walk around and infect other people because they got a long-lasting negative PCR test.

4.3 Delivery from restaurant and supermarket

In this scenario, we want to explore actions taken by actors other than governments to fight the virus. For such, We simulate the delivery of food provided by restaurants and supermarkets. In the baseline, agents have a chance to eat at home or a restaurant. If they eat at home, they consume a unit of groceries, which they can refill by going to the supermarket. We make three variants where 3a) agents no longer go to restaurants; instead, another agent brings one unit of food from the restaurant to their house. 3b) agents no longer go to the supermarket; instead, another agent brings enough units of food for 3 to 7 days. 3c) agents no longer go to restaurants and supermarkets; a combination of the previous cases.

4.3.1 Results. This subsection compares the baseline and three delivery strategies (food from restaurants, supermarkets, and both places). We start analyzing the cumulative cases, proceed to infections per location, then discuss the insights obtained.

Figure 9 shows the number of people that are infectious per day. As can be seen, "delivery-supermarket" does not reduce the total number of infections, having a similar trend to the "baseline" with about 4200 total infections and a peak of about 2000 infected people. On the other hand, "delivery-restaurant" and "delivery-both" drastically reduce the total number of infections, flattening the curve with about 3000 total infections and a peak of about 850 infected people.

Figure 10 shows the number of infection on each building type. As can be seen in the baseline, restaurants are hotspots of infections, having the highest number compared to all the other places. On the other hand, supermarkets have one of the lowest infections (behind only laboratories and barbershops). As expected, the number of infections at restaurants and supermarkets is reduced to almost zero when these places are closed to the public (allowing only delivery). The infection at these places does not reduce to zero because workers can infect each other. Interestingly, because restaurants and groceries are closed, there is less movement on the streets, reducing the number of infections "on the road" compared to the baseline.

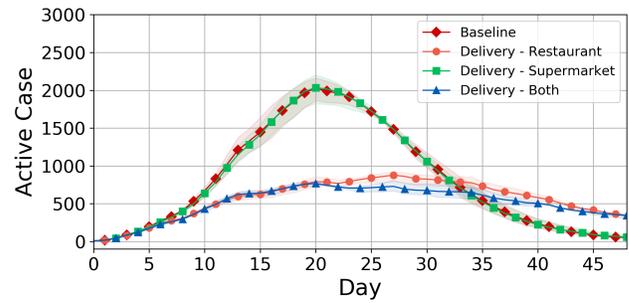


Figure 9: Active cases for Baseline and three delivery strategies (restaurants, supermarkets, and both). Baseline and delivery-supermarket present the same trend of infection, peaking at about 2000 cases. Delivery-restaurant and delivery-both have reduced the number of infections, peaking at about 800 cases. Strategies targeting restaurants (hotspots) are more effective in reducing infection.

4.3.2 Discussion. These results highlight the importance of identifying hotspots before taking action. One may wrongly close facilities that have little impact on the number of infections, potentially causing financial problems to these places without helping fight against the virus (supermarkets in the simulation). On the other hand, we can get better results at fighting a pandemic by identifying potential hotspots in advance and then reducing the flow of people in these places (restaurants in the simulation). Providing delivery requires a specific infrastructure that many places (e.g., small restaurants) may not have. For this reason, it is essential to focus the resources at the right place since governments and companies have limited resources. In the simulation, this translates as providing the delivery infrastructure to restaurants instead of supermarkets.

5 DISCUSSION

We observed that identifying hotspots of infection is essential when choosing restriction measures. By targeting these locations, it is possible to create policies that have lesser economic impact but are still effective in reducing the transmission of the disease.

Another important observation is that infections on the road, while not high, are still relevant. By closing hubs, agents move less, and as a result, the cases on the road also decrease.

Surprisingly, the massive number of PCR tests reduced the infections from the asymptomatic source but raised the infections from the symptomatic source. Our results show that having a long validity period for the PCR results caused agents infected after the test to infect more people by behaving as if they were healthy. Other than that, it was shown in the simulation that PCR testing places can be a new cluster for infection. These results highlight the importance of being careful when implementing a massive number of tests.

Finally, the comparison with Kagoshima active cases of COVID-19 shows that, when simulating an intervention, the simulator can indeed produce results similar to those found in the real world — displaying its capacity to simulate realistic scenarios.

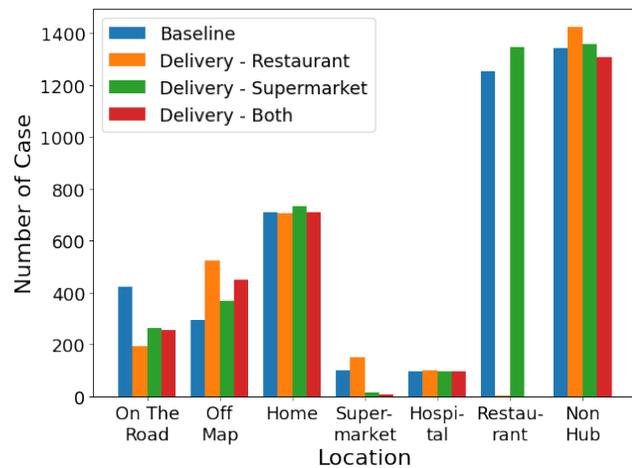


Figure 10: Infection by location for the baseline against the three delivery strategies (restaurants, supermarkets, and both). The three delivery strategies have slightly reduced infections "on the road" and slightly higher infections "off-map".

6 CONCLUSION

In this paper, we develop a pandemic simulator and explore three different interventions to reduce the spread of the virus. We observed that our lockdown intervention was very similar to a real intervention in Kagoshima, Japan [1], which also had a similar trend of new cases per day. We also noted that most interventions targeting places where people gather, such as restaurants and supermarkets, reduce the total number of infections. At the same time, the PCR testing might create a cluster in the testing center due to the increased flow of people, which also is similar to the infection cluster at vaccination center case in Malaysia [12]. These results suggest that simulator can provide insights on how the disease spread, helping decision-makers design public policies.

Our simulator has some limitations. Some data about the simulated area was incomplete. This project would benefit greatly from integrating more detailed demographics, job distribution, mobility, and missing or incomplete information about buildings. Due to time and processing power limitations, we had to limit the number of simulated days and agents in the simulation. This lower number of agents resulted in a lower population density in the simulated area. Consequently, this lower population density resulted in a slower spread of infection due to the lower interaction between agents. Finally, some features that have not been implemented at the time of writing are: transportation methods (all agents only walk), the chance of death, and different compliance levels to the interventions.

This work's natural progression is to incorporate real movement data generated from data collected by phone carriers into the simulation. Another interesting future research is to explore the interaction between natural disasters and epidemics where a cluster of infections might form in evacuation centers.

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