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# Overdose Prevention Sites Placement Informed by Simulation

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# Overdose Prevention Sites Placement Informed by Simulation

**by**

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**Honor Thesis**

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This paper is part of the requirements for the honors program in computer science. The signatures below, by the advisors, a departmental reader, and a representative of the depart-mental honors committee, demonstrate that Jing Dong has met all the requirements needed to receive honors in computer science.

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# Overdose Prevention Sites Placement Informed by Simulation

## Abstract

In Philadelphia, people are experiencing the greatest opioid crisis in a century. Placing the Overdose Prevention Site (OPS) can alleviate this crisis. However, the journey to the successful launch of the first OPS in the USA is rough. It was first accused of having a collision with federal drug laws. While Safehouse won the lawsuit and the OPS was judged to be legal in 2020, other pressure rose afterward such as the against from the public and the COVID19, which delayed the plan to open the OPS. Without solid research on the effectiveness of OPS, we thought it is necessary to provide scientific evidence to support the OPS program. In our research, we apply both the Markov Chain model and the agent-based model to investigate the effectiveness of placing OPSs in Philadelphia. Our final conclusion shows that the OPS can effectively save people from fatally overdosing. In general, we hope to promote the launch of the OPS and also bring out some public health implications for future OPS placement based on our research.

# DEDICATION

To my dear family, mentors and friends. To my undergraduate life at the University of Richmond, the place where my dream began.

## ACKNOWLEDGEMENTS

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# Contents

# 1 INTRODUCTION

All over the United States, and particularly in Philadelphia, people are experiencing the greatest opioid crisis in a century. To combat this, a non-profit organization called Safehouse was founded to save lives by providing various types of overdose prevention services. One of the important services they aim to provide is an Overdose Prevention Site (OPS) in the city. An OPS is a safe place for people to inject illicit drugs under medical supervision. It also provides education programs to educate active drug users on how to avoid injection-related harms and how to safely use drugs. Besides that, an OPS offers clean injection supplies to reduce disease spread throughout the whole city. However, founding an OPS has encountered several challenges. The first major challenge was an accusation from the government that an OPS would break federal drug laws. In 2020, Safehouse won the lawsuit brought by the federal government when the OPS was judged to be legal. Other pressures arose afterward. The proposal of opening the OPS encountered public pressure while COVID19 spread globally, which delayed the plan to open the OPS in Philadelphia. Given the lack of research on the effectiveness of OPS, we decided to investigate the usefulness of placing an OPS in Philadelphia. Thus, our main goal of this research is to apply simulation models to make predictions on the effectiveness of placing an OPS in Philadelphia.

## 1.1 Research Contribution

In this research, we investigated the effectiveness of placing an Overdose Prevention Site (OPS) in Philadelphia. We aimed to determine how it can alleviates the serious situation of the opioid crisis in Philadelphia. We created a Markov Chain type model and an agent-based model to predict the number of fatal and nonfatal overdoses that would occur after the OPS has been placed for a year. Our final conclusion shows that the with reasonable design, the OPS can effectively save people from fatally overdosing. We hope that this research provides more scientific evidence to support the plan to open the first OPS in Philadelphia.

## 1.2 Outline

Chapter 2 provides an overview of the current opioid crisis and reviews the previous work related to the opioid crisis and Overdose Prevention Sites. Chapter 3 talks about the important parameters and equations that we will use later in both of the models. Chapter 4 introduces the Markov Chain approach with model design, experiment description, and the results. Chapter 5 describes the experiment to determine the most efficient programming language for the agent-based model. Chapter 6 describes the approach for the agent-based model. Chapter 7 draws the conclusions.

# 2 PRELIMINARIES AND RELATED WORK

## 2.1 Opioid Crisis and Overdose Prevention Site

In the United States, the opioid crisis has become much more severe than 20 years ago. The research of the CDC showed that the number of drug overdose deaths was four times higher in 2018 than the number in 1999 [30]. There were three waves of opioid overdose deaths from 1999 to 2018. The first wave came from an increased prescribing of opioids in the 1990s. The second wave began in 2010 when there was a rapid rise in heroin overdose deaths. The third wave started in 2013, with serious increases in synthetic opioid overdose deaths. Currently, the opioid crisis has become one of the biggest social problems in a century, which needs to be addressed urgently. Pennsylvania has become the fourth highest age-adjusted overdose death rate in the United States[1]. Among all counties in Pennsylvania, Philadelphia has the second-highest overdose death rate[8].

Hence, Philadelphia initiated the Resilience Project, mobilizing 35 city departments to combat Philadelphia's opioid epidemic in October 2018 [23]. This project focuses on the most urgent needs and important neighborhoods, centered on Kensington, a highly impacted neighborhood, and surrounding areas. There are seven mission areas:

- Clearing major encampments.

- Reducing criminal activity.
- Reducing the number of unsheltered individuals.
- Reducing trash and litter.
- Reducing overdoses and the spread of infectious diseases.
- Increasing treatment options.
- Mobilizing community resources.

As for the mission of reducing overdoses and the spread of infectious disease, in June 2019, the project has made some significant progress:

- Conducted nearly 2,500 HIV tests in Kensington
- Distributed opioid prescribing guidelines to 16,000 healthcare providers by mail and another 1,300 by direct, in-person outreach
- Provided all Fire Department ambulances with "leave behind" naloxone (Narcan) to distribute after responding to overdose calls
- Reduced fatal overdoses 8% in 2018 compared to 2017, with the sharpest reductions occurring in the Kensington area

Even with that significant progress, there is still an extremely large number of people using opioids in the city and many people still overdose and die.

Hence, to better alleviate the opioid crisis, Safehouse was founded. It is a "privately funded 501(c)(3) tax-exempt, Pennsylvania nonprofit corporation whose mission is to save lives by providing a range of overdose prevention services" [11]. This organization seeks to open the first safe injection site in the U.S., which can provide a range of overdose prevention services (Overdose Prevention Sites (OPS)), including safe consumption and observation rooms staffed by a medical staff member prepared to administer overdose reversal if needed. There may also be some additional services such as onsite initiation of Medically Assisted Treatment, recovery counseling, education about substance use treatment, basic medical services, and referrals to support services such as housing, public benefits, and legal services.

The OPS is not a new measure to prevent overdose in this world. As early as 2003, the first overdose prevention facility in North America was opened in Vancouver, Canada. Since then it has managed thousands of drug overdoses without a single fatality on site [28]. In one study [20], they showed that the overdose prevention site led to a 30% reduction in the rate of drug overdose deaths in the neighborhood immediately around the facility. Even with that great improvement, the proposal of opening OPS was not smooth in Philadelphia since it collided with the federal drug laws. The opening of OPS was controversial. Safehouse experienced a two-year legal battle and was finally judged as legal to open an OPS. In 2020, Safehouse was scheduled to open an OPS in Philadelphia in March. However, the local opposition from neighbors living near the site impeded its opening [7]. The COVID-19 pandemic worsened the overdose situation and delayed the opening again. Hence, providing some compelling evidence to present to the community that OPS is beneficial for the whole society is an urgent need. In our work, we applied simulation modeling to investigate the effectiveness on overdose rate of placing an OPS in the city of Philadelphia. By the application of both a Markov Chain model and an agent-based model, we predict the number of users that will fatally and nonfatally overdose with or without an OPS in a year. Our goal is to investigate the direct and indirect effects that the OPS brings and also to provide further public health implication information.

### 2.2 Previous Works

Several papers talk about opioid epidemic modeling and also the evaluation of overdose intervention practice in Canada. In [22], the authors apply dynamic models to investigate the opioid epidemic deterministically and stochastically and concluded that stringent control over how opioids are administered and prescribed is a must to achieve an addiction-free equilibrium. In [12], the authors develop a stochastic compartment model to dive deeply into the asymptotic exit optimal control study of the opioid epidemic. There is also dynamic compartmental modeling on 11 policy responses to the opioid epidemic [3]. Additionally, in [24], the authors apply an age-stratified ordinary differential equation hepatitis C Virus transmission model of people who inject drugs aged 15-64 to study opioid use by young people. Also, in[19], the authors develop a Bayesian hierarchical latent Markov process model to estimate monthly overdose and overdose-death risks, along with the impact of interventions. Finally, in [4], the authors implement an agent-based model to investigate the potential effects of opioid-related policies and interventions at the local level. None of these works focused on the effects of placing an OPS.

Our first attempt at simulating the effect of placing an OPS followed [19] and [4], first building a Markov Model and then generalizing to a more realistic agent-based model. We used a Markov Model as a first model, thinking most of the relevant information was what state the user was in currently. As a final part of our project, we are in the process of developing an agent-based model to combine more personalized features of agents and to keep track of each user's behaviors and personal qualities, including their distance from the OPS, to make a better predictions of the effects of placing an OPS or multiple OPSs in the city.

# 3 MARKOV CHAIN APPROACH

## 3.1 Model Design

### 3.1.1 Model Overview

In this section, we will describe the Markov chain model we used to investigate the effect of Overdose Prevention Sites (OPS) in Philadelphia. We will use this model to make predictions about the number of fatal and nonfatal overdoses with and without the placement of an OPS.

In probability, a discrete-time Markov chain is a sequence of random variables, known as stochastic processes, in which the value of the next variable depends only on the value of the current variable. Thus, it does not rely on any variables in the past (memory-less) [25]. Here is the mathematical representation [9], where $X$ is a sequence of random variable and $x$ is the event : if $\Pr(X_1 = x_1, \ldots, X_n = x_n) > 0$

$$\Pr(X_{n+1} = x \mid X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n) = \Pr(X_{n+1} = x \mid X_n = x_n) \tag{1}$$

What this says is that the probability that someone moves to state $x$ given that they were in states $x_1$ through $x_n$ in the previous iterations, is their probability of moving to state $x$ only knowing that they were in state $x_n$ in the previous iteration. So all information about where someone transitions in the model comes from where they currently reside. We use this Markov property and particular transition probabilities gleaned from data and from assumptions to determine how each person in our model moves from state to state.

We designed and implemented a Markov Chain Model to simulate the transitions of those drug users within 6 states: 1) users not currently using drugs (user), 2) users currently using drugs outside the OPS (using), 3) using in the OPS, 4) nonfatal overdose, 5) fatal overdose, and 6) recovery. We assigned probability distributions to the Markov model based different states. The worst hit neighborhood in Philadelphia is called Kensington and Safehouse has suggested that the first OPS will be placed there. In collaboration with the University of Pennsylvania Injury Science Center and the Philadelphia Department of Public Health, we received first-hand data, collected by the Injury Science Center, containing demographics for those who overdosed in 2017-2018 and locations of where they overdosed. We approximated the distances from the OPS for all users based on this overdose data and considered the population of users in the model at 12 distances from the OPS placed in Kensington. Therefore we ended up with 72 total states, the 6 different states spelled out above for each of the 12 locations (see Figure 1). The OPS is shared by all users. The main idea here is that users will be less likely to use the OPS if they live farther away from it, so the placement of the OPS will determine who it serves and helpful it is.The Figure 1, created by Dr. Ami Radunskaya, shows the transition possibilites for the Markov Chain model.

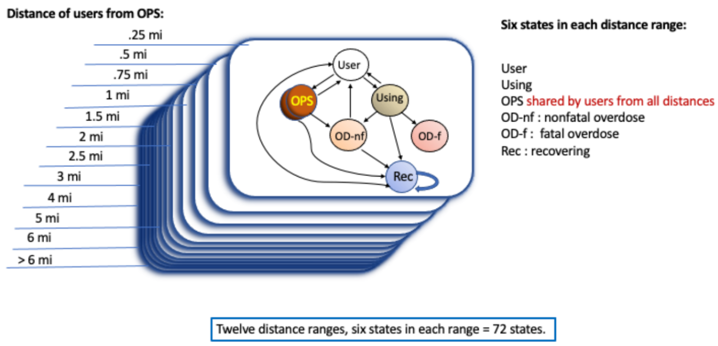


Figure 1: OPS Design

#### 3.1.2 Assumptions

In our model, users exist in one of the following 6 states at one of the 12 distances from the OPS:

1. Users in the user state are not currently using the drugs. They have three options: to use drug which means to go to the using state, to use drugs in the OPS which means to go to the OPS state, and do not use drug anymore which means go to the recovery state.

2. The using state means patients are currently using drugs outside of the OPS. From this state, a user can fatally or nonfatally overdose. If they do not overdose, they go back to State 1, or they may go to the Recovery state.

3. The OPS state means patients are using drugs in OPS. Users in this state may

nonfatally overdose, come back to the users state which means they are currently not using the drugs, or recover. It is important to notice that we assume there will be no fatal overdoses in the OPS. No fatal overdoses have been reported in OPSs.

4. In the recovery state, people are recovered which means they are in treatment and not currently using drugs. People in this state can either stay in this state or go back to being a user.

5. In the nonfatal overdose state, users also overdose but they do not die. We assume that all overdoses are nonfatal if they occur in the OPS. From this state, a user can either return to the user state, or go to the recovery state.

6. In the fatal overdose state, users remain in this state since they died. In the language of Markov Chains, this state is an absorbing state.

## 3.2 IMPORTANT PARAMETERS AND EQUATIONS

In this section, we discuss the important parameters and equations used when building the Markov models. Many of these same parameters are also used later when building the agent-based model. Many of these parameters are the transition probabilities between different states in the model.

### Active Users and Users in Recovery

We estimated that there were 55,000 current opioid users in Philadelphia [18]. Since we assumed that about 15% of users enter treatment [2], and that of those that go into recovery 50% go back to using each year, we also started with around 13,000 users in the recovery state. We used the equilibrium amount for a model that contained only the user and recovery states to decide on the number of users initially in recovery.

### Distribution of Users Based on Distance from OPS and Willingness to Visit OPS

In Philadelphia, there are many hotspots where opioid users cluster. Assuming that the OPS is placed in the Kensington neighborhood, and utilizing the overdose data provided by the city of Philadelphia, we approximated the percent of users in rings around the OPS. We also approximated the willingness of users at those distances to go to the OPS using Behrends, et.al, [5]. We first assumed that users closest to the OPS would have around a two-thirds likelihood of going to the OPS, assuming that they would likely go if they were very close but that still a significant portion of them would not. The willingness below is then multiplied by this amount, decreasing as distance from the OPS increases.

The data in Table 1 is the user percentage related to the distance from the OPS and also the willingness to visit the OPS in regards to the distance the user lives from the OPS

[5].

| Distance From OPS | User proportion | Willingness |
|---:|---:|---:|
| 0.25 | 0.025098527 | 1 |
| 0.5 | 0.075295582 | 0.84 |
| 0.75 | 0.091682224 | 0.716 |
| 1 | 0.113047086 | 0.585 |
| 1.5 | 0.071147065 | 0.463 |
| 2 | 0.055382701 | 0.298 |
| 2.5 | 0.055382701 | 0.185 |
| 3 | 0.043559428 | 0.095 |
| 4 | 0.111180253 | 0.0513 |
| 5 | 0.096245592 | 0.0227 |
| 6 | 0.134826799 | 0.0101 |
| $> 6$ | 0.127152 | 0.002667855 |

Table 1: User Distribution & Willingness

The data points of the willingness to visit OPS within 3 miles was taken from [5], while the willingness for distance data greater than 3 miles was estimated. To estimate the larger distance data, we created a function fit to the previous data assuming that the willingness to go to the OPS will decay exponentially with distance.

The function fitted to the first three miles of willingness data that we then used to approximate the greater distances is

$$P(d) = (1.3326 \times 0.443^{d})$$

where $d$ is the user's distance from the OPS, and $P$ is the willingness of visiting the OPS.

## Transitions

We first distribute all of the users, both active and recovered, into their distances from the OPS so that we have the correct proportion in each location. After this, we step through the simulation in time steps of one-half hour. Every half hour, we use the transition probabilities defined below to determine which state each of the users moves to in the next time step. For each parameter that we found in the literature as a yearly percentage, $x$, we converted this to a half-hourly rate, $P$, using the compound discount formula:

$$x = 1 - (1 - P)^{365 \cdot 48}$$

### Transition Probabilities

Below is a description of how users transition from state to state. A summary of the transition probabilities is given in Table 2. We assume users do not change housing in the year and stay in the same distance ring throughout the year.

- Users to Recovery: represents the annual probability of a user"recoverying" which means "not using drugs." We assume it to be 15% per year.

- Users to Non-fatal Overdose & Users to Fatal Overdose: represents the rate of users non-fatally overdosing and the rate of users fatally-overdosing. We used the data from Philadelphia Department of Public Health and calculated the proportion of fatally and non-fatally overdosing users from 2017-2018 and assuming 55,000 users, we ended up with rates of 0.0188 and 0.069 per year respectively.

- Users to OPS: represents the rate that users try to go to the OPS as described above.

- Users from OPS to Recovery & Users from Non-fatal Overdose to Recovery: means the annual probability of an individual "recoverying" after visiting the OPS or the annual probability of an individual non-fatally overdosing going to recovery. We assume that the value is the same as the general probability of each user recovering, which is 15%.

- User from OPS to Nonfatal Overdose: The probability of an individual non-fatally overdosing while at the OPS. Since we assume that all people who fatally overdose in the OPS will be revived, there will be no users dying in the OPS. At the same time, those who are saved from fatally overdosing will non-fatally overdose. Hence, the value of probability of users from the OPS to non-fatally overdose is the sum of the probability of users to non-fatal overdose and the probability of users to fatal overdose.

- Users from OPS to Fatal Overdose: The probability of a user fatally overdosing while at the OPS. Since there will be no users dying in the OPS, the probability of users from the OPS to fatal overdose is 0.

- Users from OPS to Using on the Street: This is determined by the number of times a users uses drugs per day, which we assumed was 4.
- Users from non-fatal overdose to OPS: The probability of a user overdosing but not dying, and then visiting the OPS. We assume it is the same as the probability of users to OPS [5].
- Users from non-fatal overdose to using outside the OPS : The probability of a user overdosing but not dying, and then using again outside of the OPS. Hence, the value is 1 minus the sum of probability of users from non-fatal overdose to recovery and the probability of users to OPS.

In the next part, I will talk about our setting related to the OPS program.

- Time Steps: We let the time steps in our experiment to be 48, which means each time step is a half hour.
- Total Time of the Simulation : It means the total time of the OPS program in our simulation which is a year: 365 days.
- Working Hours: It represents the working hours for the OPS which we set as 20 hours. The OPS closes for 4 hours a day and no one can enter then.

- Maximum Capacity: It represents the maximum capacity of an OPS. In our baseline model, we set it as 30. The maximum capacity is important since it determines how many users will be affected by the OPS program. If the OPS is full, then the users attempting to go to the OPS will come back to their original states.

### 3.3 Experiment Description

In this section, we present the results from our experiments using the Markov model. They can be divided into five separate parts: direct effects, location effects, indirect effects, increasing the recovery rate for all users, and varying the willingness to go to the OPS. For each experiment, we ran 3000 simulations for each choice of parameters and each time set new random seed to ensure that the simulations chose different random numbers. A random seed specifies the start point when a computer generates a random number sequence[27]. After picking a random seed, for each set of parameters, we run 3000 year-long simulations and the output we want to generate is the average from all of the simulations of the total number of fatal and nonfatal overdoses after one year.

The time step for simulation is one-half hour. The length of the whole program is a year so each simulation runs for a whole year with 55000 active users and 12896 recovering users. Each half-hour, we track each person in the simulation and use the transition probabilities to determine what their state will be in the next half-hour. The working hours of

| Name of Variables | Description | Estimated value |
| --- | --- | --- |
| Users to Recovery (u2r) | Annual probability of a user "recovering" (not using) | .15 |
| Users to Non-fatal Overdose (u2od_nf) | Annual probability of a user non-fatally overdosing | .069 |
| Users to Fatal Overdose (u2od_f) | Annual probability of a user taking a fatal overdose | .0188 |
| Users to OPS (u2ops) | Probability for the user to OPS | Average frequency_of_use * dt * $\frac{2}{3}$ *(1-(u2r+u2od_nf+u2od_f)) |
| Users from OPS to Recovery (P_OPS_Recover) | Annual probability of an individual "recovering" (not using) after visiting the OPS | .15 |
| User from OPS to Nonfatal Overdose (P_OPS_OD_nonfatal) | Probability of a user over-dosing but not dying while at the OPS (we assume that all users who overdose at the OPS are resuscitated) | u2od_nf+u2od_f |
| Users from OPS to Fatal Overdose (P_OPS_OD_fatal) | Probability of a user dying from an overdose while at the OPS | 0 |
| Users from OPS to Using on the Street (P_OPS_user) | Probability of an individual leaving the OPS and using outside the OPS | 1 - P_OPS_Recover - u2od_nf - u2od_f [5] |
| Users from Non-fatal Overdose to Recovery (P_OD_nonfatal_Recover) | Probability of a user over-dosing but not dying, and then ceasing to use drugs (recovering) | .15 |
| Users from non-fatal overdose to OPS (P_OD_nonfatal_OPS) | Probability of a user over-dosing but not dying, and then visiting the OPS | u2ops[5] |
| Users from non-fatal overdose to using outside the OPS (P_OD_nonfatal_user) | Probability of a user over-dosing but not dying, and then using again outside of the OPS | 1-P_OD_nonfatal_Recover-u2ops |
| Time Steps (TimeSteps_for_Markov Chain Model) | Time step for people entering OPS each day | 48 |
| Total Time of the Simulation (Tfinal) | Total time of the simulation | 365 |
| Number of Users (N) | Number of users | 55000 |
| Working Hours (workinghours) | The working hours for OPS | 20 |
| Maximum Capacity (MaxCapacity) | The maximum capacity for the OPS | 30 |

Table 2: Parameters

the OPS, suggested by Safehouse, was set at 20 hours a day which means, if the users try to enter the OPS in the other 4 hours, they will be rejected (since it is closed). For our baseline simulation, the maximum capacity also suggested by Safehouse was set at 30. We later vary this capacity to see how expanding services would affect our results. If users are using or in the OPS, they might overdose. If they are in the OPS, they can only overdose non-fatally as described above. At the end of the simulation, we determine how many nonfatal and fatal overdoses have occurred and also determine how far from the OPS these occurred. We also keep track of how many people are in recovery at the end of the year. Below we vary parameters to determine possible effects of the OPS.

#### 3.3.1 Parallel Computing

All simulations were created in R. Initially, we tried running this model on our local laptops. However, it took about 2 hours for the model to be simulated for only 30 days. We decided we needed to increase the execution efficiency of our simulations. After testing different virtual machines, we finally decided to use Quark, which is the supercomputer at the University of Richmond used mostly by the Physics Department. It has about 30 clusters each with 12 nodes available. Here we applied the "parallel" library in R to be able to run many simulations at once. In this way, the execution efficiency was largely increased. It now takes about 85 hours to run 3000 iterations with one set of parameters.

| | Number of fatal overdose | Number of nonfatal |
|---|---|---|
| Without OPS | 1045 | 3933 |
| With OPS | 1038 | 3939 |

Table 3: Baseline Results

#### 3.3.2 Experimental Results

Below we report the experimental results of baseline model, direct effect of the OPS, location effects of the OPS,indirect effects of the OPS, combination of both direct and indirect effects of the OPS, educational effects of the OPS and the effect from the willingness to go to the OPS.

## Baseline Model

Our first experiment consisted of running the two baseline models: the simulations run with and without OPS. As for the simulation with the OPS, we set the maximum capacity of OPS as 30. All other are given in Table 2.

Table 3 shows the baseline results after running 3600 simulations for the model with and without the OPS.

Here we can see that with the OPS at 30 capacity, the number of fatal overdose users would be reduced 7 per year, which means 7 people can be saved with the inclusion of an OPS. Additionally, there are 6 more nonfatal overdoses, which means those 7 people become nonfatal overdose users and the extra 1 is the minor difference during the simulation. The 7 revived people are saved from the fatal overdosing stage into the nonfatal overdosing stage. In the OPS, since we assume all people who overdose are revived, the probability of users going to the fatal overdose stage is added into the probability of users going to the nonfatal overdose stage in the OPS (see Table 2). Thus, all the users who are saved in the OPS from death are directly transferred to the nonfatal overdose stage.

## Direct Effect of OPS

Since the previous two experiments have a limited effect on the number of reductions in both the number of nonfatal and fatal overdoses, we next varied the maximum capacity of the OPS to see what expanded services would do to overdose rates. To really have an impact, the OPS would need to be able to serve more than 30 users at a time since there are so many active users in Philadelphia.

Thus, we investigated the effects of the maximum capacity changes, which means the OPS can serve more users, on the number of users who fatally overdose and nonfatally overdose. Hence, we designed the experiment to make the maximum capacity increase from

30 to 240 by adding 30 each time. From the result, we can see that by increasing 30 slots in the OPS each time, the number of users who fatally overdose will be reduced by 5 or 6. At the same time, the number of users nonfatally overdosing will also increase in the range of 5 to 7, which corresponds to the reduction of fatally overdosing users. The reduction in fatal overdose and the increase in nonfatal overdose are almost the same. This is because we assume that all users who go to the OPS will be revived. Additionally, the nonfatal overdose rate in the OPS is equal to the original fatal overdose rate plus the original nonfatal overdose rate to represent that all saved users will nonfatally overdose. This experiment confirms that the maximum capacity of OPS is one key factor to reduce fatal overdoses.

### Location Effect of OPS

Besides the effects of the OPS's maximum capacity, we also investigated the location effects of the OPS which means the effect of the distance from OPS to each group of users. The Figure 2 and the Figure 3 are the results.

From the chart about population distribution, it can be seen that the population within 1.5 miles from the OPS only accounts for 38% of the overall population in Philadelphia. However, 86.2% of the people revived from the OPS live within 1.5 miles from the OPS. Thus, for the OPS with 300 capacity, it is mainly effective for the users living within

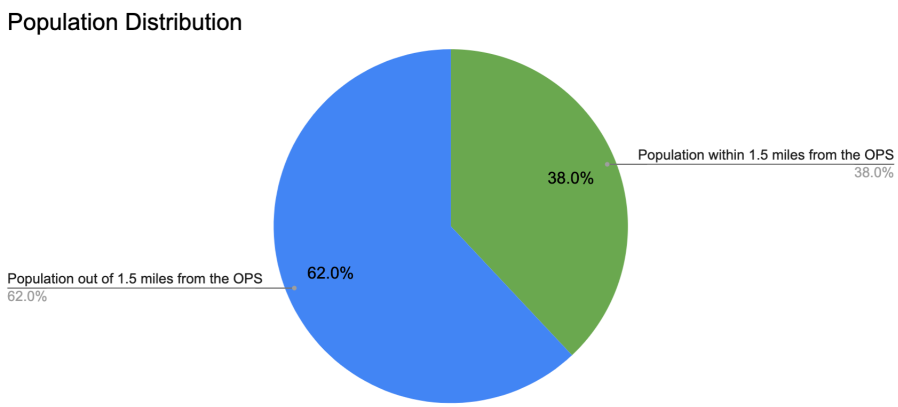


Figure 2: Population Distribution

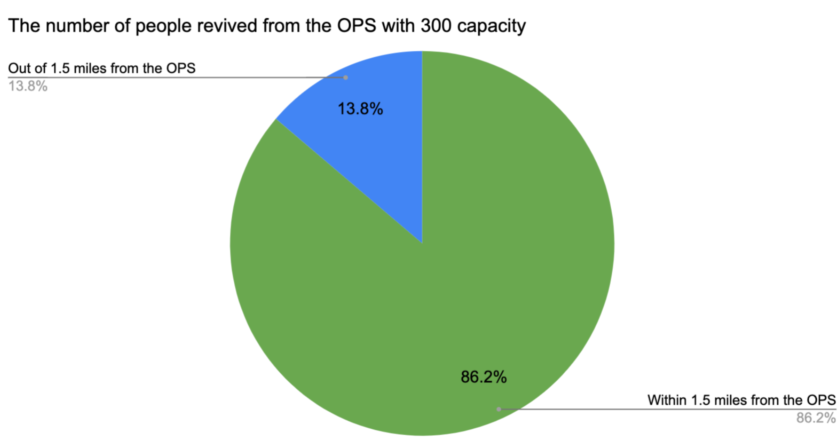


Figure 3: Revived Users Distribution

a 1.5 miles radius. It also implies that there should be more than one OPS opened in Kensington county to guarantee that all the population can reach one of the OPSs in 1.5miles. Demographic differences in Philadelphia suggest that other OPSs will be needed in other parts of the city also. We will investigate this in future work.

### Indirect Effect of OPS

In the OPS, there are more services provided than helping the users revive from overdose. There are some indirect ways that overdoses might be reduced in number. For example, the OPS can provide a place for safer injection, provide safety instructions and clean injection instruments, such as clean needles and also test drugs from more deadly unwanted additions such as fentanyl, all of which can potentially decrease the nonfatal overdose rates of users in the OPS.

Hence, in this simulation, we investigate the effect of the OPS on reducing the nonfatal overdose rate. It is important to notice that users will never become fatally overdosed in the OPS because we assume that in the OPS all users will be saved from death. Hence, in all of our simulations, the baseline overdose rate for the OPS is the nonfatal overdose rate plus the fatal overdose rate.

In the current experiments, we assume that the OPS provides other services that could lower the nonfatal overdose rate in the OPS. We varied the nonfatal overdose rate in the OPS by multiplying it in increments of 0.1 from 0.9 to 0.1, with a reduction of 0.1 each time. The lower the scaling factor, the better effect of the OPS on reducing nonfatal overdose. We did the simulation by modifying on the baseline model whose OPS has 30 maximum capacity. The model predicts that the OPS would save 2 or 3 users from overdosing while reducing the scaling factor by 0.1. While changing the overall overdose rate in the OPS, the number of users fatally overdosing remains the same. The result is valid since we already assume that all users in the OPS will be prevented from death. Additionally, the OPS only has 30 spots which will always be full to serve current users who tend to go to the OPS compared with about 550000 users in general. The capacity of the OPS is too small to make a change. We also experimented with 0.1 as the scaling factor and increased the maximum capacity by 30 from 30 to 300. The model predicts that the number of people nonfatally overdosing will decrease in the range of 17 to 21.

Based on these two experiments, we are interested to see more generally the effect of the combination of these two factors.

### Combination of Direct and Indirect Effect of OPS

From the experiments with direct effects and indirect effects, we found that increasing

| | 30 | 60 | 90 | 120 | 150 | 180 | 210 | 240 | 270 | 300 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.1 | 3914 | 3896 | 3876 | 3858 | 3839 | 3818 | 3800 | 3782 | 3760 | 3743 |
| 0.2 | 3917 | 3901 | 3885 | 3869 | 3853 | 3835 | 3820 | 3804 | 3786 | 3771 |
| 0.3 | 3919 | 3907 | 3894 | 3880 | 3867 | 3852 | 3840 | 3826 | 3811 | 3799 |
| 0.4 | 3922 | 3912 | 3902 | 3891 | 3881 | 3868 | 3859 | 3848 | 3836 | 3827 |
| 0.5 | 3925 | 3918 | 3910 | 3902 | 3895 | 3885 | 3878 | 3870 | 3861 | 3854 |
| 0.6 | 3928 | 3923 | 3919 | 3913 | 3909 | 3902 | 3901 | 3893 | 3886 | 3882 |
| 0.7 | 3931 | 3929 | 3927 | 3924 | 3923 | 3919 | 3919 | 3915 | 3911 | 3910 |
| 0.8 | 3934 | 3934 | 3935 | 3935 | 3937 | 3935 | 3938 | 3937 | 3936 | 3938 |
| 0.9 | 3936 | 3940 | 3944 | 3946 | 3950 | 3952 | 3957 | 3959 | 3961 | 3966 |
| 1 | 3939 | 3945 | 3952 | 3957 | 3964 | 3969 | 3976 | 3982 | 3986 | 3993 |

Figure 4: Results of Combination of Indirect and Direct Effects

maximum capacity leads to increase the number of nonfatally overdosed users because less people fatally overdose when the maximum capacity is increased. We also saw that decreasing OPS scaling factor, or increasing the effect of the OPS on reducing nonfatal overdoses, leads to an decrease in nonfatally overdosing users. Hence, these two factors have opposite effects. We next investigated the effect of the combination of these two factors and determined the balancing point of these two effects.

Figure 4 shows the experimental result. It can be seen that when the scaling factor reaches 0.8 which means when the OPS can help to reduce the nonfatal overdose rate by 20% in the OPS, these two effects come to the balance point for total nonfatal overdoses. Hence, it means that when the OPS reduces more than 20% of overdose rate for the users in the OPS, the increase in nonfatal overdoses due to those who would have fatally overdosed but were revived would balance with the decrease overall of overdoses in the OPS. Also, as the overdose rate decreases even more, the number of nonfatal overdoses will be reduced from baseline, even with an increased maximum capacity.

## Educational Effect of OPS

Besides these two factors, other services of the OPS should also be considered – the educational programs. There will be education provided to users about entering recovery. The OPS can provide a safe place for the users to seek treatment and also safe drug use instructions. To see the broader effects on the community, we varied the overall effect of having an OPS on the entire population by changing the annual recovery rate for every user from values of 0.05 to 0.5, with increments of 0.5. We expect that the OPS will help people overall not just when they are in the OPS and this is one way to test these effects. Table 4 presents the results.

From Table 4, it can be seen that by only increasing the recovery rate from 15% to 20%, the number of fatal overdosing users can be lowered by 17 and the number of nonfatal overdosing can be lowered by 90. Also, when the user to recovery increases to 0.25, there will be about 24 less fatal overdoses. The educational program can lead to less people using drugs in general. Thus, the implication here is that the educational program should be enhanced so that users can be well-educated on how to use drugs safely so that users are helped with recovery.

| U2r (rate enter recovery) | fatal | nonfatal | recovery |
|---|---|---|---|
| 0.05 | 1084 | 4111 | 8581 |
| 0.1 | 1061 | 4025 | 10731 |
| 0.15 (baseline) | 1038 | 3939 | 12899 |
| 0.2 | 1015 | 3849 | 15088 |
| 0.25 | 990 | 3758 | 17295 |
| 0.3 | 965 | 3663 | 19524 |
| 0.35 | 940 | 3567 | 21779 |
| 0.4 | 912 | 3466 | 24062 |
| 0.45 | 884 | 3359 | 26378 |
| 0.5 | 856 | 3251 | 28734 |

Table 4: Results of Education Effect of the OPS

### Varying the Willingness to go to the OPS

Besides the objective factors above, we also tested the "subjective" or "more human" side of the model – the willingness for people to enter the OPS. We first made the assumption that 2/3 of the closest people would choose to go to the OPS to use drugs and others' willingness would scale by distance. Then we tested with 40 percent and 20 percent and the result did not change. The reason is that even if the willingness decreases, the people trying to enter the OPS is far more than the maximum capacity – 30 each time step. Thus, there is no change in the number of overdoses. We expect this result would change if the availability of the OPS increased significantly.

# 4 EXPERIMENT ON PROGRAMMING LANGUAGES FOR AGENT-BASED MODEL

## 4.1 Overview

Using the Markov Chain model, our simulation can only replicate a situation where transitions are only based on the current state and there is no memory in the simulation or heterogeneous features of the users. Whereas Markov models lump users together into homogeneous groups, agent-based models can be used to simulate particular agents and hold information about each user, including information about their past or personal characteristics.

Thus, we next decided to adopt an agent-based modeling approach to investigate the opioid problem and to see how placing an OPS could help reduce overdoses.

In [10], it mentions the following: "An agent-based model (ABM) is a computational model which is modeled as a collection of autonomous decision-making entities called agents. Each agent individually evaluates its situation and makes decisions based on a set of programmed rules. Agents may execute various behaviors suitable for the system they represent. At the simplest level, an agent-based model consists of a system of agents with heterogeneous traits and the relationships between them related to different events. A simple agent-based model can exhibit complex behavior patterns and provide valuable information about the dynamics of the real-world system that it emulates. Also, agents may be capable of evolving, allowing unanticipated behaviors to emerge. A sophisticated ABM sometimes incorporates neural networks, evolutionary algorithms, or other learning techniques to allow realistic learning and adaptation."

Next, we built an event-oriented agent-based model to simulate user's behaviors. We define a finite set of events corresponding to the users in the agent-based model. During the execution, the agent-based model will have an event list which maintains the execution times chronologically and goes to the next event. After initializing the event list, the model will execute in the following sequence of steps: (1) the next event in simulated time is found in the event list; (2) the simulation clock is set to the time of that event; (3) an algorithm related to the specific type of the event is executed; and (4) the event list is updated including the future event generated by the current event[13].

Our first attempt involved building a baseline agent-based model in NetLogo. However, the computational efficiency seemed quite low. To make the computation as efficient as possible for the agent-based model, we decided to test three programming languages: NetLogo, Java with Mason, and Python to find the quickest programming language and platform. To test the speed of the software, we applied a test program – epiDEM basic, a simple model simulating the spread of an infectious disease in a closed population [6]. We chose this model as the toy model to do the experiment because it shows every necessary element an agent-based model needs and it is easily implemented.

NetLogo is a multi-agent programmable modeling environment, implemented in Java [29]. Mason is a Java-based agent-based model environment that is extremely fast and has been optimized for execution time [26]. In python, we used the Mesa library, which is a modular framework for building, analyzing, and visualizing agent-based models [21].

### 4.2 Flow Chart for the Experiment Model

Figure 5 is the flow chart of our baseline model. This model comes from a classical

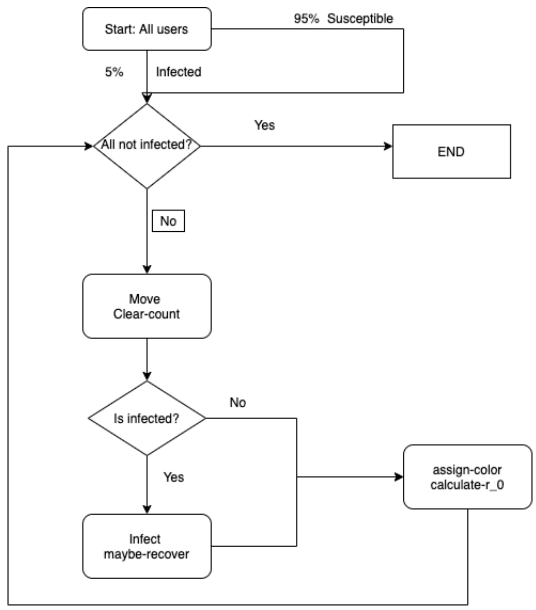


Figure 5: Flow Chart of epiDEM

susceptible-infective-recovered (SIR) model [17] in epidemiology. Initially, the simulation start will 95% of the population susceptible and 5% infected. In each iteration, the simulation first checks whether all users are infected. If so, the simulation finishes. If not all users are infected, then the users will move randomly. For each user, if they are infected, they may infect other users and also check whether they recover or not. If the user is not infected, then they directly go to the final step of the current iteration, which is to update the current status and assign color based on the current state.

The NetLogo code was taken from sample code on the NetLogo website. Then we implemented the same program with the same logic but different programming languages:

Python and Java. We made sure that every parameter is the same as for the original. Then, for each program, we increased the population size, from 100 to 2000, and ran the program recording the execution time. We ran each program 10 times with the specific population and then took the average execution time. Our goal was to determine the execution efficiency and find the fasted language. Once determined, we would use that language to build the agent-based model related to the OPS. Figure 8 in the appendix is the sample code of the main method of the Java program. Figure 9 in the appendix shows the piece of code from the Python with Mesa. Figure 10 in the appendix shows the piece of Netlogo code with the go procedure, which is the main method in the Netlogo.

### 4.3 Results

The results in Figure 6 were surprising: Java with the Mason library stands out over the other two programming languages. From the Figure 6, it is clear that Python has the longest execution time and Java works best. For example, when the population is 2000, it takes Python 76.55 seconds to execute. However, Netlogo takes 0.86 seconds, better than Python, but still worse than Java with Mason which takes 0.53 seconds. Thus, we decided to use Java to implement our agent-based model. It makes sense that Java works much faster than Python. The reason is that Java is a compiled language. In [15], it mentions the following: " Its efficiency depends on its Just-In-Time compiler. The Just-In-Time compiler is a component of the runtime environment that compiles bytecodes to native machine code at runtime to improve the performance of Java applications."

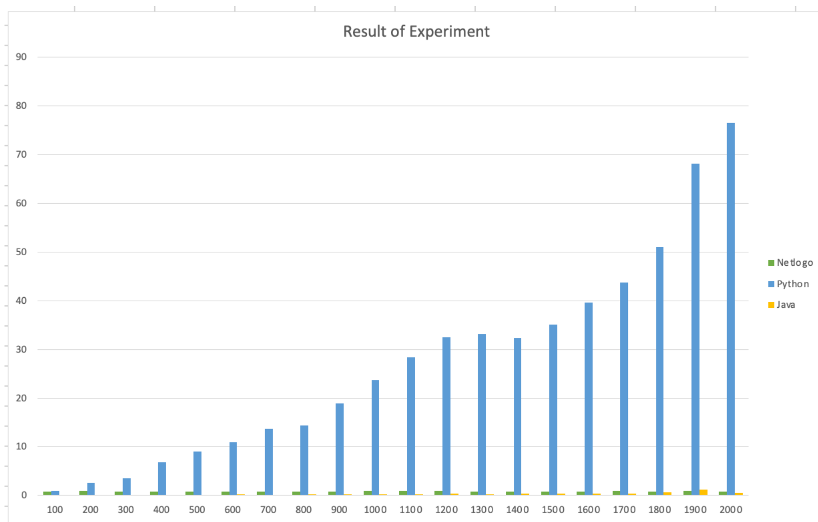


Figure 6: Bar Chart of the result

As for Python, the main reason that why Python is slow is because of its dynamic typing. Python is dynamically typed rather than statically typed. This means that at the time the program executes, the interpreter does not know the type of the variables that are defined which makes the program slower[14].

# 5 AGENT-BASED MODELING APPROACH

In this section, we will introduce the agent-based model approach used for testing the effects of the OPS. Currently, we have finished the prototype of the model. Future work will focus on more comprehensive in-depth execution of the model to explore the solutions related to placement of OPS.

In our research, the agent-based model can:

- keep track of heterogeneous traits of users, which can help us determine who the OPS will help
- keep track of past events of importance, like last time to the OPS
- consider the effects various OPS placements around the area of Philadelphia utilizing the users distances to the various OPSs

Instead of only “remembering” the previous state, the agent-based model can keep track of various attributes of users. Additionally, the transitions of the behaviors of each user do not need to happen on a timestep. Instead, their “next event time” is drawn from a distribution of times, and simulation time acts more continuously.

## 5.1 Model Design

Our simulation is an “event-oriented” agent-based model to simulate users’ behaviors. In the simulation:

1. The next event in simulated time is found in the event list, which is the first item of the sorted list.

2. The simulation clock is set to the time of that event [13].

3. An algorithm related to different states: drug-using, recovering, relapsing, and leaving the OPS is executed.

4. The sorted event list is updated with the new event generated by the current event with binary insertion. The binary insertion sort applies the binary search to find the right position to insert an element into a sorted list [16].

#### 5.1.1 Flowchart

The flow chart in Figure 7 shows the basic flow of the simulation. For all users, the simulation will first initialize their current status. The majority will be active users and the rest are those who are in the recovery stage. After initializing the next recovery time and next use time for every active user, the model will put the earliest event of each agent in the event list. After the initialization, the model sorts the event list in order of time and then starts to go through the events in order.

For the agent who acts first, if the event is to use drugs, then the model will decide whether the agent wants to go to the OPS, based on their distance and willingness, whether the OPS is open, and whether the OPS has a spot for them. If so, then the agent will use drugs in the OPS and the model will check whether the agent is overdosing or not. If they are overdosing, then they will go to the nonfatal overdose stage and the nonfatal overdose counter will increase by one. Then the agent will have a leave OPS time chosen and if this is before their next recovery time, this will be set as their next event. Then this updated event will be inserted into the event list.

As for those users who use drugs on the street or at home, the model will check whether they nonfatally overdose or not. If not, the model will check whether they fatally overdose. If so then the agent will directly die and the event list will never consider this agent anymore. Otherwise, a new next event time will be generated for that agent. By comparing with the recovery time, the model picks the earliest time as the agent's next event time. Then the updated event of this agent will be inserted into the event list. Below, we list the conditions that decide the next event time:

- If the agent does not use drugs but instead goes to recovery, the only possible next event is to relapse. The model will generate the next relapsing time and insert this event into the event list.
- If the agent relapses at the current state, it will generate a new recovery time and then generate the next use time. The model then picks the earliest event to be the next event and inserts it into the event list.

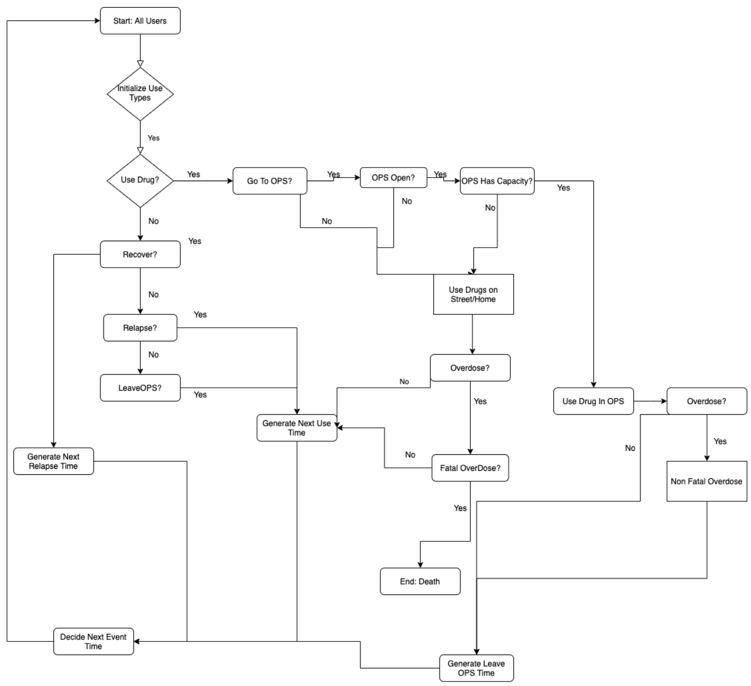


Figure 7: Flow chart of the agent-based model about the OPS

- If the agent currently leaves the OPS, then it will generate the next drug use time. The model then picks the earliest event to be the next event and inserts it into the current event list.

These are the transition scenarios of all of the users. At the end of each iteration, the model will pick the current earliest next event for all of the users to continue the simulation.

To date, we have completed a first draft of the code for the agent-based model in Java. Future work will be to simulate results using the parameters above and to include more heterogeneous parameters into the model so that we can answer more questions than we were able to with the Markov model.

# 6 CONCLUSIONS

In this work, we presented two approaches to demonstrate the effectiveness of placing an OPS in the Kensington neighborhood of Philadelphia. Specifically, we determined how the OPS can reduce the number of fatal and nonfatal overdoses. With sufficient experiments, our model suggests that an OPS with the capacity of 30, without regard to other indirect effects, can save 7 people from fatally overdosing in a year.

As for the direct effect of the OPS, each time we increase the capacity of the the OPS by 30 slots, the number of users who fatally overdose will be reduced by around 6. Hence, the maximum capacity of the OPS is a key factor to revive users from fatally overdosing. The larger the OPS, the more people will be saved. This is only limited by the number of users and overdoses that occur each year. Having multiple OPSs could have the same effect.

As for the location effect of the OPS, the experiments show that the population within 1.5 miles from the OPS only accounts for 38% of the overall population in Philadelphia while 86.2% of the people revived from the OPS live within 1.5 miles from the OPS. To reach different segments of the user population more than one OPS should be opened in Philadelphia to guarantee that all segments of the population are helped.

As for the indirect effects, our experiments showed that those indirect solutions to regulate the whole process of using drugs, such as providing a safer environment and fentanyl testing, will lead to a greater reduction in nonfatal overdose.

Nonfatal overdoses, whose total numbers increase when people are revived in the OPS, can be reduced overall as long as the OPS program guarantees the indirect solutions can provide a 20% reduction in the overall overdose rate. Results also suggest that the education programs of the OPS can effectively increase the effectiveness of the OPS. By enhancing the educational program to the users in the area so that the recovery rate increases from 15% to 20% in the whole population, other lives will be saved.

Our modeling techniques can be applied to other cities if they replace the Philadelphia data with their own. As far as agent-based modeling platforms, Java was much more efficient than NetLogo and Python. We were able to design and build an agent-based model for our system in Java. Future work will consist of utilizing our Java built agent-based model to make better predictions about the effects of placing an OPS in Philadelphia.

# 7 APPENDIX

```java
    public static void main(String[] args)
    {
        long startTime = System.nanoTime();
        doLoop(Epidemics.class, args);
        long endTime = System.nanoTime();
        long timeElapsed = endTime - startTime;

        System.out.println("Execution time in milliseconds : " +
                            timeElapsed / 1000000);

    }
}
```

Figure 8: Java Code for Testing

```python
def main():
    model = Epidemic_Model(initial_people, 1000, 1000)
    done = False
    while not done:
        done = model.step()

    #let's inspect the results:
    out = model.datacollector.get_agent_vars_dataframe().groupby('Step').sum()
    print(out)

import time
start_time = time.time()
main()
print("--- %s seconds ---" % (time.time() - start_time))
```

Figure 9: Python Code for Testing

| N | Netlogo | Python | Java |
|---|---|---|---|
| 100 | 0.83 | 0.9 | 0.041 |
| 200 | 0.88 | 2.63 | 0.066 |
| 300 | 0.83 | 3.51 | 0.101 |
| 400 | 0.84 | 6.84 | 0.121 |
| 500 | 0.84 | 8.97 | 0.151 |
| 600 | 0.82 | 10.91 | 0.202 |
| 700 | 0.85 | 13.69 | 0.164 |
| 800 | 0.74 | 14.37 | 0.262 |
| 900 | 0.87 | 18.86 | 0.246 |
| 1000 | 0.88 | 23.66 | 0.227 |
| 1100 | 0.89 | 28.35 | 0.285 |
| 1200 | 0.89 | 32.52 | 0.34 |
| 1300 | 0.87 | 33.17 | 0.308 |
| 1400 | 0.85 | 32.39 | 0.439 |
| 1500 | 0.84 | 35.13 | 0.443 |
| 1600 | 0.86 | 39.69 | 0.453 |
| 1700 | 0.89 | 43.77 | 0.356 |
| 1800 | 1.12 | 51.01 | 0.687 |
| 1900 | 1.24 | 68.21 | 1.214 |
| 2000 | 1.23 | 76.55 | 0.533 |

Table 5: Results from the programming languages testing

```
to go
  if all? turtles [ not infected? ]
    [ stop ]

  ask turtles
    [ move]

  ask turtles with [ infected? ]
    [ infect
      maybe-recover ]

  tick
end
```

Figure 10: Netlogo Code for Testing

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