Using Novel, Agent-Based Periodic Mobility Model with Super Spreaders to Analyze Vaccination Strategies for COVID-19

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September 24, 2021

Abstract

Background With the innovation of vaccines to fight against the COVID-19 pandemic, following an effective vaccination strategy is crucial in mitigating deaths and hospitalizations and offering the greatest protection to a community or locality within the early months of vaccine-availability, when resources may be scarce. By using a novel agent-based periodic mobility model that captures periodic movement, which attempts to model human movement patterns, super spreaders, and ICU hospitalizations, this study attempts to find the best strategy for vaccinating individuals to mitigate the damage of COVID-19.

Results This study found that a vaccination strategy that first vaccinates the elderly would be most effective at mitigating deaths and lowering the ICU hospitalization peak during the first two months of vaccine rollout.

Conclusion For communities that are early in their vaccine campaign or that have limited resources for vaccination, we recommend that they prioritize vaccinating the elderly who are more susceptible to COVID-19 first.

1 Background

On December 31, 2019, the Wuhan Municipal Health Commission of China reported a batch of pneumonia cases in the city of Wuhan in the Hubei Province of China. Eventually, the virus was declared to be a new coronavirus, named SARS-Cov-2, with the disease it causes being called COVID-19. The virus spread out of China and the World Health Organization (WHO), declared it a pandemic on March 11, 2020. Countries such as Italy initially struggled to contain the disease, with hospitals being overrun with patients and having a shortage supplies like ventilators and beds. This led to the tragic scenario where hospitals had to pick patients who were treatable and remove older patients who had slimmer chances of surviving.

But the, on December 11, 2020, the United States Foods and Drugs Administration (FDA) granted Emergency Use Authorization (EUA) to the BNT162b2 Pfizer-BioNTech mRNA COVID-19 vaccine, after which vaccines from Moderna and Johnson & Johnson were approved. However, with this new vaccine, there were questions about what the best strategy was to distribute the vaccine.

Using a novel periodic mobility model that captures aspects such as hospitalizations and super spreaders, this paper investigates the best strategy for distributing vaccines in small localities or communities.

2 Methods

2.1 Periodic Mobility Model

In this study, we employed a novel discrete-time stochastic periodic mobility agent-based model. This model makes individual move along circles with different radii. The reason the individuals move along the circle is to emulate the routines that exist within individuals' lives [1]. The different movement radii are meant to capture how far people travel in their daily routines, such as length of commute to work and similar factors. For example, someone with a larger movement radius may find themselves traveling a greater distance to work compared to someone with a smaller movement radius. The movement radius of each individual generated in the simulation had a movement radius randomly picked from a normal distribution with mean of μ_R and standard deviation of σ_R.

The movement of each agent is performed at the end of each time step. The new angle, $\Delta\theta$, which an individual agent moves along his movement circle is generated from a uniform distribution $U(0, 2\pi)$. This is then added to their current angle, θ_{t-1}, and then used in the following equation:

$$\langle x(t), y(t)\rangle = \langle h, k\rangle + R\langle\cos(\theta + \Delta\theta), \sin(\theta + \Delta\theta)\rangle, \tag{1}$$

where the center of the movement circle (h, k) is determined at the beginning of the simulation.

In this model, in order to calculate whether an infectious agent successfully infects a susceptible individual, we calculate the probability, $w(r)$, using the following function [2]:

$$w(r) = \begin{cases} w_0(1.0 - \frac{r}{r_0})^2, & 0 \le r \le r_0 \\ 0, & r > r_0. \end{cases}$$

In this model, r is the distance between the infectious individual and susceptible individual, w_0 is a constant that is between 0 and 1, inclusive, and represents the probability of an infectious individual infecting the susceptible individual if $r = 0$, and r_0 is deemed to be the "spreading radius" of the infectious individual. For each agent, this radius is randomly generated from a normal distribution with mean μ_{r_0} and standard deviation σ_{r_0}. Additionally, this radius reflects the inherent ability of each individual to propagate the COVID-19 infection. The spreading radius and the movement radius together help reflect the presence of super spreaders, agents who have an unusually high number of transmissions [2]. Those with higher spreading radii and movement radii would reflect the super spreaders that propagate the infection more-so than the average agent.

In this model, we also restrict each agent's (x, y) position to an $G \times G$ square with vertices $(0, 0)$, $(G, 0)$, (G, G), and $(0, G)$ at every time step.

2.2 ICU Compartmental Model

At the beginning of the COVID-19 pandemic, hospital capacity was a huge concern for many countries. Public officials feared that the hospital system would not have sufficient resources to handle the number of infected individuals who required Intensive Care Units (ICU). Therefore, in addition to modeling simply infected individuals, modeling the number of individuals who require an ICU is crucial to help countries make informed public policy.

When constructing the compartments for this new model, there are many factors to consider. This model should be an open model because we assume that the death rate is far higher than the birth rate. Additionally, studies have shown that COVID-19 has a period where the virus incubates within them but doesn't spread, which can be considered an exposed E compartment. There is also evidence suggesting that the immunity one receives after recovering from COVID-19, represented by variable R, is temporary, after which an individual returns to being susceptible for reinfection, represented by variable S [3].

Additionally, because the number of patients in the (ICU) is being modeled, we must also include a lag compartment, defined by variable L, which includes people that are infectious and are destined to go to the ICU. This is because the number of patients in the ICU lags behind the number of positive cases; without the lag compartment, the number of people in the ICU would not lag behind the number of active cases [4]. From these considerations, the following transition matrix was formed:

$$P = \begin{array}{c} \\ S \\ E \\ I \\ L \\ ICU \\ R \\ D \\ V \end{array} \begin{array}{c} \begin{array}{ccccccccc} S & E & I & L & ICU & R & D & V \end{array} \\ \begin{pmatrix} 1-\delta-(1-\delta)\eta & \delta & 0 & 0 & 0 & 0 & 0 & (1-\delta)\eta \\ 0 & 1-\rho & \rho(1-\phi) & \rho\phi & 0 & 0 & 0 & 0 \\ 0 & 0 & 1-(1-\mu)\gamma-\mu & 0 & 0 & (1-\mu)\gamma & \mu & 0 \\ 0 & 0 & 0 & 1-\chi & \chi & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1-(1-\omega)\psi-\omega & (1-\omega)\psi & \omega & 0 \\ \kappa & 0 & 0 & 0 & 0 & 1-\kappa & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \end{array} \tag{2}$$

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In this transition matrix, the row represents the starting compartment, and the columns represent the compartment transferring to. For example, $P_{S,E}$ reflects the probability of leaving the S compartment to go to the E compartment. Special variables worth explicitly defining are δ, ρ, and ϕ. In this model, $\delta = w(r)$. ρ is the probability that someone leaves the E compartment and ϕ is the probability that an agent moves from the E compartment to the L compartment, given that the agent is leaving the E compartment. Another important note is that we consider those in the E and ICU compartments to not be infectious enough to spread disease, while those in the I and L compartments are infectious. ϕ is a function of age, which will be defined in a later section.

2.3 Age-Dependent Hospitalization

Frederick K. Ho et al. found that age was a primary risk factor of mortality from COVID-19 [5]. During this pandemic, there have been many reports that those who are older are more susceptible to hospitalization and death if they were to contract COVID-19. Therefore, rather than having a fixed probability of going to the L compartment from the E compartment, we experimented with having it be based on the age of each individual person. During this pandemic, there have been many reports that those who are older are more susceptible to hospitalization and death if they were to contract COVID-19.

2.3.1 Sigmoid Function

According to Ho et al. [5], an exponential association was found between age and COVID-19 mortality. However, in order to ensure that $0 < \phi < w_0$, a sigmoid function was used instead. This is because the sigmoid function $S(x)$ still allows for a period of exponential growth, but afterwards $\frac{dS}{dx}$ approaches 0.

In order to transform this function to be applied to our model, the $\phi = S(x)$, where x is the age of a person, is defined as follows:

$$S(x) = \frac{1}{1 + e^{-(x-65)}}. \tag{3}$$

The traditional sigmoid function was translated 65 units to the right because it is suggested that after 65, the risk of hospitalization and death quickly increases to be far more than if one is under 65 [6].

2.4 Different Vaccination Strategies

In order to minimize the number of hospitalizations and deaths, vaccine distribution plays a crucial role in protecting people from the disease of infections, such as COVID-19. In order to gain some insight into which strategy would be best, we ran 1000 Monte-Carlo simulations in order to assess which strategy would minimize hospitalizations and deaths.

2.4.1 Random Distribution

In the random vaccine distribution strategy, each individual in the simulation has an equal probability, $\eta = 0.03$, of receiving a vaccine. There is no consideration for other parameters. This strategy is a form of a control strategy that the following strategies were compared to.

2.4.2 Age-Based Distribution

In the age-based vaccine distribution strategy, each person has a probability defined by $V(x)$, where x is the individual's age. In the simulation,

$$\eta = V(x) = \frac{.1875}{1 + e^{-(x-\mu-\sigma)}}, \tag{4}$$

where x is the age of the individual, $\mu = 45$ is the mean age of the normal distribution of ages, and $\sigma = 20$ is the standard deviation of the normal distribution of ages. This distribution was picked in order to make those above 65 years old roughly 15% of the population, as described in the 2019 US Census Data [7].It is important to note that the following vaccination strategies will have similar $V(x)$ functions, with the numerator, defined as p_0, varying slightly between strategies. More information for how the numerator of the $V(x)$ was determined can be found in the Appendix.

2.4.3 Movement Radius Dependent Distribution

In the movement radius distribution strategy, $V(x)$ was defined as follows:

$$\eta = V(x) = \frac{.15646}{1 + e^{-(x-\mu-\sigma)}}, \tag{5}$$

where x is the individual's movement radius, $\mu = 12$ represents the mean of the normal distribution of movement radii and $\sigma = 3$ represents the standard deviation of the normal distribution of movement radii.

2.4.4 Spreading Radius Dependent Distribution

In the movement radius distribution strategy, the $V(x)$ was defined as follows:

$$\eta = V(x) = \frac{.0718}{1 + e^{-(x-\mu-\sigma)}}, \tag{6}$$

where x is the individual's spreading radius, $\mu = 3$ represents the mean of the normal distribution of spreading radii, and $\sigma = 0.5$ represents the standard deviation of the normal distribution of spreading radii.

2.5 Experiment Details

For each vaccination strategy, as well as a scenario with no vaccinations, 1000 runs of 61 day simulations were conducted for which a 90% confidence interval was constructed for each day for each compartment. The parameters that were used in the experiment were as follows:

S_0	999
E_0	0
I_0	1
R_0	0
μ_R	12
σ_R	3
μ_{r_0}	3
σ_{r_0}	0.5
ρ	.3
γ	.35
ψ	.3
ω	.2
χ	.15
κ	.2
μ	.001
η	0.03
μ_{Ages}	45
σ_{Ages}	20
G	100

Additionally, a left-sided two sample Welch's t-test was conducted to test for a statistically significant difference in prevention of deaths and ICU hospitalizations between vaccination strategies, with $\alpha = 10\%$.

3 Results

Plots for the progression of mean deaths (1) and ICU hospitalizations (2), respectively, are below. The thick line is the mean total deaths/active ICU hospitalizations each day across the 1000 simulation runs, while the gray lower and upper boundaries in 1 and blue shaded region in 2 reflect the 90% confidence bands for each point.

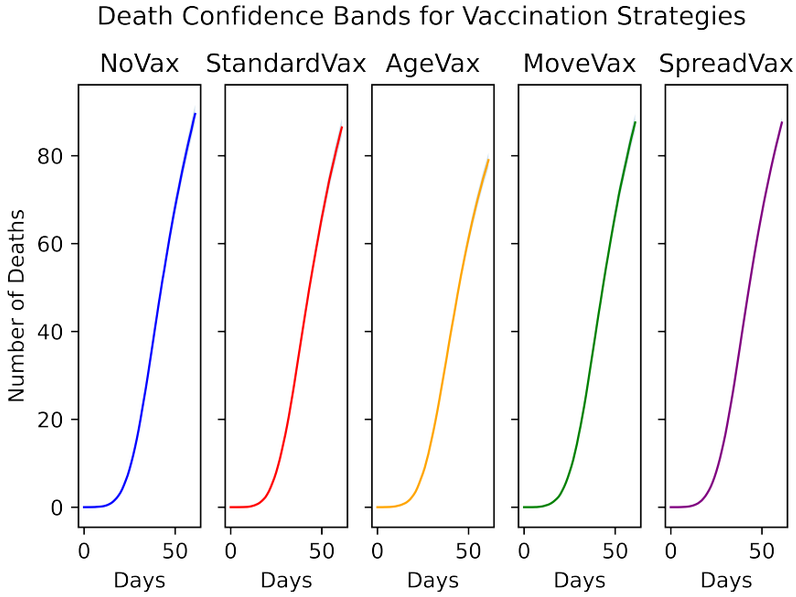

Figure 1: The mean total people in death compartment each day across 1000 runs in solid color, 90% confidence bands in gray.

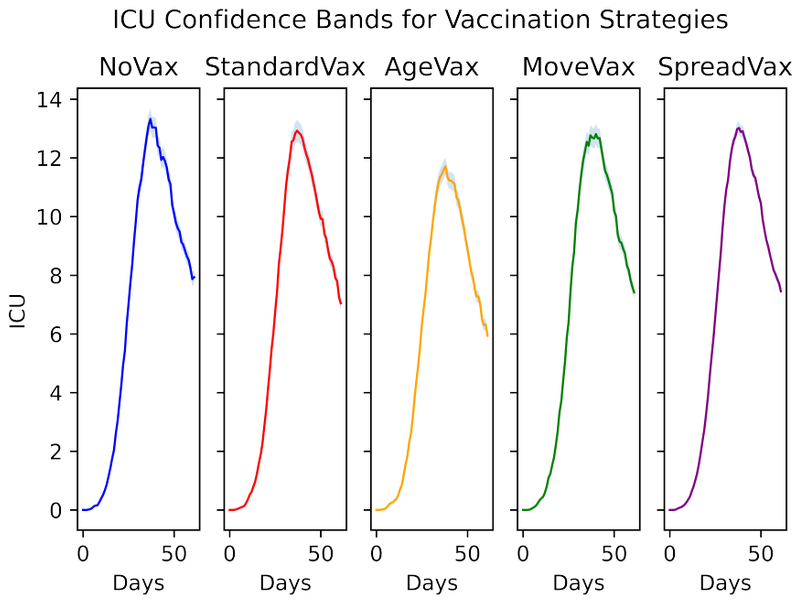

Figure 2: The mean active hospitalizations each day across 1000 runs in solid color, 90% confidence bands in light blue.

Table 1 shows the p-values of the left sided two-sample Welch's t-test to find a statistically significant difference in number of deaths between vaccination strategies. Table 2 shows how each vaccination strategy compared in preventing hospitalizations on the 61st day of the simulation. Each p-value tests to see if the strategy in the row is less than the strategy in the column.

Table 1: p-values of Vaccination Strategies in Preventing Deaths

	NoVax	StandardVax	AgeVax	MovementVax	SpreadingVax
NoVax	5.000000e-01	9.010669e-01	1.0	8.549332e-01	7.137826e-01
StandardVax	9.893314e-02	5.000000e-01	1.0	4.034832e-01	2.233372e-01
AgeVax	5.599492e-11	6.185106e-08	0.5	1.216626e-08	3.777323e-10
MovementVax	1.450668e-01	5.965168e-01	1.0	5.000000e-01	3.021436e-01
SpreadingVax	2.862174e-01	7.766628e-01	1.0	6.978564e-01	5.000000e-01

Table 2: p-values of Vaccination in Preventing ICU Hospitalizations

	NoVax	StandardVax	AgeVax	MovementVax	SpreadingVax
NoVax	5.000000e-01	9.671282e-01	1.0	9.728810e-01	9.775163e-01
StandardVax	3.287175e-02	5.000000e-01	1.0	5.292537e-01	5.566792e-01
AgeVax	1.806568e-29	8.402528e-22	0.5	7.782143e-22	7.128996e-22
MovementVax	2.711897e-02	4.707463e-01	1.0	5.000000e-01	5.275719e-01
SpreadingVax	2.248374e-02	4.433208e-01	1.0	4.724281e-01	5.000000e-01

As can be seen in Table 1, when $\alpha = 10\%$, the Age-Based vaccination strategy had statistically significantly fewer deaths on the 61st day than all of the other strategies. The only other strategy to be statistically significant at preventing deaths when compared to another strategy was the Standard Vaccination Strategy when compared to no vaccine distribution.

In Table 2, when $\alpha = 10\%$, it can be seen that the Age-Based vaccination strategy is also the best strategy when it comes to preventing hospitalizations, as it had the lowest number of ICU patients by day 61. It also had the lowest peak, reflected in Table 3, with a peak mean of 11.7 active ICU hospitalizations on day 38. The second lowest peak mean was of the Spreading Radius vaccination strategy, with a mean of 12.63 active hospitalizations on day 40.

Table 3: Peak Number of Mean Active Hospitalizations

Strategy	Peak	Day
NoVax	13.328947368421051	37
StandardVax	12.927631578947368	37
AgeVax	11.713815789473683	38
MovementVax	12.8125	40
SpreadingVax	13.01998001998002	38

4 Discussion

Based on the simulation data and tables, it appears that the age-based vaccination strategy worked best in both minimizing deaths and ICU hospitalizations in small localities. These results suggest that the optimal vaccination strategy in small localities is to vaccinate those who are most likely to die from a disease first and then those who have lower risk next. For COVID-19 specifically, those with comorbidities such as hypertension, diabetes, and old age [8] should be vaccinated before the rest of the population.

The reliability of this data is impacted by not accounting for transmissions of the virus and the assumptions made for vaccinated individuals. This study assumed that the virus did not mutate at all during the simulation. However, as the virus is transmitted from one person to another, a mutation could occur spontaneously in the replication process or damage to the nucleic acid [9]. For COVID-19, this is an important limitation because variants have been shown to exhibit properties such as being more transmissible and/or more deadly. Additionally, viruses like the Delta variant of COVID-19 seems to be just as transmissible from vaccinated people [10], which could potentially impact the results of this study. The second main assumption that this study makes is that vaccinated people can never get infected with the disease, not transmit the disease, and are instantly protected after the shot. While vaccines like Moderna and Pfizer-BioNTech mRNA vaccines work remarkably well, with the BNT162b2 mRNA vaccine of Pfizer and BioNTech having a 95% protection [11], there are documented cases of breakthrough infections, which are only increasing with the new Delta variant [12]. However, because of breakthrough infections' rarity, it is unlikely they would have impacted the ICU hospitalizations and deaths greatly, leading the results found in this study to continue to be valid.

In future studies, it would be beneficial to account for extraneous variables, such as the impact of variants and vaccine efficacy.

5 Conclusion

With the advent of vaccines, the greatest weapon in the fight against COVID-19, it is imperative to understand the optimal vaccine distribution strategy in order to protect society. This study found that the best vaccination strategy to fight against COVID-19 is to prioritize vaccinating the elderly first in the early stages of vaccine availability, when vaccines may be scarce. This will lead to less overall deaths and a smaller peak in hospitalizations than the other strategies tested in this study. For the policymakers of communities whose vaccination campaigns are still in their early stages, following this age-based protocol will most likely lead to the most favorable results.

6 Availability of Data and Software

All of the data generated and analyzed, as well as the software used to generate and analyze data, can be found in the GitHub repo *here*: https://github.com/ mjacob1002/COVID-19_Simulation. This software was heavily based upon the *Eir* Python package that allows users to simulate epidemics [13]. For the data gathering, analysis, and visualization the Python packages SciPy, NumPy, pandas, and Matplotlib were used [14] [15] [16] [17]. For the regression used to find the $V(x)$ functions, scikit-learn was used for the linear regression [18].

Additionally, the age census data of the United States in 2019 was found *here*.

7 Acknowledgements

We would like to thank Dr. Ernest Battifarano, Dr. Jantine Broek, Dr. Shirshendu Chatterjee, and Dr. Bud Mishra for their support and mentorship during this project. We would also like to thank Holden Mui and Elena Su for their support.

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8 Appendix

8.1 Numerical Methods: Finding p_0

Previously, we defined a function $V(x) = \frac{p_0}{1+e^{-(x-\mu-\sigma)}}$ that is used to determine the probability of an individual getting a vaccine for some parameter $x \sim \mathcal{N}(\mu, \sigma^2)$. For each vaccination strategy, a different p_0 value was used so that the theoretical average vaccinations for each strategy remains the same. To do a relationship between the average value of $V(x)$ when applied to a normal distribution and p_0, we broke up p_0 into tiny differentials of 0.001 in the range $[0, 1]$. After substituting that value of p_0 into the $V(x)$, 10000 values of x, all belonging to the normal distribution, were generated and used as input for the $V(x)$ function. Finally, the mean of the $V(x)$ outputs were taken for each value of p_0 and a linear regression was performed on the data to find a relationship between p_0 and the average value of $V(x)$. By using this relationship, we'd be able to determine which p_0 value should be used to have the same vaccine constraints as a certain η value.

For example, let us take the Age-Based Vaccination Strategy. For this strategy, we defined the distribution of ages X be distributed as follows:

$$X \sim \mathcal{N}(45, 20^2).$$

Furthermore, we let the distribution be truncated from $[0, \infty)$ so that ages do not become negative. After randomly generating the data and then performing a linear regression, the regression line in Figure 3 was created, where $\hat{y}$ is the predicted average of $P(x)$ and X is the p_0 value. This equation has $r^2 = .998$, indicating that it has a strong linear relationship.

$$\hat{y} = .16X,$$

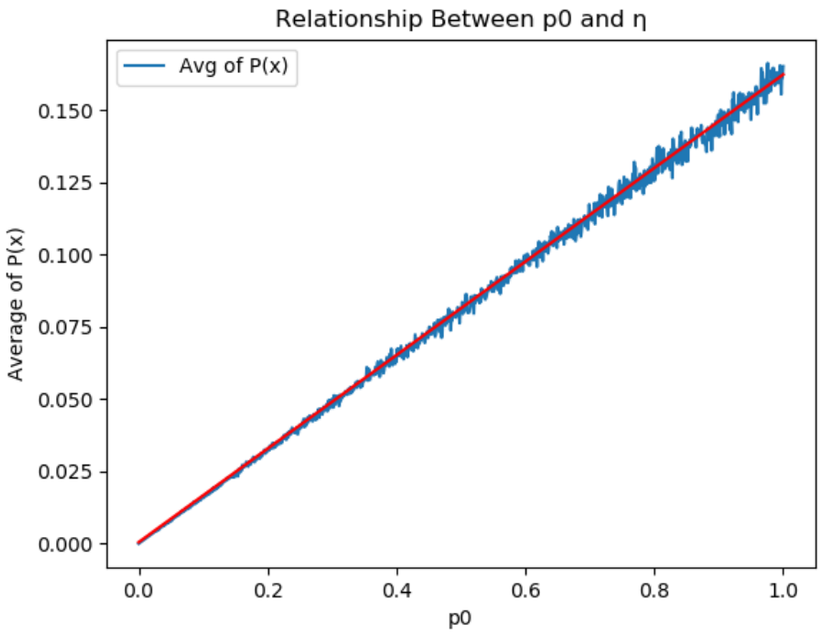

Figure 3: Plot of the generated data in blue; linear regression line plotted in red.