Simulating the Impact of Hospital Capacity and Social Isolation to Minimize the Propagation of Infectious Diseases

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ABSTRACT

Infectious diseases can spread from an infected person to a susceptible person through direct or indirect physical contact, consequently controlling such types of spread is difficult. However, a proper decision at the initial stage can help control the disease's propagation before it turns into a pandemic. Social distancing and hospital capacity are considered among the most critical parameters to manage these types of conditions. In this paper, we used artificial agent-based simulation modeling to identify the importance of social distancing and hospitals' capacity in terms of the number of beds to shorten the length of an outbreak and reduce the total number of infections and deaths during an epidemic. After simulating the model based on different scenarios in a small artificial society, we learned that shorter social isolation activation delay has a higher impact on reducing the catastrophe. Increasing the hospital's treatment capacity, i.e., the number of isolation beds in the hospitals can become handy when social isolation cannot be activated shortly. The model can be considered a prototype to take proper steps based on the simulations on different parameter settings towards the control of an epidemic.

CCS CONCEPTS

• **Computing methodologies → Multi-agent systems**; **Multi-agent planning**; **Uncertainty quantification**; *Artificial life.*

KEYWORDS

agent-based modeling; multi-agent simulation; social distancing; epidemiological modeling; decision support; covid-19

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1 INTRODUCTION

The advancement of the modern medical system is still not adequate to fight against epidemics. Moreover, people's physical interaction with each other has the most significant impact on transmitting infectious diseases [1]. Because of globalization, the transmission from one part to another part of the world is just a matter of time. Currently, the world has been suffering from the Coronavirus pandemic known as COVID-19, and thousands of deaths every day represent that the world is not prepared enough to fight against such epidemics. Therefore, the proper steps towards the spread of infection are much necessary rather than the treatments. Before Coronavirus, the world witnessed several epidemic outbreaks in recent years, including the Zika virus outbreak in 2016, the Ebola virus in 2013, the Middle East respiratory syndrome (MERS), which is also known as camel flu in 2012, the H1N1 influenza epidemic in 2009, and the SARC elaborated as Severe Acute Respiratory Syndrome in 2003. Although most of the outbreaks started locally, spread all over the world, and sometimes come back a few years later by changing its earlier nature, for example, several countries outside the middle east region of Asia also suffered from the outbreaks of MERS in later years.

Proper decisions on time would help reduce the disease spread dynamics and the overall loss rather than solely depending on the existing medical system to fight against a new virus. While fighting against the novel Coronavirus, most countries failed miserably to make two significant decisions on time. One of the major decisions is when to activate social isolation among demographics by declaring emergency lockdown. Another critical decision is when to increase hospitals' capacity by constructing temporary hospital beds to give treatment to overloaded patients. There is no such research work by combining the impact of social distancing and hospital capacity with the best of our knowledge, thereby proposing a novel simulation model to make such decisions. We did not model any specific infectious disease; instead, we tried to model an unseen epidemic that would help society prevent a local outbreak from spreading around the glove in the future.

The rest of the paper has been distributed as follows: In section 2, other related research studies are given, and the novelty of our model has been described. Section 3 describes the approach and parameters of our proposed model. Results of different experiments and overall discussions based on the outcomes of different simulations are described in section 4. Finally, we conclude the study by summarizing the work along with limitations and future scope in section 5.

2 BACKGROUND STUDY

Researchers all over the world developed various models to represents epidemic with different levels of complexity. However, no particular work has been done to look into the combined effect of the hospital's capacity and social distancing as per the best of our knowledge. The most common and famous mathematical model is known as the SIR model developed by Kermack and McKendrick in 1927 [2]. According to the SIR model, the overall population is divided into three categories susceptible (S), infected (I), and recovered (R). Each group of people is counted based on the rate of change using differential equations with respect to the independent variable t, which is time measured in days. The SIR model is still considered as the base for epidemic modeling, and a large number of researches has been done solely based on that pure mathematical model [3,4,5,6]. Some research also used the SIRS model [7], considering that a recovered person may become susceptible after a certain period [8,9]. Researchers also use another popular variation of the SIR model is Susceptible-Exposed-Infected-Recovered (SEIR) model. The model includes another category E, which represents individuals who cannot infect others even though they bear the virus [10]. Some researchers also extended the SIR and SEIR model with vaccination strategies [11,12].

However, most mathematical models' approaches are quite simple and cannot directly handle the complex human interaction parameter like social distancing. Moreover, this model mainly shows the recovery rate based on the statistical assumptions that do not consider improved healthcare facilities. Agent-based modeling (ABM) is considered by many researchers to handle complex scenarios to make the proper decision by estimating an epidemic more accurately, thereby simulating the real world in a more practical way [13,14]. ABM models simulate an individual as an agent in a discrete-time frame and space interacting with the environment based on recommended regulations. The daily actives and dynamics of human interaction can be easily depicted by agent-based modeling [1, 15]. In ABM models, an agent can participate in different activities and interact with each other, thus become challenging to consider various aspects of interaction. Some researchers [16] also point out, challenges of agent-based model frameworks while forecasting the 2014-15 Ebola outbreak in Liberia.

In this study, we applied ABM to simulate infectious disease; the outcome of the model largely depends on the physical interaction between various agents, like most other agent-based research approaches on epidemiology [17,18,19]. Notably, we derive a novel model from advancing the state-of-the-art in the domain of ABM epidemic, which can help to take proper decision based on specific parameters as follows:

- It is possible to assign a separate immunity level based on age and other parameters to determine critical patients using the agent-based simulation model.
- The number of hospitals bed can be used as a parameter to check the impact on disease propagation, and which further can be used to analyze the direct relationship between recovery and death rate.
- The impact of social distancing can be determined to reduce the length of an outbreak and prevent it before it turns into a pandemic.

3 PROPOSED MODEL

We have used the Repast Symphony to build and implement the simulation model. Repast Symphony is an open-source agent-based modeling platform that supports a variety of languages [20]. In our project, we have used java as the primary language. We defined each agent as a java class with individual property and functionality. Five different agents have been created to simulate the model, namely, Susceptible, Infected, Recovered, Dead, and Hospital. Susceptible, Infected, and Recovered agents represent humans with different levels of immunity based on their age. All the agents also have movement functionality except for Hospital and Dead agent. Infected agents mainly move towards Hospital agent to get the recovery, while other agents move randomly. Moreover, the Infected agents have two unique functionalities; one of those is likely to transform a Susceptible agent into an Infected agent when the Susceptible agent comes into close contact. Another unique feature is to convert itself into a Dead agent. If an Infected agent fails to reach the Hospital before the threshold value of immunity, the Infected agent transformed into a Dead agent. Here, the threshold value had been set to one. On the other hand, the Hospital agent does not content immunity as the property, and this agent solely represents the number of isolation beds. The Hospital agent can convert an Infected agent into a Recovered agent. This is due to the fact that the Dead agents neither have any property nor have any ability to move. We have used Continuous Space to simulate the movements of agents. Grid cells are used to determine the nearby agent. Detection of a nearby agent is essential to transform a Susceptible agent into an Infected agent and find out the nearby Hospital to get the recovery. Figure 1 depicts the schematic representation of the proposed model for a single observation with predefined social distancing criteria and the hospital's capacity.

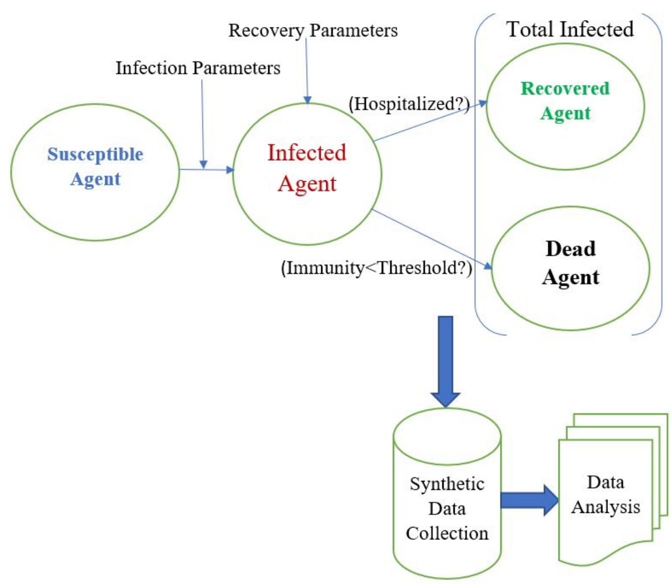

Figure 1: Schematic representation of the proposed model for each observation based on different predefined parameters.

To implement the social distancing, we kept a social distancing property to each movable agent. The social distancing property is mainly a variable that can hold different or same values, after which the movable agents become static. We have kept the infection rate at a moderate level to simulate a moderately populated area, where each infected agent can spread the disease to at most two susceptible agents in a single day, considering the close contact with susceptible agents. If an infected agent comes close contact to more than one susceptible agent within twelve hours, the probability of transformation of susceptible to infected will be as follows based on random selection:

$$P(I) = \begin{cases} S, & \text{if } S = 0, 1 \\ \frac{1}{S}, & \text{Otherwise.} \end{cases} \quad (1)$$

Where, P(I) is the probability of susceptible agent to become infected, given that the agent is now in the same cell of an infected agent. S represents the number of susceptible agents respectively in a cell at a given time.

Thus, a susceptible agent must need to be in close contact with an infected agent to become infected. The infection period, i.e., during the period an infected agent may transmit the disease to susceptible agents are set as 15 days. Since our primary purpose is to see the number of recovery and death with a variable length of hospital size and social distancing activation days, we kept the incubation period very low to the model. Table 1 represents the parameters related to infection and recovery:

Table 1: Summary of infection and recovery parameters.

Parameter	Value
`Infection Rate`	Maximum 2 Susceptible agent per day by an Infected agent based on close contact and infection probability.
`Infection Period`	15 Days
`Incubation Period`	1 Day
`Immunity Range`	0 to 100 (Integer value)
`Death Threshold`	1
`Critical patients`	50%

It is essential to mention that we have kept 50 percent of populations with a critical immune condition, who need to be transferred to the hospital within ten days of getting infected to get the recovery, this is due to check the effectiveness of the different number of hospital beds.

4 EXPERIMENTS, RESULTS AND DISCUSSIONS

Each simulation is made of 400 hundred discrete simulation ticks, and each of the tick corresponds to 12 hours in the real world. Therefore, one day is comprised of two discrete ticks. For each simulation, we have kept the initial susceptible population as 500 and initially infected agents as 2. We simulate the environment with different hospital's capacity, i.e., the number of isolation beds that require the treatment of a patient with infectious disease. We kept the different numbers of social isolation starting or social isolation activation delay counted from the initial day of our simulation to observe the effect of the total duration of the epidemic and the total number of death and recovery cases. Social isolation can be implemented through lockdown imposed by government or social awareness, and we considered the lockdown scenario. We achieved social isolation by stopping the movement of agents in continuous space, similar to the lockdown scenario. Practically, it is impossible to stop the movements of all the people in society for a long time. Therefore, to make the simulation more realistic, we allowed regular movement of 10% to 15% of people, especially those who need to go to the hospital on an emergency basis. The duration of the epidemic is the number of days it took to eradicate the number of infected agents.

4.1 Experiments

The initialization of the model's environment during each experiment is entirely random, along with the location of initially-infected agents and hospitals. Susceptible agent's movement and their physical contact with an infected agent are also random. Therefore, we ran each simulation five times with a fixed hospital's bed and social isolation starting day. Then we collected the data of each simulation in CSV format. Finally, we calculated the average number of infected, susceptible, recovered, and dead agents corresponding to each day to graphically represent the number of agents from day 1 to 200. Since the number of people cannot be fractional, we keep round of the average value instead of keeping it as fractional. Following experiments are performed on the simulation to collect and analyze the data:

4.1.1 Experiment 1: In this experiment, we implemented social isolation from day 20 and kept the number of isolation beds as 10. It is observed that the outbreak lasted more than 150 days. The disease spread to around 95% of overall people, along with more than 40% death. Fig 2. shows the change of population of each category from day 1 to day 200. Figure 2. shows the change of population of each category from day 1 to day 200.

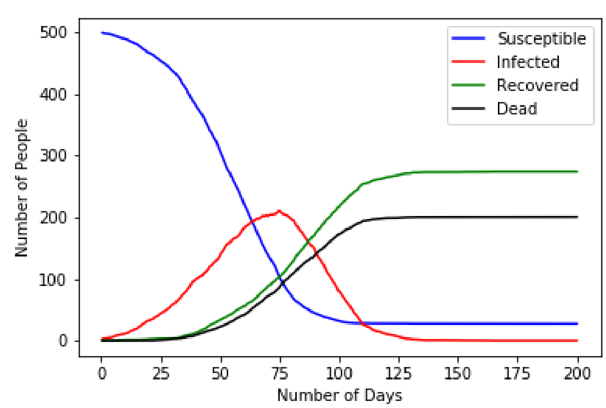

Figure 2: Change of population in each category with 10 isolation beds and social isolation activation delay of 20 days.

4.1.2 Experiment 2: Here we started social isolation from the same day of experiment 1; however, hospitals increased isolation beds to three times. It is observed that the epidemic took place almost for the same period. At the same time, the total number of infections reduced to 72%, and the death rate decreased to around 22% of the overall population. Figure 3. shows the change of population of each category from day 1 to day 200.

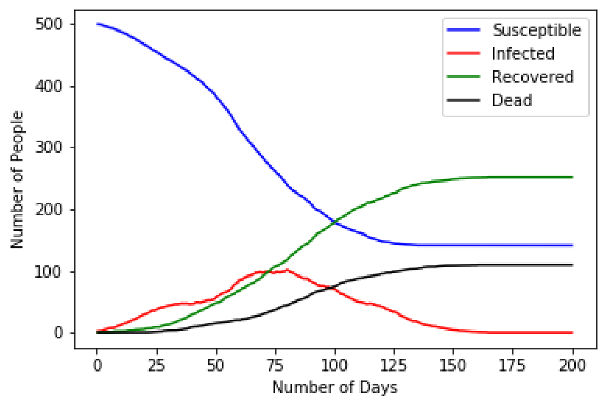

Figure 3: Change of population in each category with 30 isolation beds and social isolation activation delay of 20 days.

4.1.3 Experiment 3: After increasing hospital isolation beds capacity to 5 times compared to experiment 1, we observed a drastic change in total infection. We have found on an average 78 agents got infected, which is approximately 14% of the initial susceptible population, and only 21 people died at the epidemic, which is around 5% of the total population. However, the duration of epidemic around took the same days compared to experiment 1 and 2. Figure 4 shows the change in the population of each day.

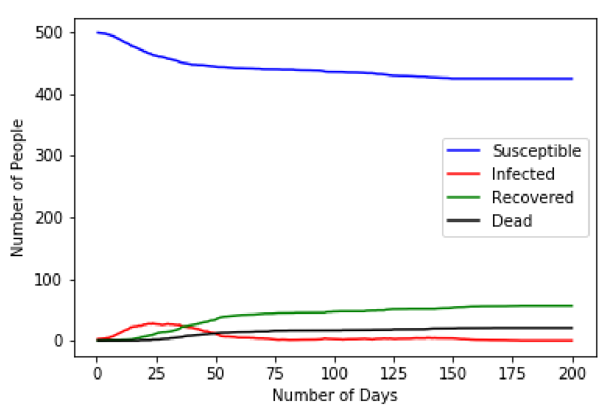

Figure 4: Change of population in each category with 50 isolation beds and social isolation activation delay of 20 days.

4.1.4 Experiment 4: This simulation has been performed by reducing the social isolation activation delay to 15 days with 10 isolation beds. The epidemic took around 150 days to disappear with similar infection and death patterns compared to the experiment 1. Figure 5 depicts the change in population each day.

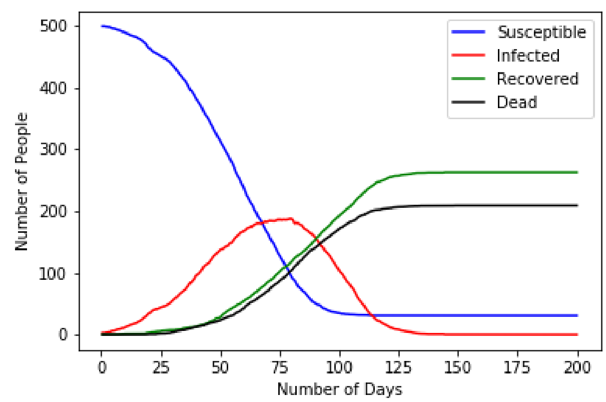

Figure 5: Change of population in each category with 10 isolation beds and social isolation activation delay of 15 days.

4.1.5 Experiment 5: In this experiment, paraments are kept the same as the previous one except hospital beds increased to 3 times. Although the duration of epidemics increases a bit, the total number of infections and deaths reduced in a similar pattern that we have seen in experiment 2, the change in population represented in Figure 6.

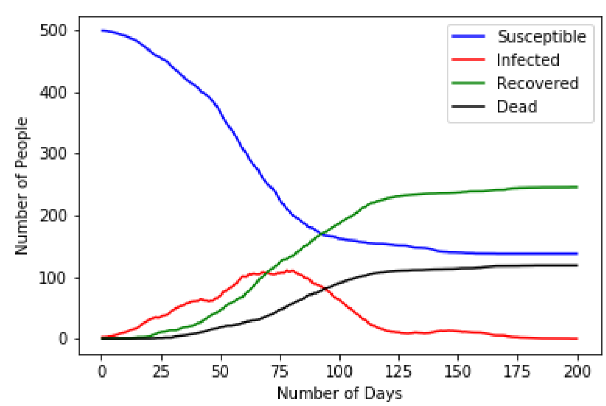

Figure 6: Change of population in each category with 30 isolation beds and social isolation activation delay of 15 days.

4.1.6 Experiment 6: After increasing hospital isolation beds capacity to 50, we observed a drastic change in total infection. The total number of infected people reduced to 20%, with only 26 deaths on average. Figure 7 depicts change of population over time.

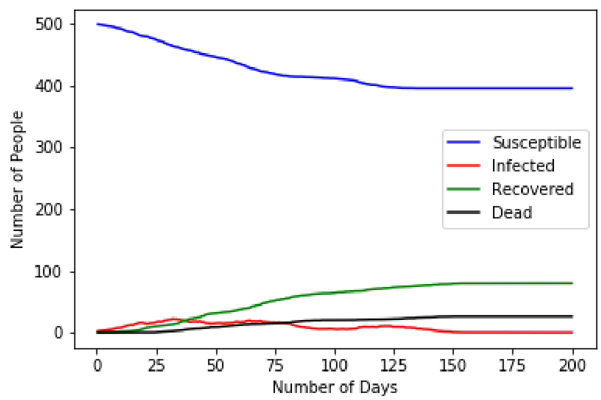

Figure 7: Change of population in each category with 50 isolation beds and social isolation activation delay of 15 days.

4.1.7 Experiment 7. This time we started social isolation from day 10 with the hospital capacity of 10 beds. The duration of the outbreak is still similar to other experiments with the same number of hospital beds capacity. However, the average number of infected people was reduced to just about 50less than the previous two experiments with the same amount of isolation beds. Around 18disappears completely. Which is still less than half of the percentage of two previous cases. Figure 8 depicts the change of population in each category during the epidemic.

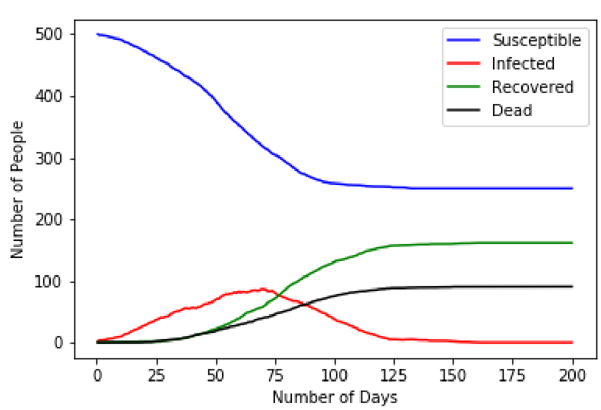

Figure 8: Change of population in each category with 10 isolation beds and social isolation activation delay of 10 days.

4.1.8 Experiment 8: We increased the isolation bed to 30, and the social isolation activation delay kept the same as 10 days. Almost 21% got infected, and only 6% of people died before the outbreak disappears on day 131. Thus, the infection and death rate reduced 50% and 16%, respectively, compared to experiments 2 and 4 with the same number of isolation beds. The change of population in each category from day 1 to day 200 are illustrated in Figure 9.

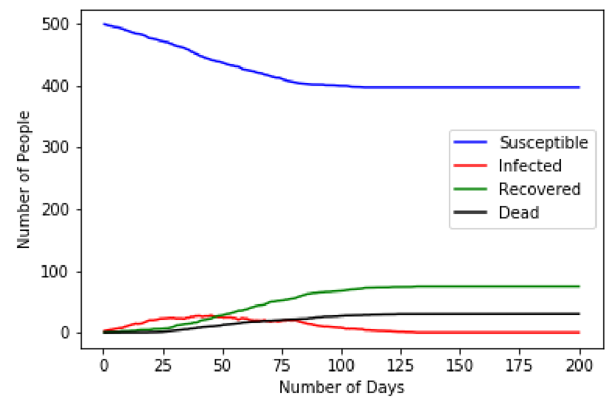

Figure 9: Change of population in each category with 30 isolation beds and social isolation activation delay of 10 days.

4.1.9 Experiment 9: After increasing the hospital's capacity to 50 beds and keeping other parameters the same as the previous experiment, the diseases spread to only 45 people, which is 9% of the total population with only 13 average deaths. The change of population in each category with respect to the number of days represented in Figure 10.

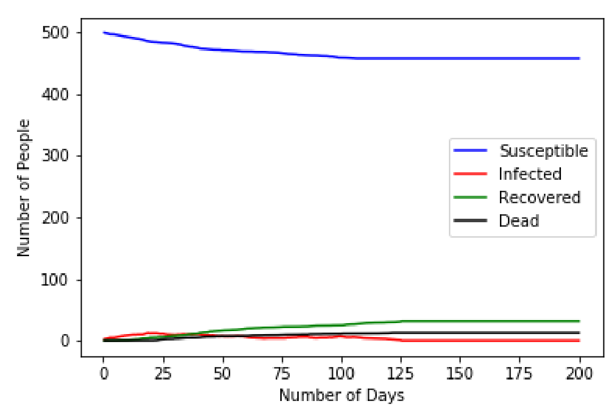

Figure 10: Change of population in each category with 50 isolation beds and social isolation activation delay of 10 days.

4.1.10 Experiment 10. In this experiment, we reduced the social isolation delay to 5 days and kept the hospital's capacity of 10 beds. The average number of infections has been counted as 47, which is slightly higher than 9% of the overall population, and average death was only 11. The average duration of the outbreak reduces to only 67 days, which is remarkably small compared to other experimental scenarios described earlier. The change has been presented in Figure 11.

4.1.11 Experiment 11: In this experiment, social isolation has been implemented from day 5, and the hospital's capacity set to 30 beds.

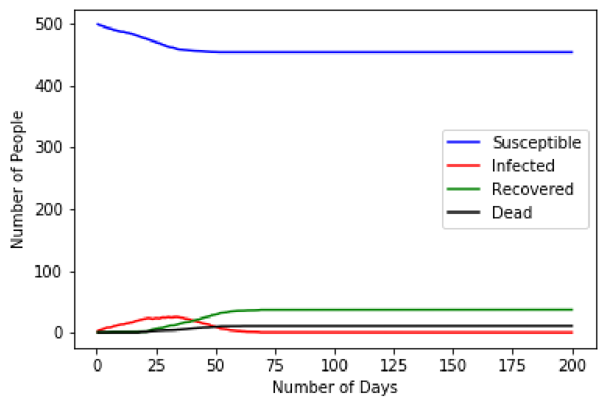

Figure 11: Change of population in each category with 10 isolation beds and social isolation activation delay of 5 days.

This time, the average duration of outbreaks is slightly below two months, and the total infection reduced to 4% of the whole population, and 4 people died, which is less than 0.1% of the total population. The plot has been depicted in Figure 12.

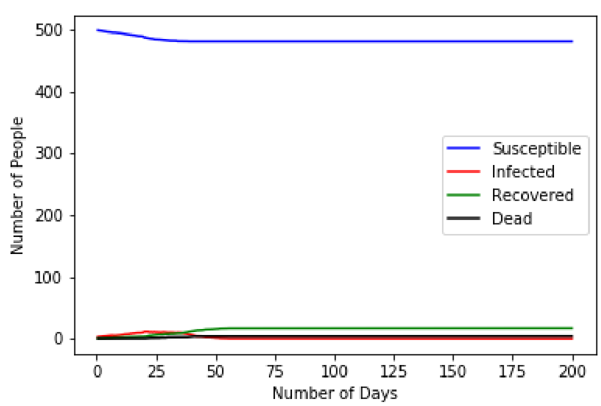

Figure 12: Change of population in each category with 30 isolation beds and social isolation activation delay of 5 days.

4.1.12 Experiment 12: In our final experiment, we kept social isolation activation delay as same as the previous two cases and increased the number of hospital beds to 50. The model outperformed all the previous models with an average of 2 deaths, which is only 0.4% of the whole population. While the number of infections is almost the same as experiment 11 and duration of outbreaks are around 2 months, which is nearly the same as two immediate previous cases. The change of population in each category depicted in fig. 13.

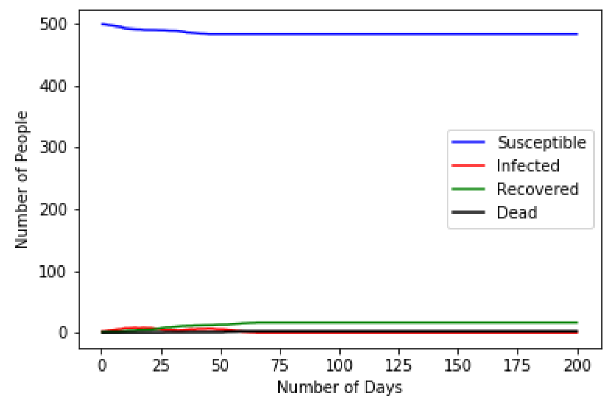

Figure 13: Change of population in each category with 50 isolation beds and social isolation activation delay of 5 days.

4.2 Discussion

Overall, the lesser lockdown activation delay helps in a higher reduction in the infection rate. The rapid activation in social distancing reduces the overall duration of an epidemic in a large number, which helps flatten the death and overall infection curves. The highest number of people got infected with greater activation delays and fewer isolation beds in hospitals. In comparison, the opposite scenario has been observed with shorter activation delay and a higher number of beds in the hospital. The average of all the simulated data is summarized in Table 2.

It has been observed that a hospital's capacity does not relate much with the duration of an epidemic. Instead, social isolation plays a vital role in determining the length of a pandemic. Table 2 clearly shows that the pandemic stayed around 52 to 67 days with the lockdown activation delay of 5 days after detecting the first two cases of infection. Similarly, the duration is 154 to 157 days when social isolation implemented on day 20. Changing the hospital's capacity does not make any remarkable impact on both cases.

Although a shorter delay in implementing lockdown reduces the casualty, it does not have much impact after delaying more than one to two weeks. However, the higher number of treatment capacities can reduce the catastrophe a significant amount in such scenarios. Table 2 shows that total infections, especially death cases, reduced to around 50% and 90% with an increment of the hospital's capacity to 3 times and 5 times, respectively. It is hard to modify the existing hospital's structure. Therefore, constructing temporary hospitals with isolation beds at the initial stage of the epidemic can increase the treatment capacity in large.

5 CONCLUSIONS AND FUTURE WORK

The aforementioned experimental study is the first agent-based simulation model with the best of our knowledge that suggests the link between the capacity of hospitals and social isolation activation delay to simulate the outbreak of a contagious disease. Precisely the model puts forward some proposals to reduce calamity in terms

Table 2: Summary of all the simulated data.

Lockdown Activation Delay (Days)	Hospital Capacity (Isolation Beds)	Length of Epidemic (No. of Days)	Total Infected (No. of People)	Total Recovered (No. of People)	Total Death (No. of People)
20	10	154	475	274	201
20	30	164	361	251	110
20	50	167	78	57	21
15	10	145	472	263	209
15	30	184	363	245	118
15	50	151	106	80	26
10	10	153	251	161	90
10	30	131	105	75	30
10	50	125	45	32	13
5	10	67	47	36	11
5	30	52	20	16	4
5	50	61	18	16	2

of human deaths. That is, a smaller delay in executing social distancing helps to reduce the casualty; it does not have much impact after delaying more than one to two weeks, thereby increasing the capacity of hospitals can help to reduce the total number of infections and death in such types of scenarios. The outcomes of the disease propagation model indicate that the model can deal with various complex scenarios to generate an estimated prediction. The model is also capable of changing infection parameters, such as rate of infection, incubation period, and other recovery parameters. Therefore, the model can be used to validate and simulate any epidemic event with actual data related to lockdown activation delay, total lockdown period, and hospital's capacity of any specific city or country.

One of the significant limitations of our model is that we only considered the lockdown scenario as the form of social isolation, which can be extended further based on the degree of strictness to follow. Furthermore, we could not validate our model to any current or historical epidemics because of the lack of data and information related to social isolation. We are currently working to collect the dataset related to social distancing, hospital capacity of different cities and to obtain actual infection and recovery parameters of the COVID-19 pandemic. In the future, the model can be validated with the COVID-19 epidemic once it is over, and all the related datasets will be available to simulate the model with a more validated outcome.

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