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A Parametric Multi-Agent Simulation Framework to Emulate Social Isolation During the Pandemic

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Abstract

Many people worldwide have been at home for months and practicing social distancing to mitigate the spread of coronavirus (COVID-19). What may have started as a single case is now in at least 180 countries. Preliminary surveys indicate that the COVID-19 pandemic has caused people to feel more lonely and isolated than they did before. It may be due to the fear of the virus, death of loved ones, and the lock-downs restrictions imposed in some countries. This paper proposes a parametric multi-agent simulation framework to emulate Social Isolation during the pandemic. Using the proposed simulator we mimic real-world area of 144 km^2 and population size of 200,000 in order to have near-accurate settings. Various parameters, such as the number of hospitals and capacity, infection rate, recovery, hospitalization, and death, are considered. The simulation is validated on a real-world scale artificial society and is parameterized to a great extent to simulate various settings.

Keywords: Social Computing; COVID-19; Social Isolation; Multi-agent; Simulation

1. Introduction

Times have changed with the outbreak of the novel COVID-19 (2019-nCov), which was declared a global pandemic by WHO on March 2020. The virus steadily reached around the globe, and now at least 180 countries have confirmed COVID-19 cases. Till now, there are over 24 million confirmed cases globally and over 800,000 deaths [26]. Due to the gravity of the situation and the increasing number of deaths, some countries and territories administered varying measures. The two significant measures taken to mitigate the spread of this virus is lock-down and social distancing [13]. Some governments, policy-makers, and decision-makers worldwide had imposed lock-downs of different degrees that restrict the time spent outside the home for non-essential needs. Over 100 countries had imposed either a full or

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partial lock-down by the end of March 2020; this affected billions of people. Moreover, some countries have also shut down their borders, limit international travel, and established lock-down strategies [10]. Out of these countries, some have adopted a stage-wise re-opening framework. These changes force people to reconfigure their established norms and society [14].

The measures of lock-down, quarantining, and social distancing have aggravated an already severe problem. Apart from the essential workers, this pandemic has forced limited physical proximity. Regardless of living situations, the interactions with people outside the home have plummeted. Some research suggests that during the first month of the pandemic, loneliness amongst the population increased by 20-30 percent [22]. The research also suggests that nine out of ten people feel more anxious and stressed due to COVID-19 than before [22]. Recent research confirms the problem of social isolation and loneliness may be much more common now than it was previously before the pandemic [17]. Studies show that social isolation can have many adverse effects on the health and well being of human. It is associated with depression, heart attacks, anxiety, Alzheimer's disease, cognitive issues. [5]. Thus it is crucial to understand the changes observed in social isolation due to the social reconfiguration done to mitigate COVID-19 spread.

To address this problem, we propose a multi-agent based framework to simulate different situations which can be happened during the pandemic in terms of social isolation. The primary step is to define the scenario and the pandemic simulation. Therefore, we consider various classes and states of agents in our proposed simulator, such as Susceptible, Infected, Asymptomatic.

The rest of the paper has been divided as- Section II, explains the problem statement, and Section III reviews the background study and the literature. Section IV describes the details of design and implementation of our framework. Section V discusses the results of this research, and the last section is conclusion and future work.

2. Problem Statement

The problem of social isolation during a pandemic can be divided into two sub-problems, a) simulating the spread of disease in the population, b) measuring the its impact on the individual's interactions. To convert this problem in a formal and mathematical model, first we define the analogy between the simulation and the real-world scenario. An *individual* in the population is represented by an **agent**, a_i, in our simulation, where $1 \le i \le n$, and n is the size of the population. Therefore the population, $A = \{a_1, a_2, \ldots, a_n\}$.

Meanwhile, the population (A) consists of four main classes of agents, Susceptible (S), Infected (I), Recovered (R), and Dead (D). Each agent can belong to one of these classes at the same time. Meanwhile, the infected class has multiple states such as Asymptomatic (AS), Quarantined (Q), Hospitalized (H), ICU (IC), and Wait-listed (W). The infected agent can be in one or more of these states depends on its disease progression. It is to mention that these classes are dynamic, and an agent migrates from one group or state to another over time based on their attributes or health status. For this purpose, a fixed- size binary vector with the length of v, is assigned to each agent, $\vec{a}_i \in \{0, 1\}^v$. Each bit represents the temporal state and class of the agent. If the bit is 1 then the corresponding attribute is **True**, otherwise **False**. For example, assuming the second bit represents an Infected class, the infected agents will have this bit as 1. In the initial time, the majority of the population belongs to the susceptible (S) class. This is the class of agents which are healthy and could be potentially exposed to infection.

On the other hand, the infected (I) class are those agents who have been exposed to the virus and carry the virus. The infected agent can spread the virus to the susceptible agents within a particular distance (e.g. 2 meters) where the risk of transmission is high. Each agent has a X and Y coordinate, and this position changes over time. Therefore, if two agents a_i and a_j have the Chebyshev distance (L_∞ metric) less than or equal to 2, then the risk of transmission is high. The distance between two agents, a_i and a_j is calculated as follows: $dist(a_i, a_j) = max(|x_i - x_j|, |y_i - y_j|)$

The number of susceptible agents that can be expected to be directly infected in by a single infected agent is defined as the basic reproduction number, B_0. Some studies suggest that the value of it is 2.4, which means that an infected person can infect 2.4 susceptible people at once [12]. The probability of the transmission of infection from an infected agent to a susceptible agent is denoted by $P(I)$.

The infected agents have a latent period (λ days) in which they do not show any symptoms. During these λ days, the agent is asymptomatic and unaware that it is infected; this agent moves normally, and may infect susceptible agents. After the λ days, when the symptoms appear, the agent quarantines itself. After quarantining for at least λ^Q days, two consequences may happen as follows.

Situation 1: With a probability of $1 - P(H)$, where $P(H)$ is the probability of hospitalization, the agent passes the period of disease, λ^R, at home waiting for the recovery, without the need to be hospitalized. It is expected to have majority of infected agents, follow this path.

Situation 2: With a probability of $P(H)$, the symptoms of an infected agent will be aggravated and the agent must be transferred to the **hospital**. In this case, three situations may happen.

Situation 2.1: The agent occupies a normal hospital bed, and stay in the hospital for λ^H days, and after this period, they either recover or die with a probability of $P(D|H)$.

Situation 2.2: The agent's situation requires critical care, and it needs to be transferred to an ICU. The probability of this happening is $P(IC)$. After a period of λ^{IC}, this agent either recovers or dies with a probability of $P(D|IC)$.

Situation 2.3: In this framework we also consider the capacity of hospitals, and hence the concept of **wait-list**. An infected agent who needs the hospital service but due to the lack of vacant beds is being put in the wait-list. These wait-listed infected agents, are still quarantining at home but are given priority while assigning hospital beds, as soon as they are available. Due to the lack of medical care, the probability to die in this case $P(D|W)$. It is to mention that $P(H) > P(ICU)$ and $P(D|W) = P(D|IC) > P(D|H)$. It is to emphasis on the need of hospital care to a wait-listed patient, even if they are non-critical at the time of admission. Therefore, the population (A) at time t can be defined as: $A(t) = S(t) \cup I(t) \cup R(t) \cup D(t)$. Since, initial population consists only by mainly susceptible and some infected agents: $A(0) = S(0) + I(0)$. The total number of agents also does not change over time: $\frac{dS}{dt} + \frac{dI}{dt} + \frac{dR}{dt} + \frac{dD}{dt} = 0$.

3. Background Study

The research done to simulate the COVID-19 pandemic provides an abundant source of knowledge to understand the virus's spread and the impact of various parameters. Various mathematical models are inspired by the SIR model proposed by Kermack and McKendrick in 1927 [11]. The SIR model stands for Susceptible (S), Infected (I), and Recovered (R). It assumes that a Recovered can not become Susceptible. The SIR model is a system of non-linear Ordinary Differential Equations (ODEs). The SIR model has various derivatives and modifications which include (and are not limited to)- SIRS : considering a recovered person may be susceptible again [2], SEIR: in which an Exposed (E) category is added, which represents infected agents who are not infectious yet [1], and SEIRS. These models are solved numerically, and represented in terms of differential equations. In [9], an SEIR model is using to simulate a potential second wave of COVID-19.

Apart from these models, there is another type of modelling known as "Agent Based Modelling (ABM)". ABM is considered more suitable to be applied to complex scenarios and allows better estimation by simulating the real-world in a practical way [6, 16]. ABM can incorporate complex human behaviour and define agents with different behaviour and possible interactions. There exist several ABM simulation in literature. [19] presents a genomics survey of COVID-19 in Australia and then performs ABM to improve understanding of the spread of the virus. In the research by Silva et al. [21], the pandemic is simulated in various scenarios and its social and economic effects. It defines various socioeconomic events and agents such as persons, houses, businesses, government and healthcare systems to study the effect of implementing various settings such as lock-down, partial lock-down, vertical isolation, and the use of face mask. Various other simulations exist which cover niche topics in the COVID-19 context such as hospital beds and lock-down [20], universal use of masks and social distancing [4], and vaccine distribution [7]

Social isolation is defined as the quantified and objective impression of smaller network size and inadequate social contact [23]. It is usually associated with a lack of economic resources, mobility impairment, and close ones' death. Literature suggests that social relationships are essential to maintaining health. Various researches show that social isolation can not only aggravate already-existing diseases but also cause them [5]. There exists a significant amount of literature that links the increase in isolation and emotional distress with the pandemic [8, 15, 3]. Preliminary surveys claim that the COVID-19 loneliness due to isolation affects 1 in 3 men and 1 in 4 women [22]. The combined study of social isolation and the impact of COVID-19 is still early and in development. There are a limited number of researches done to study the effect of isolation due to coronavirus on the mental health of humans [18].

4. Design and Implementation

To address this problem, we propose a framework to simulate the population and find socially isolated nodes. As shown in Algorithm 1, first at time t = 0, all the agents will be placed at random locations, and a group of them will

be initialized as infected, and the remaining will be susceptible. These corresponding positions are considered as the home of these agents.

Algorithm 1: Algorithm For Proposed Model

Input: Parameters indicated in Table 1.
Output: S(t), I(t), R(t), D(t), $N(A)$, and $ND(A)$
Initialization;
for $t \in \{1, \dots, m\}$ **do**
    for $a_i \in \{A\}$ **do**
        if *($a_i \in S(t) \cup R(t)$)* **then**
           step(a_i) according to Step Function 2
        if *($a_i \in I(t)$)* **then**
           step(a_i) according to Step Function 1
           if *(agent.hospitalized = False)$\land$ (agent.waitlist = False)* **then**
             Infect

Compute $N(A)$ and $ND(A)$ **return** S(t), I(t), R(t), D(t)

From the time t = 1, till the end of the simulation, each class of agent performs a step function to do periodic tasks in every iteration. At the end of each tick, the number of neighboring agents that each agent has, in a neighborhood of 20 meters (distance will be recorded, in a file, along with the total neighbors distance among them, for further processing). During the simulation, except the infected agents, which move and act as defined in Step Function 1, the rest of the alive agents behave as per the Step Function 2. Generally, in our framework an infected agent can spread the diseases to the nearby susceptible agents in a radius of 2 meters during the first λ days of the infection.

As mentioned earlier, once the latent period passes for an infected agent, its state will be changed from asymptomatic to quarantine. The agent stays in this state for at least λ^Q days, after which it either goes to the hospital, or recovers after λ^R days.

In case of hospital, if the hospital has a vacant bed, the agent may stay in hospital for λ^H days. However, a small group of patient ($P(IC)$) may need to move to ICU, where they take λ^{IC} days to recover. There is always a probability for these agents to die, when they are in state of hospital ($P(D|H)$) or ICU ($P(D|IC)$).

In this framework, we also consider the capacity of hospitals, and hence the concept of wait-list. If there are no empty beds, the infected agents who try to go to a hospital are assigned to wait-list. With wait-list = True, these infected agents are staying in Q state but with a higher probability of dying (same as $P(D|IC)$). They also are given a higher priority while assigning hospital beds, as soon as they are available.

To incorporate the isolation caused to hospitalized individuals, we assume that if a_i is hospitalized at time t, then $N(a_i, t) = 0$. This is because even though they are 'physically' near the other hospitalized individuals working in hospitals, they do not interact with these people. The movement function for infected agents is described in the Utility Function 1.

The algorithm for the proposed framework can be seen in Algorithm 1. The input parameters for the models are listed with their default values in Table 1. After the simulation is completed, the analysis is performed to find the average number of neighbours $N(A)$ and the neighbor distance $ND(A)$, as explained earlier.

In our simulation, we assume that a distance of 1 unit = 1 meter, 1 day is equivalent to 4 ticks. An agent's neighborhood extends to a maximum distance (specified as 20 meters. The simulation is run for 60 days (240 ticks) for each scenario. The population and the area in which the simulation is performed, is considered to be on a real-world scale. We consider the initial susceptible population size as 200,000 and the area to be of 144 km^2.

At each day, the number of unique neighbors an agent met, the distance between the agent and its neighbors, and the total number of neighbors are recorded. The count of different agents is also plotted, to better understand the spread of virus in each scenario.

5. Comparison and Analysis

We studied the impact of social-distancing and lock-down on social isolation by simulating the following scenarios.

Step Function 1: Infected Agents

Input: Infected Agent at time t
Output: Agent at time t+1
Update agent's position according to Utility Function 1
if *agent.waitlist = True* **then**

    if *Hospital.capacity > 0* **then**

        agent.waitlist = False

        agent.hospitalized = True

else if *agent.days_infected = λ* **then**

    agent.quarantine = True

else if *$\lambda^Q \leq$ agent.days_infected < λ^R* **then**

    agent.quarantine = False

    if *P(H)* **then**

        if *Hospital.capacity = 0* **then**

            agent.waitlist = True

        else

            agent.hospitalized = True

            if *P(IC)* **then**

                agent.icu = True

    if *(agent.days_infected > λ^H) $\land$ agent.hospitalized = True $\land$ agent.icu = False* **then**

        {I(t+1)} $\leftarrow$ {I(t)} - agent

        {R(t+1)} $\leftarrow$ agent

    else if *(agent.days_infected > λ^{IC}) $\land$ agent.icu* **then**

        {I(t+1)} $\leftarrow$ {I(t)} - agent

        {R(t+1)} $\leftarrow$ agent

neighbors = Neighbor(agent, 20, t)
store N(agent, t)=size(neighbors)
store ND(agent, t) = $\sum$ dist(agent, a_j) for a_j in neighbors
return agent

Step Function 2: Alive Agents

Input: recovered/susceptible agent at time t
Output: agent at time t+1
Update agent's position according to Utility Function 1
neighbors = Neighbor (agent, 20, t)
store N(agent,t) = size(neighbors)
store ND(agent,t) = $\sum$ dist(agent, a_j) for a_j in neighbors
return agent

- **Scenario 1** *(Baseline)*: This setting illustrates population before the pandemic, and the agents followed a normal day-to-day movement where they move randomly around the grid based on the mobility. Since, this is our baseline, we considered initial population of infected agent, $I(0) = 0$. This way, the population completely behaved as if there was no coronavirus pandemic.
- **Scenario 2**: This setting illustrates the pandemic with a majority portion of population following either social distancing or lock-down. We assumed 70% of the population followed these restrictions, taking in account the other minority not following due to 'essential' work, or they are insubordinate. This was an attempt to mimic the actual pandemic situation.
- **Scenario 3**: In this setting, we assumed that there was random percentage of population that followed social distancing and lock-down. The portion of population following these restrictions is randomly changed between 50% to 80% daily.

Utility Function 1: Update Agent's Position

Input: agent
Output: agent with updated position
if *(agent.lockdown = True)* ∨ *(agent.quarantine = True)* **then**
⎿ return agent
else if *(agent.social_distancing.True)* **then**
   old_position ← agent.position
   while *size(Neighbors(agent, 2, t)≠0* **do**
   ⎿ move agent around randomly
else
⎿ move agent randomly
return agent

Table 1: Simulation Parameters and their Values.

Parameters	Domain/Unit	Current Value
Demographics		
Height	N+ /meters	12000
Width	N+ /meters	12000
$S(0)$ Initial Susceptible Agents	N+ /people	200,000
$I(0)$ Initial Infected Agents	N+ /people	27
Number of ticks in simulation	N+ /ticks	240 ticks
Number of hospitals	N+	2
Capacity of each hospital	N+	300
Mobility (per tick)	N+ /meters	[1000-8000]
Epidemiological		
λ Latent Period	N+ /days	5 days
λ^Q Quarantine Period	N+ /days	10 days
$P(I)$ Transmission rate	[0,1]	0.8
$P(H)$ Hospitalization rate	[0,1]	0.12
$P(IC)$ Critical cases rate	[0,1]	0.025
$P(D|H)$ Death rate for hospitalized agents	[0,1]	0.023
$P(D|IC)$ Death rate for critical patients	[0,1]	0.30
λ^R Total recovery time for quarantined agents	N+ /days	14 days
λ^H Total recovery time for hospitalized agents	N+ /days	19 days
λ^{IC} Total recovery time for critical patients	N+ /days	26 days

- **Scenario 4**: This setting was considered to simulate the case of no precautions of lock-down or social distancing with the virus present in the population. The agents moved around normally like there is no pandemic.

The values of the parameters for the simulation that were considered in our set of experiments are given in Table 1. The framework was ran on these scenarios, 3 independent times, and the results obtained are discussed below.
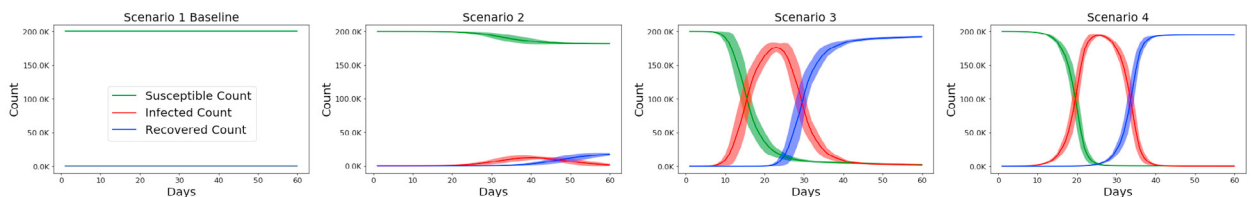

Fig. 1: Time Series Count of Susceptible, Infected, and Recovered Agents
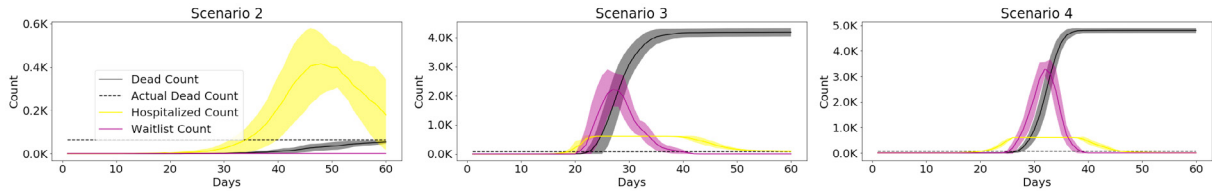
Fig. 2: Time Series Count of Wait-listed, Hospitalized and Dead Agents

Figure. 1, shows how the virus spreads in the population under different scenarios. The plots show an interesting point that the spread of the virus in the 2nd and 3rd plot has a great difference. The virus did not spread to a huge extent in scenario 2, unlike in scenario 3, where the virus spread to the majority population since a random portion of the population followed the lock-down and social distancing. The trend is similar to the 4th scenario, where there was no lock-down or social distancing followed. The peak of the infected population in scenario 3 is slightly less than the peak in scenario 4, a difference of approximately 20,000.

Figure 2 illustrates the time series graph for three different agents- wait-listed, hospitalized, and dead agents. This was done to study the importance of availability of hospital beds during such a pandemic. When the lock-down and restrictions are followed by 70% of the population constantly, there were no agents on a wait-list. But during the other two cases, since the virus has spread to the majority population, there was a huge influx of patients in hospitals. For approximately 20 days, in both scenario 3 and 4, the hospitals were completely filled, this caused an increase in the wait-listed agents. While comparing the scenario 4 with scenario 3, a slight increase in the wait-listed agents is noted. A similar increase is seen in the deaths; thus, a lot of these wait-listed agents died since the probability of dying for wait-listed agents ($P(D|W)$) is considered same as the value for ICU state agents ($P(D|IC)$). This indicates the importance of enough hospital beds for the population, and the need to curb the contagion of the virus.

We also compared our simulation results with real-world data in order to verify the performance of our simulation. Since there are 200,000 individuals in our population and an area of $144km^2$ is studied, the simulation results are compared with the city Windsor (ON, Canada), which has similar figures. According to the Windsor-Essex County Health Unit, there were 27 confirmed cases on the 1st of April 2020 [24]. Consequently, the results are compared with scenario 2, in which 70% of the population followed lock-down and social distancing. We did not compare the number of infected cases at the end of the simulation since, in reality, many cases may not be detected due to reasons such as - individuals quarantining at home without getting tested and false negatives. Thus, number of deaths were compared. Windsor reported 65 confirmed deaths on 1st June 2020 [25], which is plotted in Figure 2. According to our proposed simulation's results, the number of deaths after 60 days = 53.8 ± 6. This number is close to the actual number of deaths reported after the same duration. This implies that our simulation made a satisfactory approximation of the spread of COVID-19 in the society. Accordingly, we believe that this pandemic has a significant impact on social isolation in a real-world society which can be captured and monitored by an agent-based simulation. The outcomes and results obtained from the simulation can help to better understand the situation and make decisions for prevention strategies.

6. Conclusion

COVID-19 has made some countries impose lock-down and social distancing rules to mitigate the spread of the virus. According to the ongoing surveys, these restrictions have also aggravated the problem of social isolation amongst individuals. Our proposed framework is an attempt to create a simulator for studying the effect of these restrictions on social isolation, using agent-based modelling.

The model is capable of accepting various parameters such as the population, transmission of the virus, the number of hospital and hospital beds, and the chances of recovery and death. This parameterized model allows us to validate and simulate even other pandemic events with data simulating a region, province, or country.

The results of simulating the agents' interactions during the pandemic situation on a real-scale artificial population confirm the hypothesis and findings of various surveys that there is a significant increase in socially isolated individuals. The results also emphasize the need for enough hospital beds in a dire situation.

In the future we want to incorporate the population's demographics information because these attributes may contribute significantly to how an individual may behave during the pandemic.

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