Predicting Optimum Lockdown Pattern of Epidemic Spread Using AI Techniques

Fariha Sultana Rini[1a], Somiya Assir Jebin[1b], Merajunnesa Kumkum[1c], Md. Rajibul Islam[2*], Nadeem Ahmed[3], Md Amiruzzaman[4], and Halima Khatun[5]

[1]University of Asia Pacific, Dhaka 1205, Bangladesh
[a]18101074@uap-bd.edu, [b]18101087@uap-bd.edu, [c]18101098@uap-bd.edu

[2]Bangladesh University of Business and Technology, Dhaka 1216, Bangladesh
md.rajibul.islam@bubt.edu.bd

[3]University of Asia Pacific, Dhaka 1205, Bangladesh
nadeem@uap-bd.edu

[4]West Chester University, West Chester, PA 19383, USA
mamiruzzaman@wcupa.edu

[5]Jahangirnagar University, Savar, Dhaka-1342,
Bangladesh halimakhatun927@gmail.com

Received: September, 15, 2022; Accepted: November 22, 2022; Published: January 10, 2023

Abstract

Recent COVID-19 has revealed that we are still unable to find a sustainable approach to combat such infections in order to maintain a stable economy and minimize death rates. COVID-19 vaccine is available but when COVID-19 first arrived, restricting movement was the only option to control the spread, yet, one of its consequences is an economic crisis. This paper proposes predicting optimum lockdown patterns of epidemic spread using AI techniques (MESA ABM) which will help to balance economic fall and death rates while conducting vaccine research. We created a computer-generated environment to replicate a pandemic, such as the initial wave of COVID-19. The model was created using the SIR (Susceptible, Infected, Recovered) hypothesis for disease propagation and implemented using the Mesa, which is an agent-based modeling framework. Using this model, we develop an optimum lockdown pattern using agents (entities that act like humans). Our model produces optimal movement restrictions by randomly putting lockdowns ranging from one to a hundred days using given conditions. Additionally, we carry out several assessments and offer the justification for the action.

Keywords: Optimum lockdown pattern, Epidemic spread, Movement restriction, MESA (ABM), SIR model

1 Introduction

Global outbreaks like COVID-19 changed people's lives by leaving impacts behind such as losing lives, and deteriorating health, and apart from this pandemic creates social and economic disasters [1, 2]. Pan-

Research Briefs on Information & Communication Technology Evolution (ReBICTE), Vol. 9, Article No. 01 (January 10, 2023)
DOI:*https://doi.org/10.56801/rebicte.v9i.153*

*Corresponding author: Bangladesh University of Business and Technology Rupnagar, Mirpur-2, Dhaka-1216, Bangladesh, Email: md.rajibul.islam@bubt.edu.bd

demics are mainly caused through the transmission of a disease from one person to another such as Swine Flu in 2009 [3] to COVID-19 in 2018 [4]. To prevent and control outbreaks of infectious diseases, vaccines are essential [5]. However, an effective vaccine may take a long time to produce depending on the situation and disease [6], [7]. Movement restrictions can be used to control infectious diseases [8]. Recently, COVID-19 lockdowns impacted the economy due to loss of life, trade disruption, business closures, halted tourism industries, and the increased mortality rate.

From the very beginning of human existence, several viral communicable diseases have spread, but recent COVID-19 has shown us that we are yet to find a proper solution to fight such diseases so that we can minimize death rates and be able to keep our economy steady [9]. Many countries like China and the USA around the world suffer from COVID-19 disease spread restrictions as well as economic damage [10], [11]. During this time we have found the solution is to find an optimum lockdown that will help us to balance economical falls, the spread of diseases, and the death rate.

In order to solve this problem, we used an AI-based technique. We examined how infectious diseases spread in an initial pandemic situation. Then we use agents to generate data and to determine the optimum lockdown pattern. By following that optimum lockdown a country can balance the death rate and economic rate. We reuse a COVID-19 model to accomplish this purpose [12]. The model uses Mesa ABM (agent-based model) along with SIR theory to show how an infectious disease like COVID-19 spreads in a virtual environment.

An agent-based model (ABM) is a software program used to simulate the activities and interactions of agents (individual or collective entities such as agencies or groups) to comprehend system behavior and what determines its outcomes [13]. Utilizing either the built-in core components (such as spatial grids and agent schedulers) or customized implementations, users of MESA may easily build agent-based models, view them using a browser-based interface, and study their outcomes using Python's data analysis capabilities [14]. With the help of this existing COVID-19 model, we recreate a model that generates an optimum lockdown pattern to control the falling economy and the rise of death due to COVID-19. Our proposed model has four types of agents (Susceptible, Infected, Recovered, and Death) [15].

Our agent's goal is to generate a dataset based on given conditions and information so that a pandemic crisis can be controlled while maintaining economic balance. Since economically people are inactive due to lockdown and there are lots of deaths from infection, the economy normally starts to fall [16], [17]. In our model, we give random lockdowns so that we can find the lockdown pattern to control the death rate due to COVID-19 while maintaining the economic rate.

After analyzing the data we find the optimum lockdown that balances the economy along with the death rate. Our model results are consistent with real-life scenarios comparing China, India, and Bangladesh. We can adapt the model to the environment of any country. In addition, when new infectious diseases develop in the future and scientists conduct research on viruses, we can also adapt our model to determine the best lockdown to control the economy and mortality rates.

2 Literature review

Many researchers have proposed different types of lockdowns, some of them proposed age-based lockdowns, n-work-m-lockdown, and so on [18], [19]. Anyway, the age-based lockdown and the n-work-m-lockdown (n days without lockdown followed by m days of lockdown) strategy should not apply during critical pandemic situations. Because of the economic downturn, there are challenges in the current pandemic situation, including the challenge of implementing a lockdown pattern without affecting the economy, while minimizing the death rate. We are still struggling to make a proper effective control measure which shows that we need to find a proper pattern of lockdown so that along with battling against a pandemic we can restore our economy to balance economic equality. Additionally, various organizations quickly adapt and apply their machine learning expertise in several sectors and machine learning allows us to mimic and ingest a large volume of data to quickly understand the behavior and patterns of that given situation [20].

There has been so much research done on lockdown policies of COVID-19 and its effect on the economy and our social life but there is no proper research on how both the death rate and economic steady rate can be balanced. Various strategies of lockdown placing were taken into consideration to stop the death rate and infection rate such as by placing lockdowns based on only the high rate of active cases and reproduction rate and then the system lifts the lockdown if the rate of acid reproduction rate is low [21]. A study related to lockdown and modeling of corona spread used a dynamic mathematical model for prediction of the future infected population with the lockdown period of 14, 21, 42 days of lockdown and one of those studies was placing short lockdowns which they thought worked best to stop the spread but none of this lockdowns were considering the effects of the economy so that economy death rate both can be balanced [22], [23].

Tamer Oraby et al. developed a stochastic continuous-time Markov chain (CTMC) with eight states or compartments and discovered that shorter lockdowns appear to have a larger relative effect on the total attack rate if they begin close enough to the peak of the actual incidence and that a lockdown shorter than 90 days can achieve the goal of hospital caseload reduction. However, their study is related to give insights into how the population of that family will affect the model. There were no findings nor discussion about the lockdown's effect on the economy [24]. The Markov chain model becomes more complicated when more states and interactions are included but to create a complex model like the pandemic-like situation we need complex models so SIR models are better for generating lockdown patterns.

In [25], Caulkins et al. used SIR differential model and reported that a central strategy for responding to the COVID-19 pandemic is "locking down" parts of the economy to reduce social interaction and, contagious transmission. They said it can be optimal to have two separate periods of lockdown at the same time. Economic costs are relatively small with the short lockdown), but it is the health costs that are massive. They advocate that three qualitavely different lockdown strategy can be considered optimal at the same time. The lockdowns will depend on the value of preventing a death due to COVID-19 And they denoted this value as M. Considering the value of M as smaller, intermediate and larger they proposed lockdowns. They do seem concerned about economic disruption due to lockdowns but for placing lockdowns an optimum pattern is needed to generate by placing random lockdowns in the model. This will make the lockdown pattern more accurate and acceptable.

Manfei Yang et al. reported in [26] that UK government implemented a series of measures for England when Covid 19 first arrived. This study systematically collated and analyzed the prevention and control policies adopted by the UK during the first and second COVID-19 waves. From 23 March to 7 May 2020, the UK imposed its first lockdown, during which measures were strict after lifting the lockdown On 5 November 2020, the second lockdown in 4 weeks was imposed in England, these lockdowns were based on the mortality rate and infection rate only. There was no optimal calculation how both the economy and death rate can be balanced for imposing those lockdowns. Monthly gross domestic product (GDP) of UK in December 2020 was 6.3% below the level of February 2020, having increased by 1.2 percenatge compared with November 2020 [27]. This state of GDP shows how important an optimum lockdown pattern is which will not only focus on death count but as well as on the affected economy.

Some countries adopted the green zoning strategy as movement restrictions when the virus was under control and could recommence economic and social activities among themselves; research has shown that green zoning can recover economic declines and prevent transmission. But we see that they have not properly mentioned the parameters to declare a region as a green zone and green zones will interact by avoiding possible transmissions [28].

Our study focuses on the betterment of the economic condition that tends to deteriorate along with the death rate so that when any new pandemic starts to hit our model can predict a better lockdown pattern. In our model when the death rate and economic rate start to fall as a result of economically active people dying due to COVID-19, our model generates optimum movement restrictions by placing lockdowns randomly from one to a hundred days.

3 Method

The spread of infectious diseases is a complex problem. In the real-world humans interact with each other and also with the environment. Because of their interaction, the spread of infectious diseases leads to pandemic crises. In addition, the diseases spread randomly through infected people's interactions. Multiple models have been implemented to study the spread of infectious diseases [29]. Different types of mathematical models are used mainly using ordinary differential equations (ODE) [30].These types of models are sufficient for designing infectious diseases. But when we want to use entities called agents to act as a human we need randomness so that the model avoids overfitting. Agents (entities) require randomness in order to avoid overfitting and creating more uncertainty. Mathematical models lack randomness in terms of infection, recovery and death. So we do not implement traditional mathematical models but instead, implement a virtual environment that simulates disease transmission and has randomness [31].

3.1 The virtual environment:

The virtual environment is used to generate states and results based on some particular actions. The virtual environment is designed based on the SIR (Susceptible-Infectious-Recovered) compartmental model. Due to the randomness in various transitions, the virtual environment uses python and MESA ABM. Agent-based models can be built, analyzed, and visualized using Mesa. In agent-based models, multiple entities (agents) act and interact with one another based on their programmed behavior. Living cells, animals, individuals and even entire organizations or abstract entities can be represented by agents.

In addition, the environment sets the way that our agents are going to be able to move (i.e., they can only move like a King in chess), as well as the limits of the environment (in our case, there are no limits since we're modeling a toroidal world). The population can randomly move there. On each day, a fixed number of population (agents) performs a fixed number of random moves based on given actions.

The virtual environment contains four types of entities called agents acting as a human followed by the theory SIR. They are:
Susceptible: People who are currently not infected by the disease but have a possibility of being infected.
Infected: People who are infected by the disease and can infect someone else.
Recovered: People who are cured of the disease and do not have any chance of being infected.
Dead: People who are not cured of the disease lose their lives.

The figure 1 shows:

- Agents (i.e., people) susceptible to infection are shown as green dots
- An agent with red dots is infected
- A black star represents a location in a city, such as an airport, a supermarket, a sightseeing spot, etc. potentially visited by tourists or locals.
- Death agents are not shown.

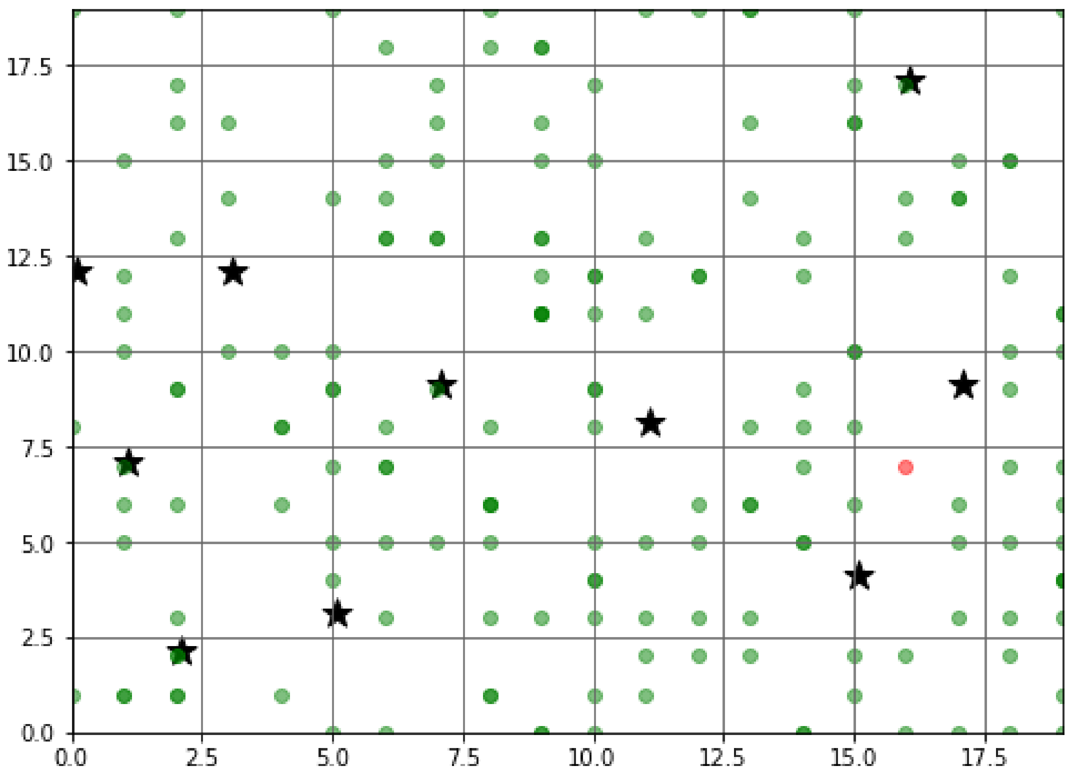

Figure 1. This is a graphic representation of the initial simulation of our virtual environment.

3.2 Transmission stages and stage generation:

In this virtual environment, all agents are susceptible to COVID-19 i.e. initially all agents are suspected of COVID-19. We assume that non-infected agents will visit the places where the infected agent has been (the black stars). So when an agent randomly comes into close contact with an infected agent it gets infected. In the beginning, there is an infected person (red dot) in the environment. After close contact with the infected agent, the susceptible agent is infected randomly and becomes the infected agent. As a result, random agents become infected gradually. After they get infected randomly agents may die or recover. The agent will be dead randomly based on dead probability. Otherwise, the infected agent can be recovered randomly if it survives the whole treatment period i.e.

$$schedule\_time - infected\_at \geq treatment\_period \quad (1)$$

In the equation (1),
$schedule\_time$ = The random time an agent activated to perform in the environment
$infected\_at$ = Time when an agent gets infected
$treatment\_period$ = The time needed for the agent to get recover from the diseases

3.3 Agent Movement

In the model, agents interact with each other and also in the environment based on some given function. They moved in the environment to reach their destination based on their position such as the initial position which is the first position of an agent for example home, target position is their destination for example from home to the airport and set of possible destinations because there are many possible ways to reach their new position. They use the shortest path (Euclidean distance) from among all possibilities. It also ensures the model that not all agents will go to the same place.

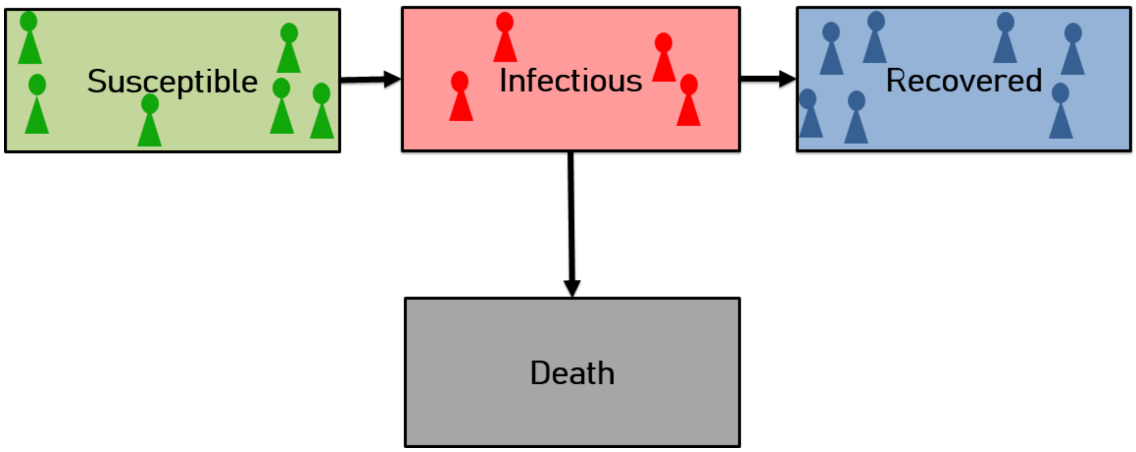

Figure 2. Stage generation of agents.

Figure 2 illustrates stage generation of agents after their movement and close contact based on SIR theory [15]. Agent goes suspect to infectious after close contact with the infected agent, after that some of the infected agents recover if they survive the treatment period otherwise die based on the equation (1)

3.4 Economy rate

According to Bangladesh statistics 2020, the employed population is (15+), million i.e. 60.8 percentage [32]. Most of the country's economically active people are 60 percentage or above [33], [34]. Therefore, we planned that 60 of agents are making money to contribute to the economy. The virtual economy is based on each individual's movement. In other words, if movement restrictions are imposed, they have an impact on the economy as well. When agents start to move they contribute to the economy directly or indirectly. Dead people are not considered for their contribution to the economy. People who did not survive cannot make any further contributions to the economy and remove it from the environment. Finally choosing their destination they started to move and make a contribution to the economy while interacting with each other. Thus they are getting infected when they get close contact with infected people. If they survive until treatment they recover otherwise they die.

3.5 Lockdown pattern

Day-wise lockdown

We give various conditions to agents to find the optimum lockdown pattern. The movement of all agents will stop when agents meet those conditions. In a pandemic situation, the agent will move freely until people start to die and the economy falls due to infectious diseases. The movement restriction will be started and the agent will not move anymore until the movement restriction will stop. To find the optimum result we give random movement restrictions from one to a hundred days to reduce the dead and balance the economy. Day by day we analyze the movement restriction to find the optimum result.

3.6 Virtual environment workflow

Flowchart of our proposed model working in the virtual environment

In figure 3, there is a visual representation of how our model is working in the virtual environment. From the flow chart, we can see there is a COVID-19 model in a virtual environment where the suspect and infected agent are moving randomly. When they have close contact with each other, the suspect

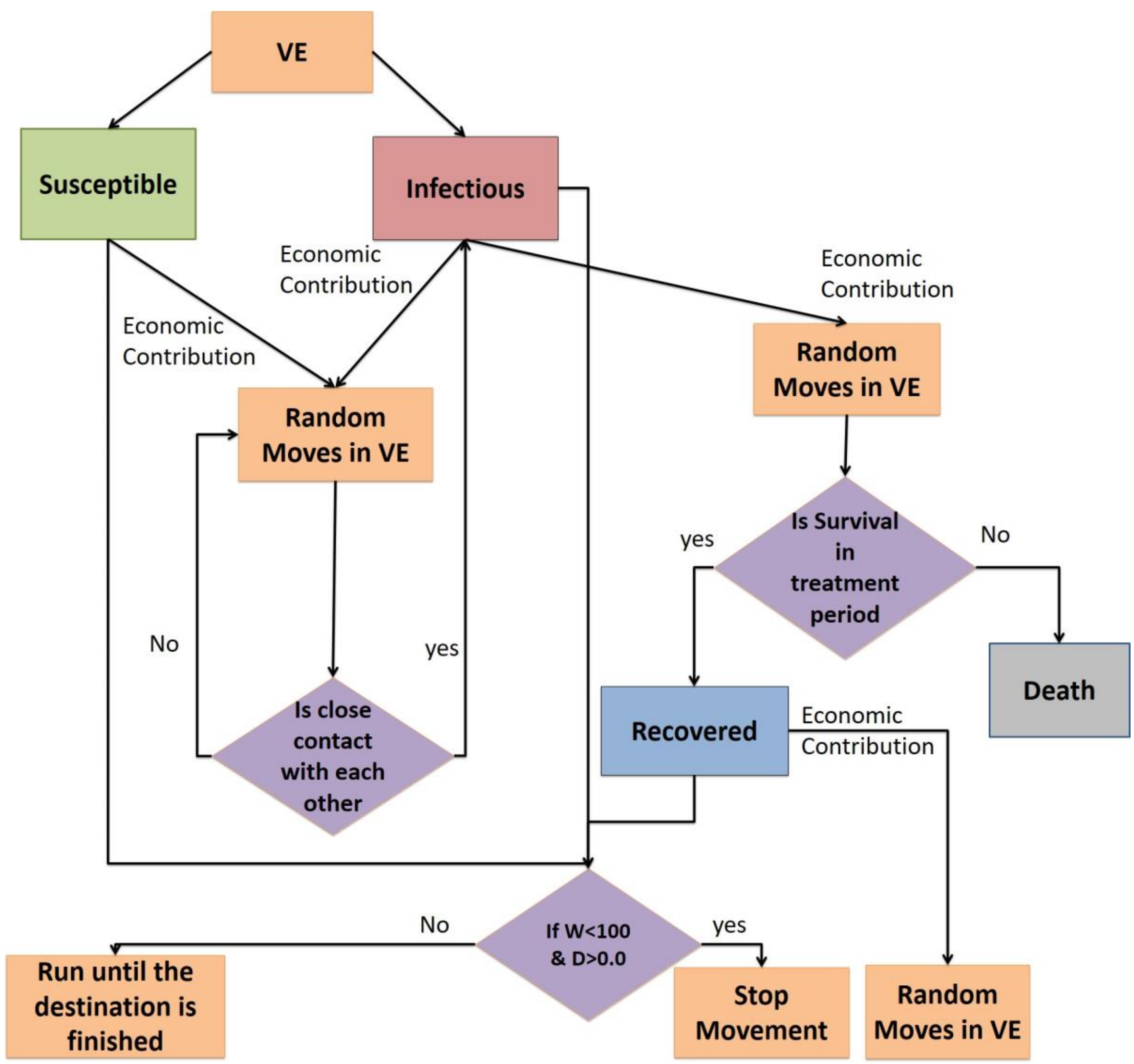

Figure 3. The figure illustrates step-by-step representation of the proposed model.

agent gets infected. If infected agents survive the whole treatment period they are recovered otherwise they die. All the moving agents have contributed to the economy except the dead agent. They move freely until there is a movement restriction. If the economy and death rate is less due to COVID-19 then their agents stop movement in the environment otherwise they continue until reaching their destination.

This is how our model is working in the virtual environment

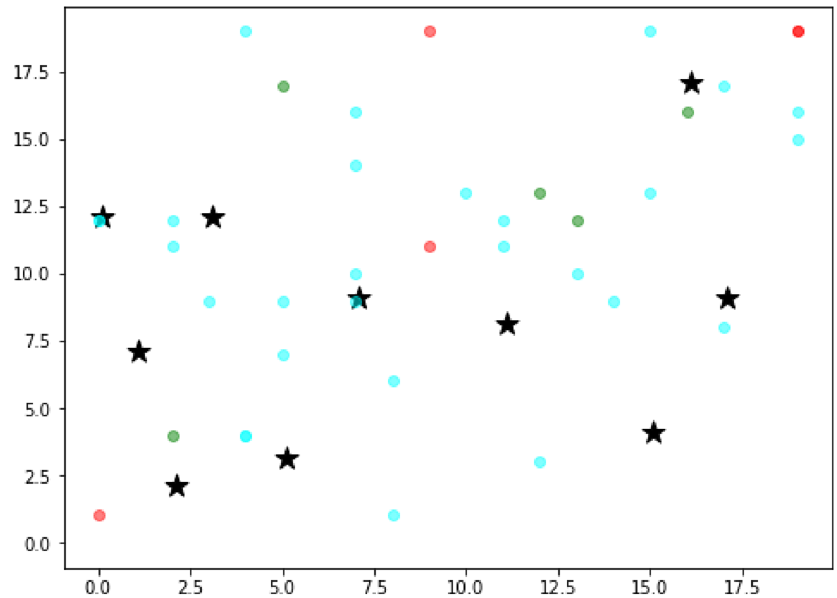

Figure 4. Final simulation of the virtual environment

In the figure 4, the final simulation of our virtual environment's graphic representation is illustrated. In the virtual environment after agents interact with each other and movement in the environment, our model will generate a data set where

•Green dots are agents who are (i.e., people) susceptible to infection

•Red dots are infected agents

•Cyan dots represent agents that have recovered from infection

•Black stars are locations in a city, such as airports, supermarkets, sightseeing destinations, etc., meant to represent the kinds of places a visitor to New Zealand or locals might visit

3.7 The Dataset collection from our model

In our model agents generate random lockdown patterns between one to hundred days and the change of economic rate, the death rate due to lockdown patterns along with the change of infected, suspected, dead, and recovered agents.

Our model's data after processing is as follows

Table 1 and 2 show our sample data set generated from our agent after our recreated model. We give some information to our agents such as infection probability, dead probability, incubation period, treatment period, and destination along with given conditions for finding the lockdown pattern to balance our economy and death rate. According to this information, this data set is generated where sim_destination represents agent destination, D, I, R, S mean dead, infected, recovered, suspected agents, the day column represents random lockdown, and w represents the economic contribution of the agents in the environment, Dead_rate represents the rate of date and rate_w represents economic rate during COVID-19 pandemic. For our model, the incubation period, treatment period, infection probability, and death probability are fixed. However, they can be changed according to any country's data.

The dataset

Table 1. Following the processing of our model data generated by agents through introducing lockdowns

sim-destination	Run	D	Day	Death-rate	I	R	S	W	rate-W	N	width	height	incubation period	treatment period	infection probability	dead probability
1	0	3	72	0.3	37	0	960	598	99	1000	20	20	3	14	0.7	0.05
2	1	1	64	0.1	9	0	990	599	99	1000	20	20	3	14	0.7	0.05
3	2	3	74	0.3	27	0	970	598	99	1000	20	20	3	14	0.7	0.05
4	3	1	93	2.1	86	0	913	599	99	1000	20	20	3	14	0.7	0.05
5	4	1	31	0.1	5	0	994	599	99	1000	20	20	3	14	0.7	0.05
6	5	1	71	0.1	27	0	972	599	99	1000	20	20	3	14	0.7	0.05

Table 2. Following the processing of our model data generated by agents without imposing lockdowns

sim-destination	Run	D	Day	Death-rate	I	R	S	W	rate-W	N	width	height	incubation period	treatment period	infection probability	dead probability
7	6	956	1	95.6	17	27	0	26	4	1000	20	20	3	14	0.7	0.05
8	7	959	1	95.9	10	31	0	24	4	1000	20	20	3	14	0.7	0.05
9	8	954	1	95.4	18	28	0	27	4	1000	20	20	3	14	0.7	0.05
10	9	957	1	95.7	13	30	0	25	4	1000	20	20	3	14	0.7	0.05
11	10	946	1	94.6	35	19	0	32	5	1000	20	20	3	14	0.7	0.05
12	11	952	1	95.2	17	31	0	28	4	1000	20	20	3	14	0.7	0.05

In the table1 and 2

1Sim destination: Sim destination is a set of possible destinations

2D: Dead agents when they could not survive COVID-19 ,

3Day: Random lockdown

4Dead rate: The rate of death after lockdown

5I: Infected agents,

6R: Recovered agents after they survive

7S: Susceptible agents of COVID-19

8Economic contribution (W): Agent movement in the environment expect dead agent

9Economic rate (rate W): The economic rate is 100% when 60% of agents are economically active [32], [33], [34]. As a result of the lockdown and when our economically active 0 people will die due to COVID-19, the rate increases or decreases.

10Population (N) We take a small sample. Our model has 1000 agents.

11Incubation period for the diseases: Most diseases take a minimum of 3 days to start having symptoms after contact with infection [35]. So the incubation period for the diseases is 3 days

12Treatment period: Most infectious disease treatment is 1 to 2 weeks [36]. So we gave a 14 day treatment period.

13Infection probability: We give an infection probability of 0.7 as 60 to 70 percent of Indian People get infected [37].

14Dead probability: We gave the dead probability 0.5 according to India's date rate which was 5 to 6 percentages [38].

4 Result and Discussion

The overall implementation is conducted using Python MESA. The experiments are conducted in a virtual environment implemented on our laptops. Therefore, we experiment with a limited number of 1,000 people and a default daily movement of 100 steps. In this section, we analyze every data from our data set using excel. In our model, we found that different lockdown types had a variety of economic effects and a higher rate of death. The lockdown pattern was increased randomly from one to a hundred days as some countries lockdowns rose to 82 days [39]. We demonstrated the graphical representation of our data in figure 5 and 6.

In the graph figure 5 and 6, the random lockdown pattern begins with 74 days, followed by 71, 32, and 100 days randomly, and continues until the model stops. Whenever the lockdown changes, the number of dead increases, and in some cases, it decreases, as well as the economic contribution. To find out the optimum lockdown pattern for all days we have to analyze all lockdowns individually using excel.

Based on our analysis, we can see how the number of dead and economic contribution changes according to the different types of lockdowns. Lockdown of fewer than two weeks has poor economic contribution due to the high number of economically activated agents dead. Our results improve if the lockdown is increased by more than two weeks. The result gets better in 21 days of lockdown. After 21 days, the number of dead increased again, resulting in the fall of the economy. According to our analysis, 66 days of lockdown resulted in a decent economy and dead results. 77 and 82 days of lockdown have similar results compared to 66 days. 82 days later, the result is not good since people have died and the economy has suffered. We have a small difference due to the small sample size.

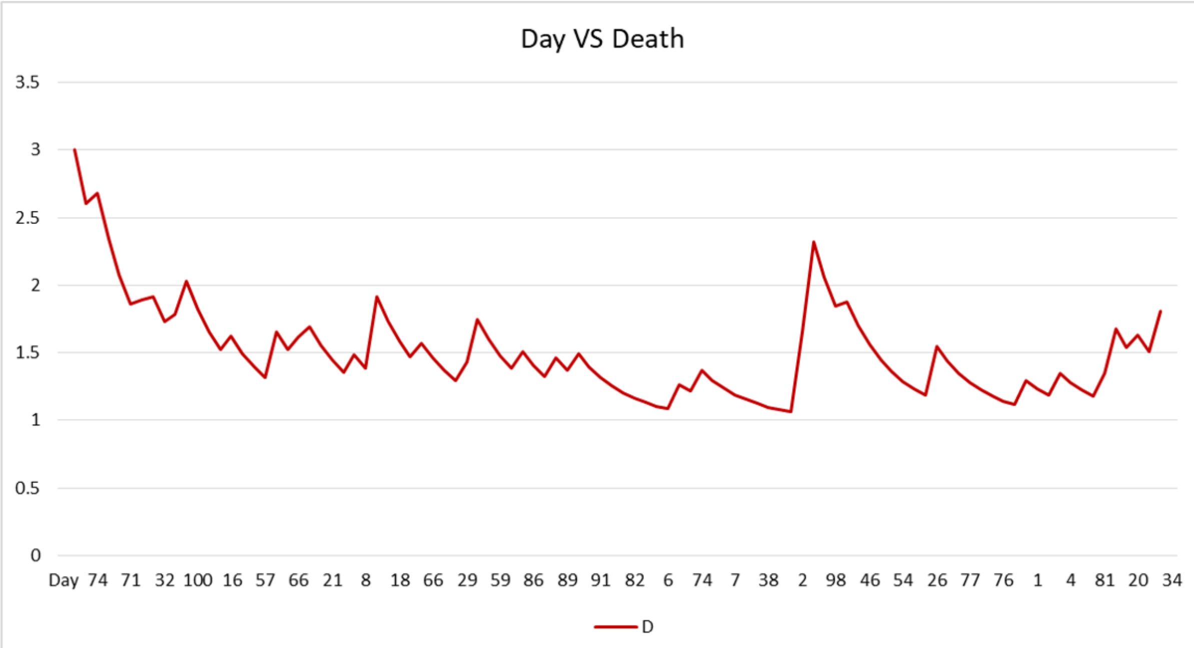

Figure 5. In this graph, the x-axis represents a random lockdown from one to a hundred days. Y-axis represents the change in death due to random lockdown.

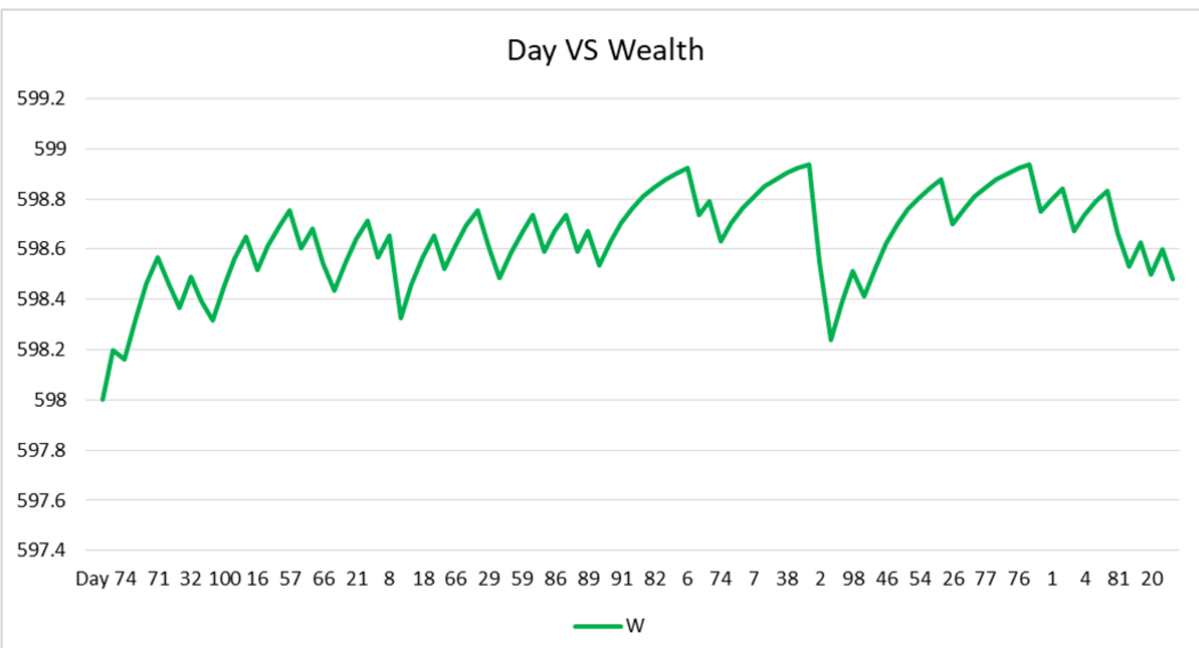

Figure 6. The x-axis represents a random movement restriction between one and a hundred days, while the y-axis represents economic contribution due to random lockdown.

4.1 Without Lockdown

If we run the model without any lockdown, we can see from figure 7 and 8 that the deaths are continuously increasing rather than the random lockdown pattern we applied in our model. Additionally, the economic contribution is continuously declining.

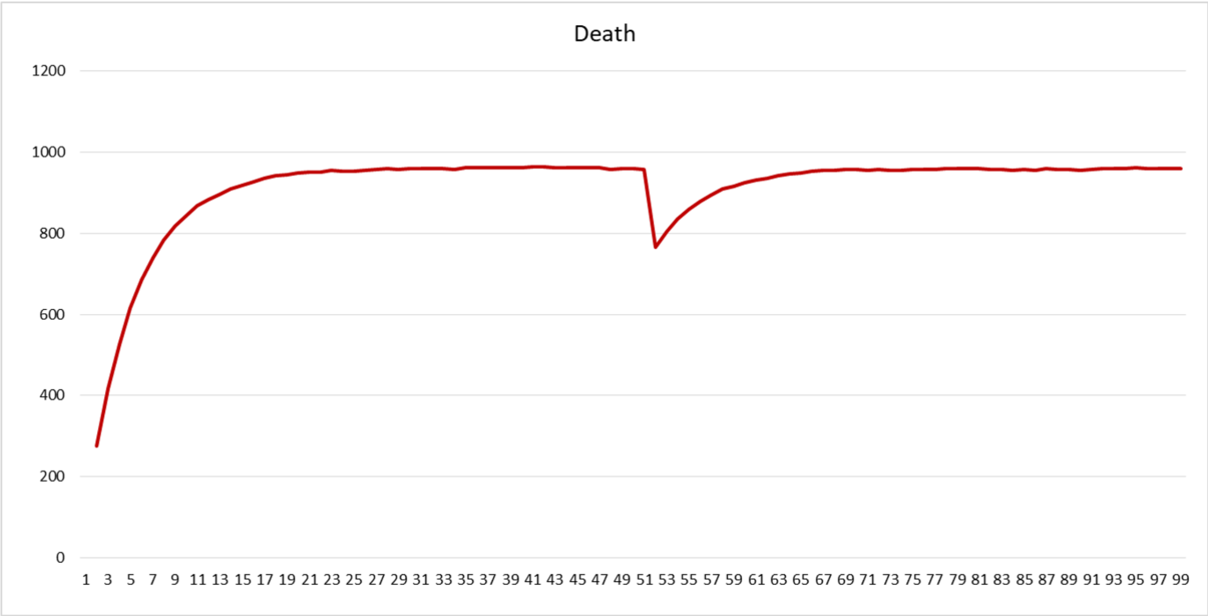

Figure 7. The graph shows the number of Dead (D) without lockdown on the y-axis.

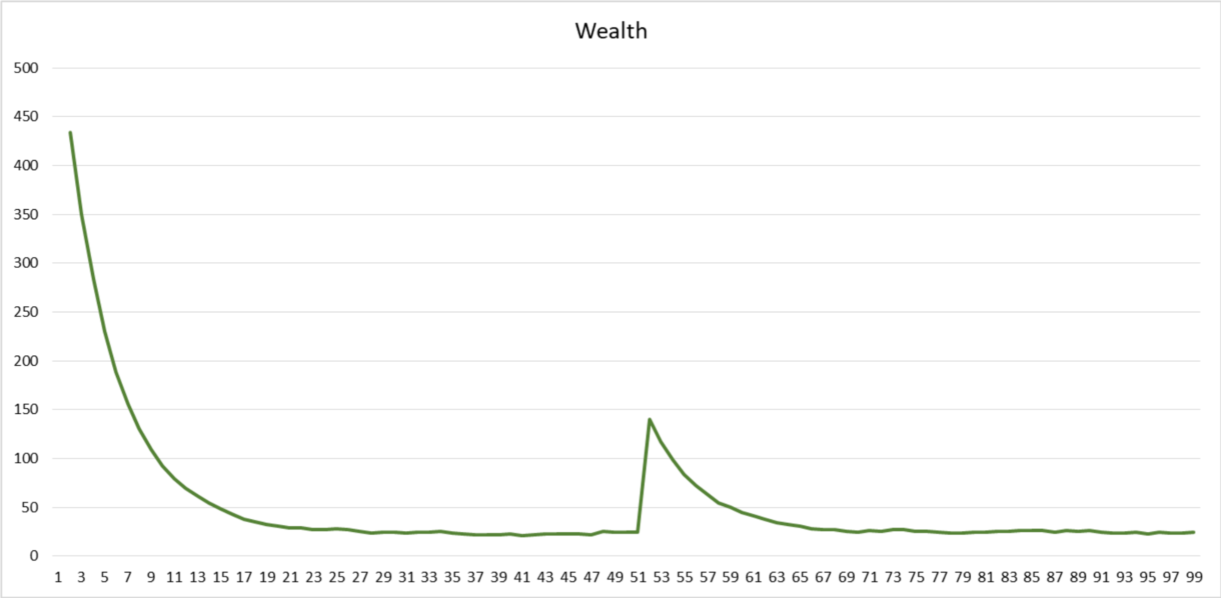

Figure 8. The graph shows the rise/fall of economic contribution (W) without lockdown on the y-axis.

4.2 Model Validation

To evaluate our model and determine if it would work in real-life, we compared it to several countries that applied lockdown patterns, such as India. In recent studies in India, there was research about the impact of various lockdown scenarios on COVID-19 transmission in India. The model was applied to predict COVID-19 transmission in India for different intervention scenarios in terms of lockdown for 4, 14, 21, 42, and 60 days [40]. Bangladesh lifted the lockdown after 66 days because the situation was much more normal than before. So we analyze how our agent works on 66 days of lockdown [41]. With growing reported cases and deaths in the US and other European countries now far outstripping those of China and once unimaginable lockdowns now becoming the norm everywhere, finally, after 77 days of lockdown, Wuhan came back to its normal form with a low infection rate and death rate [42]. In 77 days of lockdown, let's see how our model performs. In Palestine, it was back to normal after 82 days of coronavirus lockdown but enforced control measures such as avoiding crowds and sterilizing properly before or after any human or surface contact [39]. So different countries achieve different types of lockdown to find the best result. We applied all these lockdown patterns to check how our model works on these similar lockdowns. Here's what our validation looks like in the graphical form 9 and 10

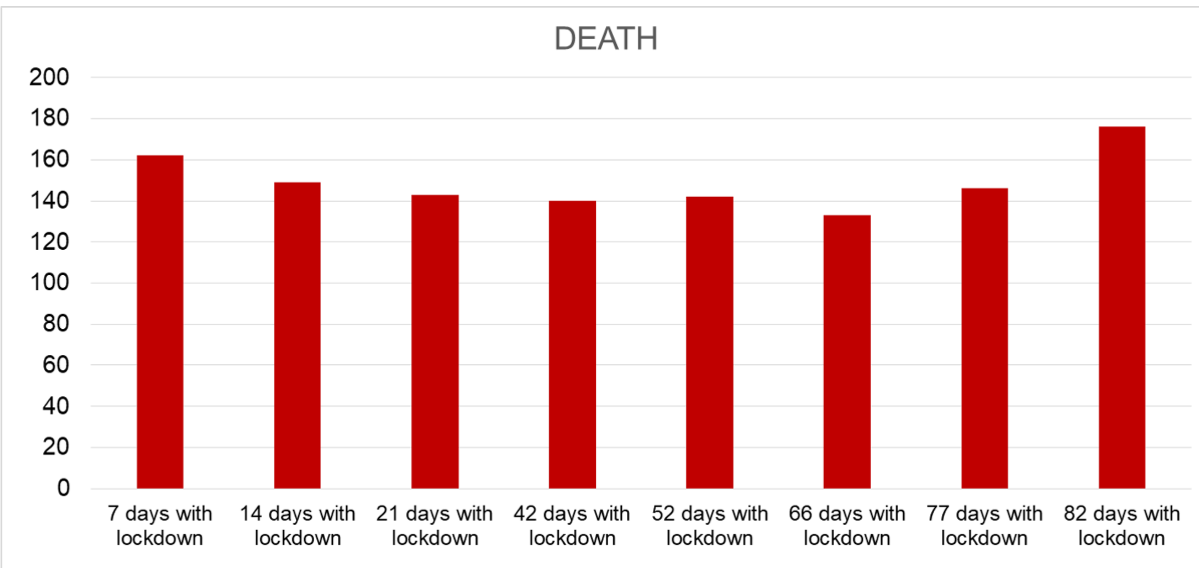

Figure 9. Change of death due to different types of lockdown.

Due to our small sample size, there is less difference between graphs 9 and 10. As a starting point, we compare it to India, a study of the infected populations predicted using the developed model. The model shows that lockdown periods of 4, 14, 21, 42 and 60 days were implemented and no significant changes in the infected population were observed in 4 and 14 days of lockdown. Other than that there were noticeable changes in the number of infected cases with lockdown periods of 21, 42, and 60 days. In the first 42 days of lockdown, the predicted cases were reduced from 378036 (non-intervention) to 70, 424 at 110 days. In the second time of placing 42 days of lockdown, the number decreases even more to 42950. The changes in predicted infectious rate were quite similar in 42 days and 60 days of lockdown. When we give 7 and 14 days of lockdown in our model 162 and 149 people died out of 74000 agents respectively where the total economic contribution is 59257 and 59265 respectively. In our model, in 21 days of lockdown 143 agents died out of 74000 agents, in 42 days of lockdown which is 140, the agent's total contribution to the economy is 59271 and 59269 respectively. Though the change is not

Figure 10. The economic impact of various types of lockdown patterns.

massive due to the small dataset, we can see the model performs well in 21 and 42 days compared to 7 and 14 days. The dead and economic contribution is better in 21 and 42 days lockdown which reduces the number of dead people from 162 to 140 out of 74000 agents in our environment and the economic contribution rises up from 59265 to 59269. As in India, the change between 42 and 60 is quite similar so we perform a lockdown between them which is a 52 days lockdown. In 52 days our dead agents are 142 and our economic contribution is 59269 which is quite similar to 42 lockdowns. We can tell from Indian research and our model that the change is quite similar from 7 days to 60 days of lockdown.

In Bangladesh, after 66 days of lockdown, Bangladesh lifted the lockdown because the situation was much more normal than before. In our model, in 66 days the dead agents out of 74000 agents are 133 and the economic contribution is 59269. The model performed well on 66 days of lockdown. The death rate reduces from 162 to 133 out of 74000 agents but the economic contribution is quite similar. We can see from our model that 66 days is better than all the previous lockdowns. After 77 days of lockdown, Wuhan came back to its normal form with a low infection rate and death rate. In our model, 146 agents died, and the economic contribution is 59267 when we give 77 days of lockdown. Here dead agents increase compared to the 66 days lockdown pattern. So we increase the lockdown days up to 82 days as Palestine is back to normal after 82 days of coronavirus lockdown. In our model, we have seen that for 82 days of lockdown the deaths are 176 and the economic contribution is 59247. We can see that 66 days of lockdown give us the best result compared to all types of lockdown. In 66 days the deaths are reduced and the economic contribution rises. Our model did not give us the best result for 77 and 82 days. We compare all the lockdown patterns below to find out the best pattern. We can see from figure: 9 that the dead fall from 21 days to 66 days after that the dead suddenly rises. Figure: 10 shows that economic contributions increase from 21 days, then slightly fall in 42 and 52 days, then rise once again in 66 days, then fall again in 77 and 88 days. When we do not lock down our model, the death rise to 92138, and the economic contribution falls to 4074.

A 66-day lockdown produces the best results for our model. In 66 days we can find all the best results for death. The number is 133, a very low number compared to others, and the economic contribution is 59279 which is the highest value among all of those days. After 66 days in 21, 42, and 52 days the number of deaths and wealth value is quite similar. Accordingly, the death value for 21 days is 143, which is not less than the number of dead for 66 days, and the economic contribution for 21 days is 59269, which is also not the highest wealth value. Seven and fourteen-day lockdowns have a higher death toll and a lower economic impact. 77 and 82 days of lockdowns did not yield satisfactory results. We then compare those lockdown patterns to the random pattern generated by our model and see a similar pattern. According to our analysis, our random lockdown pattern results in the best results after 66 days and 21 days. We also achieve better results in our random lockdown pattern when 41 days or 43 days of lockdown are implemented. 42 days of lockdown was a good solution in India. As you can see from the following table: 3, we have summarized our results and validated them based on our analysis.

Table 3. Model validation compared to actual results

Lockdown	Country	Countries' real-life scenarios	Model validation
4,14,21,42 and 60 days	India	The lockdown lasted for 4 and 14 days without any significant changes. When lockdown periods were 21, 42, and 60 days, there was a considerable change in the number of infected cases. The changes in predicted infectious rate were quite similar in 42 days and 60 days of lockdown [40]	In the event of a lockdown lasting less than two weeks, the economic contribution is poor since there are many economically activated Agents dead. Our results improve if the lockdown is extended by more than two weeks. After 21 days of lockdown, the results improve. The results are pretty similar between 42 and 60 days.
66 days	Bangladesh	In Bangladesh, the lockdown was lifted after 66 days because the situation was much better Then before [41].	66 days is better than previous lockdowns according to our model.
77 days	Wuhan, China	Wuhan returned to normal after 77 days of lockdown with low infection and death rates [42]	Compared to 66 days of lockdown, our model did not perform well in 77 days movement restriction.
82 days	Palestine	The situation in Palestine had returned to normal after 82 days of Coronavirus lockdown [39]	Our model performed poorly in 82 days of movement restrictions compared to previous lockdown days.

The COVID-19 outbreaks have disrupted daily routines and also impacted the global economy in a significant way. Moreover, these issues have motivated us to create an optimal lockdown pattern that balances the economic rate and death rate. Therefore we have validated the model through various analyses to find out the optimum lockdown pattern. We compared the lockdown pattern of different countries to prove that the lockdown pattern of our model is validated. However, we have validated our model with India, Bangladesh, China, and Palestine. By using these models any country finds a lockdown pattern by changing the parameters like age-based infection rate, death rate, and total population number. In our model, we have some limitations. One limitation was the limited and tempered data of COVID-19 measures such as infection rate, total death, and so on. Clinical trials of COVID-19 disruption were missing data, disrupted timelines and random patient population changes, and many infected people who didn't take a test of COVID-19 but eventually spread the disease is unknown in measurements of official infection rate and death rate so the model faced the problem of scarcity of real portion of data. It was also impossible for us to collect diversity-related data for our models such as the COVID-19 mortality rate and the infection rate that is different for different regions of the world. If we look into the economic unit which is per head income is different in different countries as well which affects the pattern generation of our model. It is quite hard for us to test our model for all kinds of dynamic data due to data limitations.

5 Conclusion

This study is about motivating the reader to understand the application of virtual environment and agent-based modeling to create a transmitted disease-like scenario. By analyzing the death rate, total economic contribution and other related parameters lockdown patterns can be placed in the environment. We consider our suggested plan to be persuasive in attaining the best decision while balancing the out- of-control pandemic and economic scenario. We have a strong conviction that the contribution made by this research project will bring together the study of epidemics and agent-based modeling, thereby strengthening the human race's ability to fend off pandemic crises.

To replicate a pandemic scenario, we conduct the experiments in a computer-generated environment. Therefore, we experiment with a limited number of 1,000 people or agents. In our most recent model, each agent's economic contribution is static and equal. In order to achieve the best optimum result in future, we wish to continue our studies with different conditions. For this, we apply zone-based lockdown individually for 21, 42, 52, 66, 77, 82 days of lockdown respectively instead of full lockdown. In the future, we will apply dynamic economic parameters along with zone-based lockdown in our model to ensure the best possible outcome.

References

[1] X. Lu and Z. Lin. Covid-19, economic impact, mental health, and coping behaviors: a conceptual framework and future research directions. *Frontiers in Psychology*, 12:1–9, November 2021.

[2] C. Ekpanyaskul and C. Padungtod. Occupational health problems and lifestyle changes among novice working-from-home workers amid the covid-19 pandemic. *Safety and health at work*, 12(3):384–389, 2021.

[3] M. G. Wheaton, J. S. Abramowitz, N. C. Berman, L. E. Fabricant, and B. O. Olatunji. Psychological predictors of anxiety in response to the h1n1 (swine flu) pandemic. *Cognitive Therapy and Research*, 36(3):210–218, 2012.

[4] V. Gupta-Smith and S. Briand. Episode 59 - flu covid-19. WHO, October 2021. https://rb.gy/bkfq50[Online; Accessed on 13-Oct-2022].

[5] Infectious diseases. The World Bank, September 2022. https://rb.gy/6wnbrj[Online; Accessed on 17- Oct-2022].

[6] How do vaccines work? Who, December 2020. https://rb.gy/tjp5h5[Online; Accessed on 17-Oct- 2022].

[7] Vaccine development, testing, and regulation. The College of Physicians of Philadelphia, May 2022. https://urlzs.com/mGnBg[Online; Accessed on 17-Oct-2022].

[8] B. Espinoza, C. Castillo-Chavez, and C. Perrings. Mobility restrictions for the control of epidemics: When do they work? *Plos one*, 15(7):e0235731, July 2020.

[9] R. Anderson, H. Heesterbeek, D. Klinkenberg, and T. Hollingsworth. How will country-based mitigation measures influence the course of the covid-19 epidemic? *The lancet*, 395(10228):931–934, March 2020.

[10] M.Farrer. China places millions into covid lockdown again as economy continues to struggle. The Guardian, August 2022. https://rb.gy/gykjaw[Online; Accessed on 17-Oct-2022].

[11] Economic impact of the covid-19 pandemic in the united state. Wikipedia, September 2022. https://rb.gy/iqx28u[Online; Accessed on 17-Oct-2022].

[12] N. Bohorquez. Complex system simulation with python: How does covid spread? Activestate, March 2021. https://www.activestate.com/blog/simulating-complex-systems-with-python- how-does-covid-spread/[Online; Accessed on 17-Oct-2022].

[13] Agent-based model. Wikipedia, June 2022. https://en.wikipedia.org/w/index.php?title=Agent- based model&oldid=1092258368[Online; Accessed on 17-Oct-2022].

[14] D. Masad, J. Kazil, and W. Boyu. Introductory tutorial mesa. Mesa, 2022. https://mesa.readthedocs.io/en/latest/tutorials/intro tutorial.html[Online; Accessed on 17-Oct- 2022].

[15] Jaredroach. Compartmental models in epidemiology. Wikipedia, August 2022. https://rb.gy/5dshnm[Online; Accessed on 17-Oct-2022].

[16] Supplemental data measuring the effects of the coronavirus (covid-19) pandemic on the labor market. U.S. Bureau of Labor Statistics, October 2020. https://rb.gy/7htklw[Online; Accessed on 13-Oct-2022].

[17] Habib and R. B. Karim. Covid-19 fallout: 68% lost jobs in dhaka and ctg. The Daily Star, September 2020. https://rb.gy/knvagy[Online; Accessed on 17-Oct-2022].

[18] D. Acemoglu, V. Chernozhukov, I. Werning, and M. Whinston. Optimal targeted lockdowns in a multigroup sir model. *American Economic Review: Insights*, 3(4):487–502, 2021.

[19] O. Karin, Y. M. Bar-On, T. Milo, I. Katzir, A. Mayo, Y. Korem, B. Dudovich, E. Yashiv, A. J Zehavi, N. Davidovitch, et al. Cyclic exit strategies to suppress covid-19 and allow economic activity. *MedRxiv*, pages 1–23, April 2020.

[20] S. Sivasubramanian. How ai and machine learning are helping to fight covid-19. The World Economic Forum COVID Action, 2020. https://urlzs.com/JyP2n[Online; Accessed on 17-Oct-2022].

[21] A. Q. Ohi, M. Mridha, M.M. Monowar, M. Hamid, et al. Exploring optimal control of epidemic spread using reinforcement learning. *Scientific reports*, 10(1):1–19, December 2020.

[22] A. Ghosh, S. Roy, H. Mondal, S. Biswas, and R. Bose. Mathematical modelling for decision making of lockdown during covid-19. *Applied Intelligence*, 52(1):699–715, 2022.

[23] P. Teles. Predicting the evolution of sars-covid-2 in portugal using an adapted sir model previously used in south korea for the mers outbreak. *arXiv preprint arXiv:2003.10047*, March 2020.

[24] M. Al-Zoughool, T. Oraby, H. Vainio, J. Gasana, J. Longenecker, W. Al Ali, M. AlSeaidan, S. Elsaadany, and M. G. Tyshenko. Using a stochastic continuous-time markov chain model to examine alternative timing and duration of the covid-19 lockdown in kuwait: what can be done now? *Archives of Public Health*, 80(1):1–8, January 2022.

[25] J. P. Caulkins, D. Grass, G. Feichtinger, R. F. Hartl, P. M. Kort, A. Prskawetz, A. Seidl, and S. Wrzaczek. The optimal lockdown intensity for covid-19. *Journal of Mathematical Economics*, 93(12):102489, March 2021.

[26] M. Yang, L. Shi, H. Chen, X. Wang, J. Jiao, M. Liu, J. Yang, and G. Sun. Critical policies disparity of the first and second waves of covid-19 in the united kingdom. *International journal for equity in health*, 21(1):1–11, August 2022.

[27] M. Stephens, H. Wright, and G. Luckwell. Coronavirus and the impact on output in the uk economy: December 2020. Office for National statistics, February 2021. https://rb.gy/ocqrka[Online; Accessed on 13-Oct-2022].

[28] M. Oliu-Barton and B. Pradelski. Green zoning: An effective policy tool to tackle the covid-19 pandemic. *Health Policy*, 125(8):981–986, August 2021.

[29] F. Brauer. Compartmental models in epidemiology. In *Proc. of the Mathematical epidemiology*, volume 1945 of *Lecture Notes in Mathematics*, pages 19–79. Springer-Verlag, 2008.

[30] B. Yong and L. Owen. Dynamical transmission model of mers-cov in two areas. In *Proc. of the Third Conference on Industrial and Applied Mathematics (CIAM '15),Bandung, Indonesia*, volume 1716, page 020010. AIP Publishing LLC, October 2016.

[31] ActiveState platform. ActiveState Software, 2022. https://rb.gy/0opin8[Online; Accessed on 17-Oct- 2022].

[32] Bangladesh statistics 2020. bbs, 2020. https://bbs.portal.gov.bd/sites/default/files/ files/bbs.portal.gov.bd/page/a1d32f13 8553 44f1 92e6 8ff80a4ff82e/2021-05-14-06-22- 47723b0e1476ed905d1c121f8f07d935.pdf?fbclid=IwAR0-ejUx bUYHd8oUQ9eBClfecUuefoAV6- JkRMNM44i 1zM3P6bm3XYa6k[Online; Accessed on 14-Oct-2022].

[33] ILO. More than 60 per cent of the world's employed population are in the informal economy. International Labour Organization (ILO), April 2018. https://www.ilo.org/global/about-the-ilo/newsroom/ news/WCMS 627189/lang--en/index.htm[Online; Accessed on 17-Oct-2022].

[34] A. Hayes. Labor force participation rate. Investopedia, September 2022. https:// www.investopedia.com/terms/p/participationrate.asp[Online; Accessed on 17-Oct-2022].

[35] Infection exposure questions. Seattle Children's Hospital, September 2022. https:// www.seattlechildrens.org/conditions/a-z/infection-exposure-questions/[Online; Ac- cessed on 17-Oct- 2022].

[36] F. D. Brodkey. Mild to moderate covid-19 discharge. MedlinePlus, August 2022. https:// medlineplus.gov/ency/patientinstructions/000976.htm[Online; Accessed on 17-Oct-2022].

[37] 70% of indian population had covid-19, rest at high risk: Survey. The Daily Star, September 2021. https://rb.gy/3qhxlq[Online; Accessed on 17-Oct-2022].

[38] A. Ghosh. In covid's first year, india's total death rate was same 6% as in 2019, govt data shows. The Print, May 2022. https://rb.gy/kmhqyr[Online; Accessed on 17-Oct-2022].

[39] Huaxia. Life in palestine back to normal after 82 days' coronavirus lockdown. Xinhua, May 2020. https://rb.gy/6wgekb[Online; Accessed on 13-Oct-2022].

[40] B. Ambikapathy, K. Krishnamurthy, et al. Mathematical modelling to assess the impact of lockdown on covid-19 transmission in india: Model development and validation. *JMIR public health and surveillance*, 6(2):e19368, May 2020.

[41] Covid-19 timeline in bangladesh. Better Work. https://betterwork.org/portfolio/covid- timeline-in- bangladesh/[Online; Accessed on 17-Oct-2022].

[42] J. Li. Wuhan's traumatized residents warn that the lifting of lockdowns is "not the end". Quartz, April 2020. https://qz.com/1834119/wuhan-china-lifts-coronavirus-lockdown-after-77- days/[Online; Accessed on 13-Oct-2022].

Author Biography

Fariha Sultana Rini was born in Lalbagh,Dhaka. She received B.Sc degree in Computer Science and Engineering from University of Asia Pacific in 2022. Her research interests include machine learning, deep learning, data science, artificial intelligence and bioinformatics.

Somiya Assir Jebin was born in Jatrabari,Dhaka. She received B.Sc degree in Computer Science and Engineering from University of Asia Pacific in 2022. Her research interests include machine learning, deep learning, artificial intelligence, internet of things and image Processing.

Merajunnesa kumkum was born in Rangamati,Chittagong. She received B.Sc degree in Computer Science and Engineering from University of Asia Pacific in 2022.Her research interests include machine learning, deep learning, artificial intelligence, internet of things and Artificial Neural Network.

Md. Rajibul Islam obtained his Bachelor of Computer Applications (BCA) degree from Indira Gandhi National Open University in New Delhi, India, in 2004, and his Master of Science in Information Technology (Biometric Image Processing) degree from Multimedia University in Malaysia (MMU) in 2010. Following that, he began his professional career as a Research Assistant, Software Engineer, and so on in many universityresearch institutes and R and D at Malaysian software firms. Returning to academia as a Ph.D. candidate in 2017, he was awarded his Ph.D. in Physics (Photonics Engineering) from the Photonics Research Centre, University of Malaya (UM). He currently works as an Associate Professor in the Department of Computer Science and Engineering at the Bangladesh University of Business and Technology (BUBT). He formerly served as an Assistant Professor and Head of the Department of Computer Science and Engineering at the University of Asia Pacific (UAP). In addition, he was a Visiting Ph.D. Researcher at the University of Limerick in Ireland as part of the Erasmus Mundus INTACT Program at the end of 2016. His research interests include Machine learning, Artificial Intelligence, and Data mining.

Nadeem Ahmed is an Assistant Professor at the department of Computer Science and Engineering, University of Asia Pacific (UAP). Also, he is a PhD student at Bangladesh University of Professionals (BUP), Dhaka, Bangladesh. He received the B.Sc. in computer science and engineering from the University of Dhaka, Dhaka, Bangladesh, in 2008. He completed the M.S. degree in Computer Science from the Queen Mary, University of London, UK, in 2014. He worked as a software engineer from 2008 to 2012 years. In the meantime, he did MBA from Independent University, Bangladesh. In 2013, he joined as a lecturer in Dhaka International University, Dhaka. His research interests include Machine learning, Cybersecurity, and system design. He is a member of IEEE.

Md Amiruzzaman is an Assistant Professor in the Department of Computer Science at West Chester University. Prior to joining WCU, he worked as a software developer for almost 10 years for several companies. He has also held the position of Assistant Professor at Kent State University. He has completed his Bachelor's Degree in Computer Science from National University. Along with that, he has completed three Master's degrees, majoring in Computer Engineering in 2008 from Sejong University, Computer Science in 2011 from Kent State University and Technology in 2015, also from Kent State University. He received his Ph.D. degrees from Kent State University in 2016 (Mathematics Edu), 2019 (Evaluation and Measurement) and 2021 (Computer Science). In the past, he has worked as a Research Assistant at Sejong University and Korea University. Along with that, he gained the opportunity to teach at both National University and Korea University. His research interests include Visual Analytics of urban data, Data Mining, Machine Learning, Deep Learning and Data Hiding.

Halima Khatun received her B.Sc. and M.Sc. degree in Public Health and Informatics from Jahangirnagar University, Dhaka, Bangladesh in 2017 and 2019, respectively. Her current research interests include Infectious disease and Noninfectious disease, Nutrition, Child and Adolescent health, and Mental health.