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Seesaw scenarios of lockdown for COVID-19 pandemic: Simulation and failure analysis

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ABSTRACT

The ongoing COVID-19 (SARS-CoV-2) outbreak has had a devastating impact on the economy, education and businesses. In this paper, the behavior of an epidemic is simulated on different contact networks. Herein, it is assumed that the infection may be transmitted at each contact from an infected person to a susceptible individual with a given probability. The probability of transmitting the disease may change due to the individuals’ social behavior or interventions prescribed by the authorities. We utilized simulation on the contact networks to demonstrate how seesaw scenarios of lockdown can curb infection and level the pandemic without maximum pressure on the poor societies. Soft scenarios consist of closing businesses 2, 3, and 4 days in between with four levels of lockdown respected by 25%, 50%, 75%, and 100% of the population. The findings reveal that the outbreak can be flattened under softer alternatives instead of a doomsday scenario of complete lockdown. More specifically, it is turned out that proposed soft lockdown strategies can flatten up to 120% of the pandemic course. It is also revealed that transmission probability has a crucial role in the course of the infection, growth rate of the infection, and the number of infected individuals.

1. Introduction

Humankind has always faced a wide variety of natural challenges. Infectious viruses have always been part of these problems. While devastating pandemics were being forgotten thanks to advances in medical science, the COVID-19 outbreak changed the story completely. To reduce the consequences of the epidemic, local governments and international organizations are adopting and promoting extensive measures to curb the process. However, these policies are often accompanied by widespread civil resistance, especially when they lead to business closures and livelihood difficulties.

The rate of the Covid-19 incidence is such that it left governments with little time for sustainable response (Anderson, Mckee & Mossialos, 2020). Research by Shulla, Voigt, Cibian, Scandone and Martinez (2021) clarified a unique pattern of correlation between sustainable development goals related to the quality of education, workforce and wellbeing, consumption and production, economic growth, and climate action attributed to implications of the COVID-19 pandemic.

The most crucial challenge for officials in health organizations during the epidemic is developing and using models for predicting and managing the peaks of the epidemic. Modeling, forecasting, and controlling infectious diseases has a very long history. In this regard, models based on dynamic systems have been at the forefront in terms of variety and application (Dimitrov & Meyers, 2014; Rainisch, Undurraga & Chowell, 2020). However, in the last two decades, thanks to extensive advances in the computational power of computers and machine learning techniques, network-based approaches (Castañeda, Caputo, Cruz-Pacheco, Knippel & Moutamid, 2021; Feng, Zhao & Zhou, 2020; Mansour, Kin, Said, Said & Atkinson, 2021; Sharkey, 2011) and agent-based tracing (Marini, Brunner, Chokani & Abhari, 2020) have found a special place.

Upon the invasion of COVID-19 to all major cities globally, a tremendous amount of research is being conducted in various subject areas to respond to the urgent call for action against the unprecedented situation caused by the COVID-19 pandemic. A better part of these research works is aimed at helping the more resilient and sustainable development of urban planning (Sharifi & Khavarian-Garmsiret, 2020). Kutela, Novat and Langa (2021) surveyed the geographical distribution of the research themes related to COVID-19 and the transportation sector using a text network approach. It turned out that most of the published papers in this area from the USA, China, Japan, and the UK. Although the COVID-19 pandemic has challenged the world economy,
some studies have sought to turn the pandemic threats into opportu-
nities, specifically the positive effect on the environment because of
decreasing greenhouse gas emissions (Oncioiu, Duca, Postole, Geor-
gescu & Gherghina, 2021).

Moreover, the short-term benefits of reducing air pollution due to
complete lockdown and cumulative shocks of demand and supply have
valuable lessons to learn for sustainable development for the post-
pandemic recovery period (Dasgupta & Srikanth, 2020). Ranjbari,
Shams Esfandabadi, Zanetti, Scagnelli and Siebers (2021) surveyed
implications of the COVID-19 pandemic crisis for sustainability from
various perspectives, including social, environmental, and economic
dimensions based on the triple bottom line architecture. Griffiths,
Furszyfer Del Rio and Sovacool (2021) examined opportunities and a
mix of policies that can stimulate a transition to sustainable mobility
after the COVID-19 crisis. Kim (2021) investigated the spatial data
analysis between emerging COVID-19 and urban characteristics, taking
into account the socio-ecological aspects that revealed spatial depen-
dence and spatial clusters in South Korea with 14 urban characteristics
and analyzed 225 spatial units. Li, Ma and Zhang (2021) addressed the
association between built environment attributes and the incidence of
COVID-19 in China. They proposed a mixed geographically weighted
regression model considering both the inter-and intra-city attribute,
which highlighted that population density and the percentage of the
aging people are associated with the spread.

While an in-depth analysis of the COVID-19 long-term detrimental
effects on social sustainability has to be addressed, the short-term goal of
societies is to respond to the urgent call for action against the crisis. For
this purpose, it is necessary to have up-to-date information on the dy-
namics of disease spread so that limited resources and facilities are best
planned. Gupta, Jain, Taneja, Chaudhary and Khari (2021a) developed a
predictive model of confirmed and death cases of COVID-19 for the next
30 days in India based on a deep learning algorithm that consists of two
long short-term memory layers. Mansour, Al-Kindi, Al-Said, Al-Said and
Atkinson (2021) applied a spatial modeling framework to examine the
correlation between prevalence rates and socio-demographic de-
terminants in Oman. Among a set of 11 factors, older people, popula-
tion density, diabetes rates, and available beds in hospitals were turned
out to be statistically significant determinants. Zivkovic, Bacanin, Ven-
katapultam, Nayar and Djordjevic (2021) utilized a novel hybridized
algorithm for predicting new cases of COVID-19 by integrating machine
learning, adaptive neuro-fuzzy inference system, and enhanced beetle
antennae search swarm intelligence. Gupta, Jain, Arora, Gupta and
Awan (2021b) analyzed the effect of COVID-19 on Indian states and
Union Territories, taking into account density and cultural diversity. The
authors developed a predictive regression model whose performance
was measured by using three machine learning regression algorithms.

Social distancing has been one of the public measures prescribed by
local health authorities and global health authorities. Extensive research
has also been devoted to preventing or slowing down the transmission of
the disease. In this area, Ahmed, Ahmad and Jeon (2021a) proposed a
framework based on deep learning architecture for monitoring and
controlling transmission of the COVID-19 pandemic. The overall struc-
ture of their method has two modules, including the distance monitoring
and human detection module. In addition, Ahmed, Ahmad, Rodrigues,
Jeon and Din (2021b) developed a deep learning framework to track
social distancing using an overhead perspective followed by the transfer
learning approach to improve overall efficiency. Their proposed plat-
form taught the YOLOv3 object recognition algorithm to recognize humans in video sequences. Sun and Zhai (2020) addressed two crucial
indices for quantitatively evaluating social distancing and ventilation
effectiveness in preventing transmission of respiratory disease infection
like COVID-19. Su, He, Qing, Niu and Cheng (2021) proposed a visual
social distancing method in urban public spaces that considers both
Euclidean distance between tracking objects from a static perspective
and Frechet distance between trajectories to estimate and analyze the
social distancing. Fu and Zhai (2021) applied the geographically and
temporally weighted regression model to examine the association be-
tween conventional social vulnerability indicators and social distancing
in New York City. Their results revealed that public reactions to the
COVID-19 pandemic vary and change dynamically over space and time.

Vaccination has been considered a meaningful way to prevent and
control the pandemic since the beginning of this year and with the first
signs of successful Pfizer and Moderna tests. Jadidi, Jamshiditha, Mas-
roori, Moslemi and Mohammadi (2021) developed a strategy for
vaccination that prioritizes the individuals to maximize the total im-
munity among the population. Their two-step method, which applies
graph theory and contact tracing data obtained from wireless commu-
nication networks, resulted in a 30% drop in the number of infected
individuals compared with random vaccination.

In the current paper, we seek to use stochastic simulation on different
types of contact networks to show how a middle-ground strategy can
flatten the peak of an epidemic without shutting down businesses
completely. The proposed solution is particularly a middle ground pol-
icy for developing countries whose administrations cannot support indi-
viduals affected by the recession. The remainder of this text is
organized as follows. Section 2 describes the challenges of COVID-19 for
underdeveloped and least developed countries. Section 3 presents the
implemented simulation on contact networks. Findings from the nu-
meral analysis are reported in Section 4. Section 5 concludes the study.

2. The COVID-19 pandemic in developing countries

Over the past year or so, the COVID-19 pandemic has severely
altered all health, administrative and educational systems (McKee &
Stuckler, 2020). At the starting point, the similarity of symptoms of the
COVID-19 to the flu and other respiratory diseases put the individuals in
the purgatory of the illness and its woes (Samson, Navale & Dharne,
2020). Various governments have made numerous efforts to control the
outbreak, from closing schools, cafes, and businesses to introducing
social distancing measures and masks in public places (Intawong et al.,
2020; Rahmani & Hosseini Mirmahaleh, 2021). Some countries like
Australia, New Zealand, China, and Japan, backed by solid economies
and social structures, managed the crisis with minimal aftermath. On the
other hand, many countries, including least developed countries (LDCs)
do not have the financial capacity to support closed businesses during
the full lockdowns. For many of these societies, the COVID-19 pandemic
crises has caused so much damage that they will never seem to return to
the ‘old-normal’ (Barneveld, Quinlan, Kriesler & Junor, 2020).

According to the United Nations, more than 32 million people in the
world’s poorest countries are on the verge of returning to absolute
poverty, which is defined based on having an income lower than $1.90
per day. On the other hand, this figure is estimated at 207 million by
2030 if this epidemic crisis continues (United Nations, 2020). Although
the relevant organizations promise economic aid after the COVID-19
crisis, minimum requirements of more than one billion people in the
LDCs must be provided to survive during the recession. It is also
noticeable that the COVID-19 can severely affect households in devel-
opng countries due to their socioeconomic structure and weak resil-
ience against the epidemic. Moreover, many countries experience
direct consequences due to widespread recession. In addition, in some
countries, including Iran, which is facing sanctions, economic turmoil,
and unbridled inflation, the COVID-19 epidemic has dramatically
impacted the livelihoods of vulnerable households (World Bank, 2020).
While Iran’s economy is in recession for the third consecutive year and
oil exports have plummeted, the heavy shadow of the COVID-19 has
stripped many sections of society of resilience.

In such a situation, any long-term closure of businesses raises severe
concerns in primarily poor societies. Health inequality is rampant
globally, and the unequal distribution of vaccines and the failure of the
World Health Organization to manage its distribution have increasingly
exposed the gap between rich and poor. Communities that struggle with
malnutrition are more susceptible to the pandemic. Lockdowns and
disruption in transportation placed cities with few alternative foods and drug sources at high risk, affecting the poorest citizens most. Also, the disconnection of the food supply chain causes the loss of large volumes of agricultural and dairy products (Cagle, 2020).

Typically, some measures during the epidemic are independent of the development level of countries, i.e., remote learning, social distancing, and measures for older adults. Nevertheless, the main challenge in underdeveloped countries is the existence of many self-employed businesses that people get paid every day only if they work. In many more impoverished societies, lockdowns have been imposed often at short notice (Chowdhury, 2020). Also, food security in areas that are forcibly under lockdown is a severe issue that is being ignored. In many societies, both rich and poor, the forced extended lockdowns have resulted in social tensions and public confrontation with governments. In such a situation, the complete lockdown is a double-edged sword with infection to COVID-19 on one side and the economic depression in daily livelihood on the other.

On the one hand, deadly variants of the virus kill people. India recorded a horrific record of more than 4000 deaths in one day (09 April 2021). On the other hand, the relentless pressure of closing businesses is ravaging poor societies.

### 3. Simulation of contact networks

In any society, people are in contact with each other in the form of a network. Almost all of the disease transmission in epidemics and pandemics occurs because of these contacts. Accordingly, contact networks can be helpful tools for monitoring, predicting, and controlling disease outbreaks. In effect, the contact network of individuals plays a crucial role in the pattern in which an infectious disease spreads. A contact network is a graph consisting of nodes and arcs where the nodes represent individuals, and the arcs represent the contact between the individuals. Various parameters can represent the contact network structure, and the degree distribution is its most important characteristic. More specifically, the degree of each node (individual) is the number of arcs (contacts) attached to it, and the degree distribution represents the degree for all nodes over the whole network as a probability function.

#### 3.1. Benchmark networks

There are many models and mechanisms to create random networks in the literature. We consider network models that appear to be more compatible with real contact networks. In this study, we consider six different contact networks representing the structure of the society. These benchmark networks include the following.

- **Random geometric network** with \( n \) nodes placed at random within a unit cube: In a random geometric network, two nodes \( i \) and \( j \) are connected if the distance between the nodes is less than the radius (Penrose, 2003).
- **Exponential network** generates a graph with an Exponential degree distribution.
- **Poisson network** creates a graph with a Poisson degree distribution.
- **Barabási–Albert network** generates a scale-free graph with \( n \) nodes grown by a preferential attachment model: i.e., attaching new nodes each with \( m \) arcs that are preferentially connected to the existing high degree nodes (Barabási & Albert, 1999). It contains few hub nodes with a high degree as compared to the other nodes.
- **Erdős–Rényi network** which adds each possible arc with a given probability \( p \) independent from every other arc (Erdős & Rényi, 1959).
- **Watts–Strogatz network** first generates a ring with \( n \) nodes. Each node in the ring is then connected to its \( k \) closest neighbors, followed by some shortcuts, which replace some arcs to create a small-world graph with the clustering effect (Watts & Strogatz, 1998). This network does not generate local clustering and does not form hub nodes.

In all these networks, the number of nodes is selected to be \( N \). In addition, to have comparable networks, the network generation
parameters are tuned so that the number of arcs in all networks is almost the same ($N \pm 0.01 \times N$). The degree distribution of all the benchmark contact networks with $N = 10,000$ is depicted in Fig. 1.

### 3.2. Simulation on contact networks

Herein, we have used simulation to visualize how the infection propagation behavior changes in the different graphs. In this regard, we assume that the infection starts from $m$ separate nodes in a network with $N$ nodes while all the other nodes are susceptible to be infected. Then, during each time step (day), if a person has had contact with an infected person based on the contact network, she/he will be contaminated to the infection with a transmission probability of $P_s$. The average duration of infection for each infected individual is denoted by $I_p$. Also, there is a probability of $P_d$ that the patient will die during the course of the disease; otherwise, she/he will be recovered and immunized over the whole remaining duration of the process.

We denote the number of susceptible individuals ($S$) by $X(t)$, the number of infected individuals ($I$) by $Y(t)$, the number of recovered individuals ($R$) by $Z(t)$, and the number of dead individuals ($D$) by $W(t)$. If we set the number of contacts in time step $t$ as $C(t)$, the dynamics of susceptible individuals becomes as below:

$$\dot{X}(t) = -\frac{P_s}{N} C(t) X(t) Y(t) \quad (1)$$

Meanwhile, the dynamics of infected individuals can be stated as below:

$$\dot{Y}(t) = \frac{P_s}{N} C(t) X(t) Y(t) - \frac{P_s}{I_p} Y(t) - \frac{1 - P_d}{I_p} Y(t) \quad (2)$$

Similarly, the dynamics of the recovered and dead individual can be expressed as below:

$$\dot{Z}(t) = \frac{P_d}{I_p} Y(t) \quad (3)$$

Because the total population is supposed to be constant during the process, clearly we have:

$$X(t) + Y(t) + Z(t) + W(t) = N \quad (5)$$

**Fig. 2** illustrates the status of a host population with $N = 10,000$ individuals for a random geometric graph, where the infection has been started from $m = 10$ random nodes. It is clear that for a network with random geometric structure and under the given parameters, almost the whole community will be infected at the end of the epidemic process.

The stochastic nature of disease transmission in contact networks is an integral part of the transmission chain of epidemics, especially for respiratory diseases such as Covid-19. The main idea of this section is to show how different parameters and interventions play a role in the spread of the epidemic by simulating this stochastic behavior in contact networks. On the other hand, because individuals’ contact structure can be very diverse, we examine different contact networks to assess the role of the contact pattern in disease transmission. Although many simplistic assumptions may have been made in simulating this process, the estimated results can help in planning and decision-making by health authorities. In particular, predicting the peaks of the epidemic and the effect of different strategies on the duration of the disease and the severity of the epidemic are the results of this simulation.

Herein, we coded and ran the simulation process in the Anaconda environment with Python 3.6 for evaluating the effect of different parameters and strategies on the behavior of the infection on all benchmark contact networks. With illustrative purpose, the simulation results for an exponential network are depicted in Fig. 3, where temporal variations of the susceptible ($S$), the infected ($I$), and the recovered ($R$) for transmission probability in range of $P_s = 0.01, 0.02, 0.05, 0.07, 0.10$ and $0.15$ is visualized. In addition, the time-dependent reproduction rate $R_0(t)$ is shown by the blue curve (that is scaled on the right vertical axes). The reproduction rate (number) measures the expected number of new infections which any currently infected person infects. This is a fundamental quantity that plays a vital role in becoming a disease epidemic. More specifically, the condition $R_0(t) > 1$ has been interpreted as the growing trend of the disease, which is an alarm for the surveillance authorities.

In **Fig. 3** for $P_s = 0.01$ it is clear that less than half of the population gets the disease, and after 62 days, the crisis is entirely over, where there is a slight peak around day 21. Now, comparing the trend with subsequent charts with higher values of $P_s$ shows how changes in the epidemic behavior are affected by the probability of disease transmission. Specifically, the course of the disease gets shorter, but more severe peaks and a higher percentage of infection is evident. The value of $P_s$ can be reduced by social distancing measures, mask-wearing, using hand sanitizer, etc., over the whole process of the epidemic.

### 4. Results and lessons learned

In this section, the numerical findings from the simulation on six different graphs are discussed. To investigate how lockdown scenarios, individual behaviors such as social distancing, using a face mask, and applying hand sanitizer affect the trend of the epidemic, we simulated the process for different values of $P_s$ on different contact graphs. Herein, $P_s$ is considered a control variable, while the number of infected cases, number of deaths, duration of the infection course, and maximum value of reproduction number are considered state variables. The number of individuals ($N$), the number of initially infected cases ($m$), $P_d$ and $I_p$ are supposed to be fixed parameters. As it can be observed from **Fig. 4**, for small values of $P_s$, the number of infected cases and deaths in the random geometric network is minimal. As $P_s$ increases, *Exponential network* is the contact network with the minimum number of infected cases and deaths.
Fig. 3. The effect of transmission probability \( P_r \) in an Exponential network on the susceptible (S), the infected (I), the recovered (R), the reproduction number \( R_0(t) \), and the duration of the infection course with \( N = 10,000, m = 10, P_d = 0.05, I_p = 7 \).

Fig. 4. The effect of transmission probability on the number of infected cases and deaths with simulation on benchmark contact networks \( (N = 10,000, m = 10, P_d = 0.05, I_p = 7) \).
Fig. 5. The effect of transmission probability on the maximum reproduction number during the epidemic, $R_{\text{Max}}^0(t)$, with simulation on benchmark contact networks ($N = 10,000, m = 10, P_d = 0.05, I_p = 7$).

Fig. 6. The effect of transmission probability on the duration of the epidemic process with simulation on benchmark contact networks ($N = 10,000, m = 10, P_d = 0.05, I_p = 7$).

Fig. 7. The effect of transmission probability on the peak of the infection measured by the maximum number of daily infected cases with simulation on benchmark contact networks ($N = 10,000, m = 10, P_d = 0.05, I_p = 7$).
Also, it can be noticed that when the probability of being infected exceeds about 6 per contact, almost everyone in the community will be affected by the pandemic.

Fig. 5 shows how the maximum value of reproduction number in different networks is affected by the transmission probability ($P_r$). While there is almost an increasing trend in all the networks, but this trend is more striking in Barabasi-Albert and Exponential networks.

In any epidemic, the longer the course of the epidemic, the better from the point of view of the health authorities. Because the distribution of the infected cases over a more extended period provides an opportunity to handle the crisis better. When the course of the epidemic increases, it results in fatigue of the medical staff, people’s disregard for protocols, and ultimately heightening the dire consequences of the crisis. Fig. 6 illustrates how increasing the probability of disease transmission across different networks greatly reduces the epidemic course and how adherence to protocols can help public health. While in low probability of transmission, the contact networks have different behaviors, with increasing values of $P_r$, all the contact networks converge to a crisis. Similarly, Fig. 7 depicts the impact of the transmission probability on the crisis in terms of the infection peak. While the random geometric network has a slight slope with increasing transmission probability, the trend is steeper in other networks. More specifically, the random geometric network has a peak of about 5700 infected cases per day, while in the other networks, the average maximum infection is about 3735.

To have a comparative analysis, temporal variations of the susceptible ($S$), the infected ($I$), and the recovered ($R$) with a fixed transmission probability of $P_r = 0.15$ for different networks is visualized in Fig. 8. The trend of the variables shows that a society with a random geometric network does not experience a significant peak compared to other patterns.

Now we aim to examine how different strategies and lockdown scenarios work to control the epidemic process in various networks. Like Caulkins, Grass, Feichtinger, Hartl and Kort (2021), we do not distinguish between restrictions related to business and non-business interventions. Although face masks, hand sanitizers, social distancing, lockdowns, and other health protocols are the means of crisis control advised by the authorities, they are not necessarily followed by the community. For example, the complete closure of society for three weeks can stop the whole Coronavirus crisis, but does society as the whole have the potential to accept and implement such a policy? Clearly not. Caulkins et al. (2021) studied multiple lockdowns with different intensities for Covid-19 pandemic under a SIR (Susceptible-Infectious-Recovered) model in which ‘lockdown fatigue’ is considered as a state variable. Another comparable research that examined the effect of lockdown is Srivastava1, Srivastava1, Chaudhary

![Fig. 8](image-url)
and Al-Turjman (2020), where the authors studied and predicted the lockdown effect, particularly in India, utilizing a time-varying SIR model. They concluded that their lockdown policy reduces the reproduction number and the number of infected individuals.

Contrary to Caulkins et al. (2021) and Srivastava et al. (2020), the present paper considers three strategies as seesaw scenarios for closing businesses. More specifically, the defined scenarios include closing businesses two days in between, three days in between, and four days in between. In addition, taking into account the heterogeneity of society and the level of the existing crisis, we consider four different levels for lockdowns. Herein, it is assumed that level 1 is respected by 25%, level 2 by 50%, level 3 by 75%, and level 4 by 100% of the population. The full combination of lockdown scenarios and lockdown levels is simulated on all the benchmark networks under the given parameters. A distinguishing feature of this research is that the effect of different scenarios are studied on contact networks which are very model of real-life behavior of individuals’ interactions. In effect, the findings of this kind of analysis has a better adaptation than those of SIR models under dozen of unrealistic assumptions.

Fig. 9 shows that how the seesaw interventions work. It can be observed from Fig 9 (above) that as days between business closures increase, the course of the epidemic becomes more intense, albeit with a significant difference in the random geometric network compared to the other graphs. In addition, the underneath figures in Fig. 9 show this distinction in the exponential network in terms of the number of people infected. It is noticeable that, based on a field survey of 785 people in Qazvin province of Iran, we found that the contact network of the society in April 2020 was most similar to the exponential network in terms of the degree distribution.

To examine the effects of the proposed seesaw lockdown levels on the pandemic process in detail, we focus solely on the random geometric network. To do this, we set the lockdown scenario to the first one, i.e., \( c = 2 \) (closing businesses two days in between). The resulting SIR vibration is depicted in Figs. 10. It is evident that with an increase in compliance with the prescribed policy by the community, the peak of the infection to the disease will be flattened over a more extended period. It can clearly be observed from Figs. 10 that by utilizing the proposed lockdown strategies, the number of infected individuals (red curve) fluctuates over the course of the disease. This fluctuating trend has two key practical outputs. First, it provides the healthcare system’s capacity to deliver the appropriate care and provide the healthcare let off steam. Second, the public’s level of cooperation with health protocols will be improved.

5. Discussion

Perhaps the most fundamental finding of this research is that there is a range of different scenarios that, the optimal combination of various interventions and measures can help to level the pandemic prevalence. With illustrative purpose, the detailed numerical results reported in Table 1 show that the proposed soft lockdown strategies can even flatten up to approximately 120% of the pandemic course (change from 42 days to 92 days under lockdown scenario \( c = 2 \) closing businesses two days in between, lockdown level = 1.00). Although this leveling does not significantly impact the total number of infected and death toll, it will undoubtedly make the process accountable to the authorities and the
medical staff. However, when the service capacity of the medical department is limited during the peak of the disease, it will also affect the mortality rate, which has been left out in this study.

The second major conclusion of this analysis is that the probability of disease transmission in contact of a patient with a healthy individual has a significant effect on pandemic control variables. More specifically, the length of the pandemic course and the total number of infected individuals are considerably affected by the probability of disease transmission. This conclusion highlights the impact of personal health considerations on the interactions of individuals in society on the severity of the pandemic crisis.

A third observation is simply that the prescribed strategies work differently on different contact networks. In this study, six contact networks are studied to model the spread of the epidemic and seesaw lockdown scenarios, among which exponential contact graph is given special attention due to its very close adaptation to the case of Qazvin province in Iran. This conclusion distinguishes our research from Caulkins et al. (2021), in which, regardless of the structure of people’s interactions and contacts in society, strategies involving two lockdowns are prescribed as an optimal scenario. Finally, it is worth noting that the behavior of individuals in the face of crises such as pandemics is most dependent on the different cultural and economic conditions of each society. It is even possible that the behavior of a particular community in dealing with a specific crisis will change over time. So there is never an optimal scenario for even a specific community of people.

6. Conclusion

The recent outbreak of the COVID-19 has left many officials, authorities, and governments in a difficult position to decide. Decisions that have sometimes led to adverse reactions and strong resistance from sections of society, especially low-income groups. An extended version of interventions that work for all the communities will never exist in such a situation. A clear example of this contradiction is the closure of businesses in many countries, which has sometimes been very successful and sometimes failed altogether. The root cause of this is severe financial problems in underdeveloped societies and the inability of their administrations to support suspended businesses. Every community in the epidemic process is conceivable in their contact graph, where its

| Lockdown Scenario | Lockdown Level | Duration of the process | Number of infected individuals | Number of death |
|-------------------|----------------|-------------------------|-------------------------------|----------------|
| 1                 | No action      | 42                      | 10,000                        | 515            |
| 2                 | 0.25           | 64                      | 9994                          | 647            |
|                   | 52.38%         |                         |                               |                |
| 3                 | 0.50           | 72                      | 9997                          | 641            |
|                   | 71.43%         |                         |                               |                |
| 4                 | 0.75           | 80                      | 9990                          | 643            |
|                   | 90.48%         |                         |                               |                |
| 5                 | 1.00           | 92                      | 9989                          | 603            |
|                   | 54.76%         |                         |                               |                |
| 6                 | 1.00           | 79                      | 10,000                        | 770            |
|                   | 88.09%         |                         |                               |                |
| 7                 | 0.25           | 45                      | 10,000                        | 636            |
|                   | 7.140%         |                         |                               |                |
| 8                 | 0.50           | 47                      | 9999                          | 626            |
|                   | 11.90%         |                         |                               |                |
| 9                 | 0.75           | 48                      | 9999                          | 593            |
|                   | 14.29%         |                         |                               |                |
| 10                | 1.00           | 76                      | 9998                          | 588            |
|                   | 80.95%         |                         |                               |                |

Fig. 10. The effect of different lockdown scenarios with varying levels in a random geometric network on flattening the peak \( N = 10,000, m = 10, P_d = 0.05, P_r = 0.15, I_0 = 7 \).
structure can be summarized in a degree distribution. The simulation results on the benchmark contact networks in this paper showed how the recommendations regarding social distancing could affect epidemic behavior by reducing the probability of transmission per contact. Expressly, it was specified that the exponential contact network had the least number of infected cases and deaths as the probability of transmission increases. Also, there was a significant effect of increasing the probability of transmission on the epidemic course and the maximum reproduction number. Seesaw lockdowns under different scenarios and application levels were simulated as an alternative for the complete lockdown of businesses in poor societies. Numerical results revealed that they could work in terms of surveillance measures without imposing economic pressure on poor households.

Current research can be extended in several ways. The heterogeneous structure of the contact network, which includes age, gender, and cultural diversity, can more accurately reflect the actual interactions of society. In addition, the emergence of new versions of the disease, the impact of the overloaded patients in the healthcare system on mortality rate, and the impact of the vaccination process are other topics that have the potential to be studied.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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