COMPLEX SYSTEM MODELING AND SIMULATION
ISSN 2096-9929 06/06 pp 71−82
Volume 3, Number 1, March 2023
DOI: 10.23919/CSMS.2023.0001

Simulation of COVID-19 Outbreak in Nanjing Lukou Airport Based on Complex Dynamical Networks

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Abstract: The Corona Virus Disease 2019 (COVID-19) pandemic is still imposing a devastating impact on public health, the economy, and society. Predicting the development of epidemics and exploring the effects of various mitigation strategies have been a research focus in recent years. However, the spread simulation of COVID-19 in the dynamic social system is relatively unexplored. To address this issue, considering the outbreak of COVID-19 at Nanjing Lukou Airport in 2021, we constructed an artificial society of Nanjing Lukou Airport based on the Artificial societies, Computational experiments, and Parallel execution (ACP) approach. Specifically, the artificial society includes an environmental model, population model, contact networks model, disease spread model, and intervention strategy model. To reveal the dynamic variation of individuals in the airport, we first modeled the movement of passengers and designed an algorithm to generate the moving traces. Then, the mobile contact networks were constructed and aggregated with the static networks of staff and passengers. Finally, the complex dynamical network of contacts between individuals was generated. Based on the artificial society, we conducted large-scale computational experiments to study the spread characteristics of COVID-19 in an airport and to investigate the effects of different intervention strategies. Learned from the reproduction of the outbreak, it is found that the increase in cumulative incidence exhibits a linear growth mode, different from that (an exponential growth mode) in a static network. In terms of mitigation measures, promoting unmanned security checks and boarding in an airport is recommended, as to reduce contact behaviors between individuals and staff.

Key words: Corona Virus Disease 2019 (COVID-19); intervention strategy; complex dynamical networks; artificial society

1 Introduction

Despite the scientific and technological advances of human society, the proliferation and mutation of infectious diseases continue to pose a threat to human health. According to statistics from John Hopkins University, as of April 2022, the cumulative infected cases exceeded 500 million and total deaths reached 6 million, which further imposed a negative impact on the international economy[1]. As a complex social system, a large transportation hub is a pivotal place for the import and spread of infectious diseases. For instance, an outbreak of Corona Virus Disease 2019 (COVID-19) at Nanjing Lukou Airport in 2021 led to the spread in the whole city and even to other provinces[2].

To mitigate the epidemic, many governments and scholars have devoted themselves to studying the characteristics of COVID-19 and the effects of

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※ This article was recommended by Editor-in-Chief Wenhui Fan.
Manuscript received: 2022-07-29; revised: 2023-01-03; accepted: 2023-01-11

different mitigation strategies. The simulation-oriented study is one of the most universal studies that aim to predict the development of the epidemic, such as multi-agent modeling, complex modeling, and Monte Carlo simulation. For instance, Broniec et al.[3] explored the impact of social distance on the spread of the epidemic; Chen et al.[4] evaluated the mitigation strategies of the different countries through simulation based on complex networks. Most of the studies focused on static and stable social systems[5, 6], such as cities, campuses, cruises, etc. But the research on the dynamic social system is relatively inadequate. In the dynamic social system, individuals are updated constantly and the contact is time-bound, and ignoring the spatiotemporal variations of contact behavior may draw a misleading conclusion. Morris and Kretzschmar[7] suggested that actual temporal variation should be considered in models of infectious disease transmission in their study of sexually transmitted diseases. In the pandemic of COVID-19 in recent years, Chang et al.[8] proposed a metapopulation susceptible-exposed-infectious-removed model that integrates fine-grained dynamic mobility networks to simulate the spread of COVID-19 in ten of the largest US metropolitan areas. Li et al.[9] presented a novel epidemic model considering demographics and intercity commuting on complex dynamical networks, constructing a network based on the epidemic model and the network coupling. Further, some researchers proposed a sequential network updating approach based on data assimilation techniques to achieve real-time network updates and set an efficient strategy by identifying high-risk individuals or communities through highly time-variant contact networks[10]. These studies considered macroscopic scenarios, but less focused on microscopic scenarios, such as some large public places. An airport is a typical dynamic social system where passengers enter and exit with flights taking off and landing. Therefore, we take the outbreak in Nanjing Lukou Airport as background to study the characteristics of COVID-19 in dynamical networks through computational experiments.

This paper proposes a system model based on complex networks and the multi-agent modeling method[11], where a constructed algorithm of complex dynamical networks is designed, and based on that, an artificial society is established. Moreover, based on the artificial society[12], large-scale computational experiments can be carried out to explore the spread characteristics of COVID-19 and what intervention strategies we should adopt to mitigate the epidemic in large transportation hubs like an airport[13, 14]. The main contributions of this study can be summarized as follows:

(1) We designed an algorithm to generate the moving traces of passengers at Nanjing Lukou Airport. In this algorithm, we first categorize different locations in an airport into “must-visit” and “may-visit”, then define the terminus of the path according to the departure gate and departure time. Next, passengers select the “may-visit” location to visit with the probability of distance priority and degree priority. And the moving traces are generated when all the locations that need to be visited are identified by the passenger.

(2) We proposed a method to construct complex dynamical networks in Nanjing Lukou Airport. Since the characteristics of mobility of different individuals are different, we constructed the dynamical networks by aggregating the static network of staff, the static network of passengers, and the mobile contact network. The static network represents the internal stochastic contact between staff and passengers, and the mobile contact network represents the contact caused by passengers’ movement.

(3) We constructed an artificial society based on the Artificial societies, Computational experiments, and Parallel execution (ACP) approach[15]. The artificial society of Nanjing Lukou Airport includes five aspects: geographical environment, population, contact behavior, disease spread, and intervention strategies. Specifically, we use the complex dynamical networks proposed in this paper to abstract the contact behavior, and intervention strategies are formulated as a six-tuple model.

(4) Based on the artificial society, large-scale computational experiments were conducted to simulate the outbreak in Nanjing Lukou Airport and explore the effects of different intervention strategies. According to the experimental results, it is found that the growth of the cumulative cases exhibits a linear growth mode. Moreover, reducing the contact frequency is a crucial mitigation measure to defeat the epidemic in large transportation hubs.

In what follows, we introduce the modeling course of complex dynamical networks in Nanjing Lukou Airport in Section 2. Section 3 introduces the artificial society of Nanjing Lukou Airport. Experiments are carried out in Section 4, and discussions are given in Section 5. Finally, conclusions are drawn in Section 6.

2 Modeling of Complex Dynamical Networks in Nanjing Lukou Airport

2.1 Continuous-time dynamical network model

The continuous-time dynamical network[16] is the basis of constructing complex dynamical networks in Nanjing Lukou Airport, as shown in Fig. 1, which can be expressed as Eq. (1).

$$G = \{V, E(t), A(t)\} \tag{1}$$

where V is the set of all network nodes from time 0 to time T, $E(t)$ is the set of temporal edges at time t, and $A(t)$ is the set of nodes at time t. $e_t = (u, v, t) \in E(t)$ represents the timestamp of each edge forming or disconnecting.

The continuous-time dynamical network shows the dynamic characteristics of edges and nodes[17], so it is usually used to model the relationships of complex social systems where the individuals and their behavior are time-variant, such as transportation hubs.

2.2 Modeling of static networks of passengers and staff

2.2.1 Characteristics of personal mobility

A transportation hub is an intersection of different traffic lines, which is an important part of a national or regional transport system. It is a whole of fixed and mobile equipment for multiple modes of transport, performing the function of direct operation, transit operation, and hub operation[18].

The airport is a typical large transportation hub, which can be considered a complex social system. The people involved mainly include airport staff and passengers. These individuals have a large population size and complex movement. In addition, there are significant differences in the interaction characteristics of staff and passengers.

The staff are personnel engaged in operations, services, and security in the airport, who are mainly divided into ground service, air service, and special service. Staff generally have a regular working time and fixed position, and the number of staff in various departments is relatively steady. The staff are less mobile and they have more contact with those nearby. The likelihood of contact with people at a distance and other types of staff is low, and the contact mode is generally passive. On the contrary, the passengers are not motionless, they move fast and the moving range is wide because of the strong purpose of taking the flight. Although the influence factors of passengers' mobility are complex, passengers' mobility still has some regularity. For instance, passengers in the terminal usually queue, walk randomly, follow the crowd, etc.

2.2.2 Static network construction algorithm

Since the movement characteristics of staff and passengers are different, we construct the static networks of staff and passengers, respectively. The static network of staff is directly constructed as a whole, but for the static network of passengers, we constructed it according to the date of their flights.

The internal stochastic contact cannot be accurately recorded and it is difficult to collect relevant data due to randomness. But according to the concluded regularity, the probability of contact increases with the distance between two individuals getting closer, and the contact number of a person obeys power-law distribution[19]. Therefore, we generate the static networks based on the Scale Distance Degree (SDD) model[4], and the process of the algorithm is shown in Fig. 2.

The staff and passengers are divided into numerous

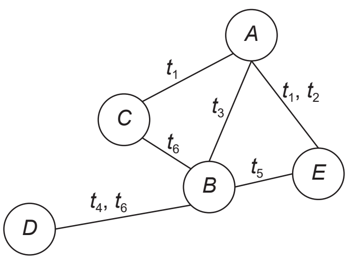

Fig. 1 Continuous-time network.

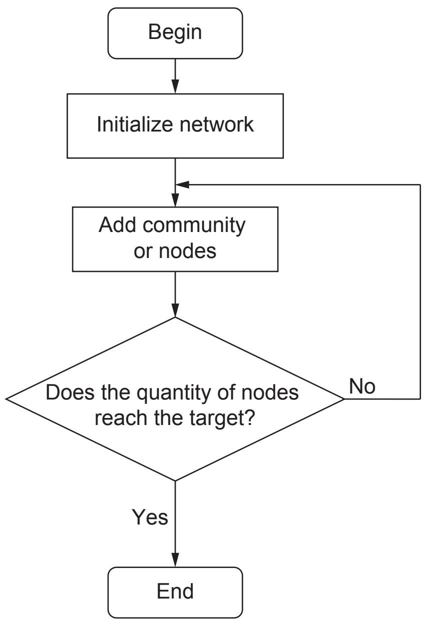

Fig. 2 Algorithm for constructing a static network.

communities based on geographic location before starting. At first, the initialization network includes c_0 communities, and there are n_0 nodes in each community. The nodes are randomly selected to generate edges between different communities when $c_0 \geqslant 2$. Next, the network starts evolving and growing. In each step of evolution, a community is added to the network with probability p and add_{num} nodes are added to a community that has existed in the network with probability $1-p$. When the total number of nodes in the network reaches a given target, the evolution ends and the static network is generated.

When a node is connected to nodes of other communities, the connections follow the gravity law. That is to say, the larger the scale of the community is, or the smaller the distance between the communities is, the higher the probability of selecting the node of the community will be[20]. The probability of community selection can be expressed by Eq. (2).

$$C_v = \frac{S(v)^{\alpha} d(u,v)^{\gamma}}{\sum\limits_{i \in V} S(i)^{\alpha} d(u,v)^{\gamma}}, \alpha > 0, \gamma < 0 \tag{2}$$

where $S(v)$ is the size of the communities v; $d(u,v)$ is the distance between the community u and v; α is the impact index of community size; and γ is the impact index of distance.

When a new connection is generated between two nodes in the same community or two different communities, the probability that a node is chosen is proportional to the temporal degree. The probability of node i connected to node j is calculated as Eq. (3),

$$N_{ij} = \frac{D_{vj} + a}{\sum\limits_{k} (D_{vk} + a)} \tag{3}$$

where D_{vj} is the degree of the node j in community v and a is the offset.

2.3 Modeling of mobile contact networks

The static networks cannot reflect the dynamic characteristics of contact between individuals, especially the passengers. They constantly move in the terminal, and the staff that they contact at each moment are probably different. Therefore, we need to model the relationships between the static network of staff and passengers with the passengers’ traces. As the mobile behavior of the passengers is complex and the moving traces are difficult to collect, it is assumed that the staff have no movement and the way how passengers move is not considered. We focus on which function area the passenger visits, if a passenger visits one function area and has contact with the staff, the place will be a part of the passenger’s moving trace.

In this paper, we designed an algorithm for constructing the moving traces of passengers. Firstly, the functional areas in the terminal are divided into two kinds: “must-visit” and “may-visit”. For instance, check-in counters, security checkpoints, and departure gates belong to the “must-visit” functional areas while the toilet, shop, and the VIP lounge belong to the “may-visit” functional areas. As shown in Fig. 3, the

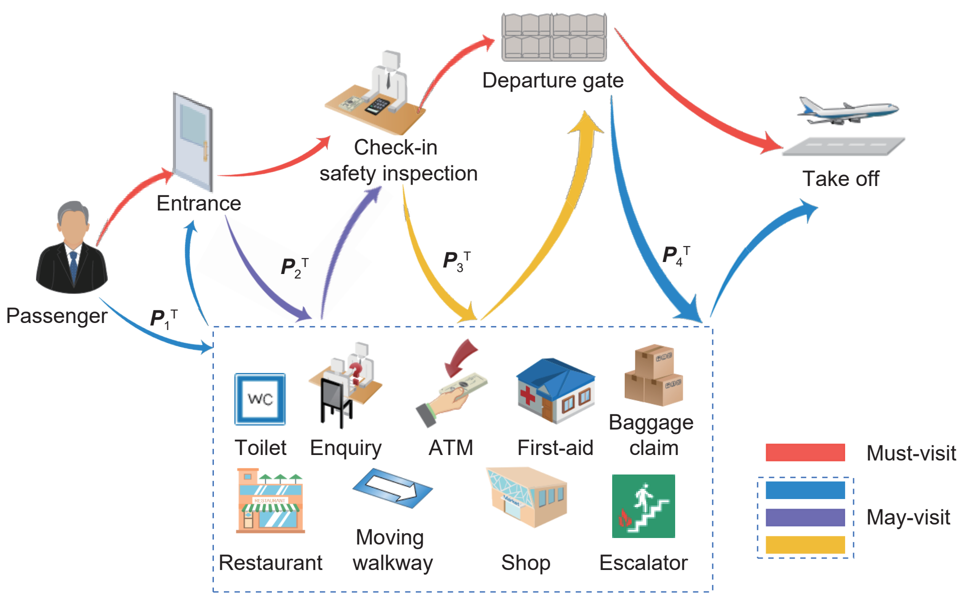

Fig. 3 Moving traces of passengers.

general procedure of taking a flight is simplified to four main activities: entering the terminal from the entrance, checking in, security check, and boarding at the end. After entering the terminal, the passenger may visit some "may-visit" functional areas before heading for the next "must-visit" functional areas with a probability vector $\boldsymbol{P}^{\mathrm{T}}$.

The probability of a passenger selecting functional areas is calculated as Eq. (4). If a functional area is visited, then the connection between the passenger and another person in the community C_i corresponding to the functional area of staff will be generated, and the probability of the staff j in the community can be expressed by Eq. (5).

$$P(C_i)=\frac{\frac{1}{d_i}}{\sum\limits_{i=1}^{m}\frac{1}{d_i}} \tag{4}$$

$$P(C_i^j)=\frac{k_j}{\sum\limits_{j=1}^{n}k_j} \tag{5}$$

where d_i is the straight-line distance between a functional area i and the passenger, and k_j is the degree of staff j in the temporal network.

In the end, the mobile contact networks are generated by establishing connections based on the passengers' moving traces. These connections are like bridges across isolated static networks.

2.4 Network aggregation

To construct the continuous-time dynamical network of Nanjing Lukou Airport, we aggregate the static network of passengers and staff and the mobile contact networks according to the correspondence between individuals in communities and nodes in networks[16].

The temporal information of an edge defines the timestamp when the edge of the aggregate network appears and disappears, which is expressed as $T_e=(t_s,t_e)$. t_s is the timestamp when the contact is generated and t_e is the disappeared timestamp of the contact. T_e can be calculated depending on the real departure time of the passengers. If the type of an edge is the stochastic contact of staff, $T_e=(0,T_{\text{end}})$, T_{end} means the end time of the simulation. If the type is the contact between staff and passengers, we define the real departure time of a passenger as t_{flight}, then the temporal information is calculated inversely based on the moving trace, as shown in Eq. (6).

$$\begin{cases} T_p=(t_{\text{flight}}-t_p,t_{\text{flight}}), \\ T_{p-1}=(T_p-t_{p-1},T_p) \end{cases} \tag{6}$$

where p is the count of the functional areas of a moving trace and t_p is the residence time of the passenger.

After all temporal information of the mobile contact is calculated, we can sum up the total interval of any passenger from the entrance to the departure gate. T_e of the passengers' stochastic contact is simplified with the intersection of two passengers' total intervals.

3 Artificial Society Modeling of Nanjing Lukou Airport

3.1 Structure of artificial society

Artificial society is a social system constructed in the computer world, which integrates the interdisciplinary knowledge of sociology, computer science, multi-agent modeling and simulation technology, and system science[21]. In this paper, the artificial society of Nanjing Lukou Airport is constructed as the experimental bed for the spread of COVID-19, and the structure of the artificial society is shown in Fig. 4.

We mainly consider five elements in the construction: environment, population, contact behavior, disease spread, and intervention strategies. The environment model is the abstract of the geographical distribution of different functional areas and departure gates in Nanjing Lukou Airport. The population model includes personal ID, flight number or functional area ID, and the state of infection. The contact behavior is characterized by complex dynamical networks. The disease spread is realized based on the Susceptible-Exposed-Infection-Recovery (SEIR) model, and we represent the intervention strategies with a six-tuple model based on the policy of Nanjing Lukou Airport.

3.2 Environment model

Nanjing Lukou Airport has two terminals, two 3600 m runways, and 70 gate positions. In 2020, the annual passenger volume exceeds 300 000 people, and the handling capacity of cargo reaches 400 000 t.

As the place where passengers experience check-in and take a short break before departure and after arrival, the terminal is the main functional area of the airport. There exists a waiting hall, functional areas, baggage claims, and other service delivery. Therefore, we divide the terminal into plenty of small-scale sites that are defined as a community, and the community is

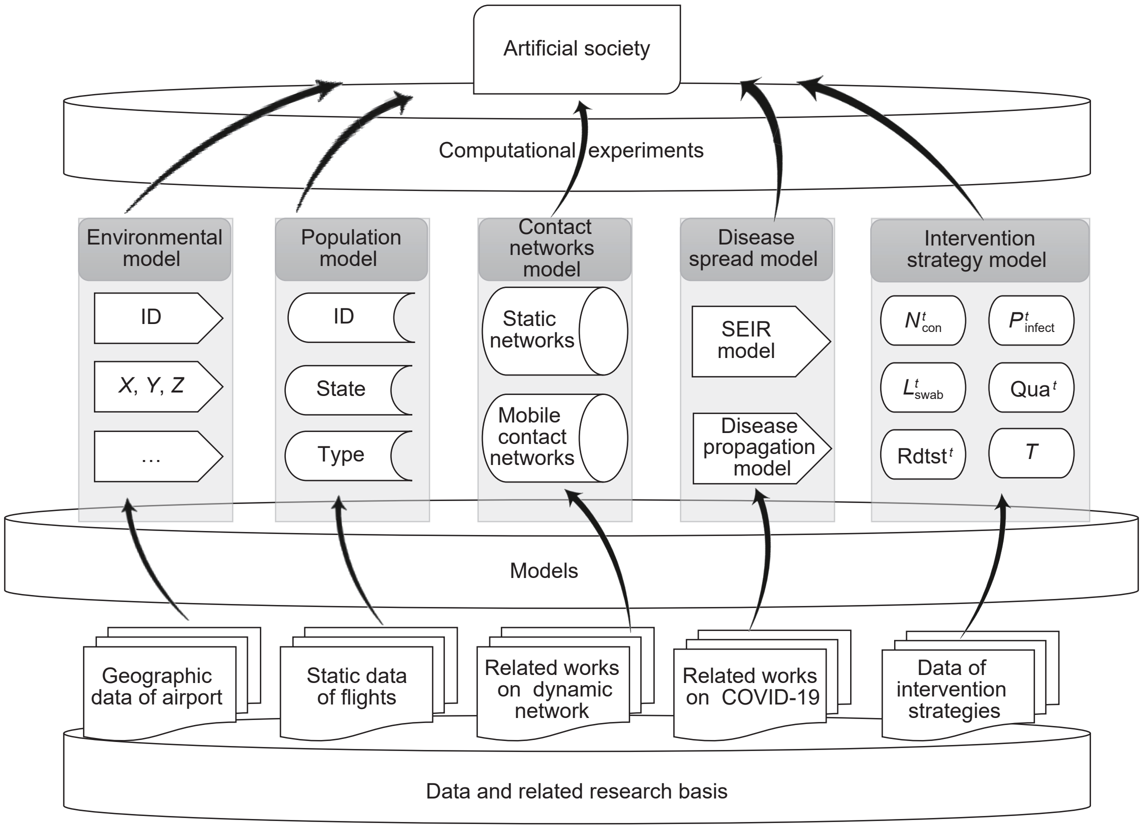

Fig. 4 Structure of the artificial society of Nanjing Lukou Airport.

considered as the interactive environment of individuals that are also agents in the artificial society.

The environment model includes the community ID, three-dimensional geographical coordinates, the population, and the type of individuals in the community, as shown in Fig. 5.

3.3 Population model

The population model is constructed based on the data of staff and real flight details at the period from the timestamp when the first case was defined to the end of the epidemic in Nanjing Lukou Airport. We conducted a statistic about the daily number of passengers and staff by collecting the flight data from July 10 to July 26. Then we assigned four attributes to the agents generated according to the individuals of flights and functional areas, they are personal ID, community ID, state of infection, and the type of agents.

The computational model based on the agent can reveal the heterogeneous behaviors between individuals, social networks, and group interbehavior in society[22]. Agents are the active passengers and staff in the artificial society of Nanjing Lukou Airport, and they are linked by a complex dynamical network. In the experiments of spreading simulation, the virus spreads between the heterogeneous agents along these links, meanwhile, the states and attributes will change with the occurrence of events, as shown in Fig. 6.

3.4 Contact networks model

Based on the artificial population generated above, the contact networks model can be constructed through the modeling of complex dynamical networks. It mainly shows the contact behavior between individuals, which is the necessary condition for spread. In contact networks, the nodes represent different agents, and the edges represent that these two agents have contact behavior and it is potential for the two agents to spread disease. The contact behavior includes two types: one is internal contact with staff or passengers and the other one is generated by the mobility of passengers.

3.4.1 Characteristics of the degree distribution of staff and passengers

Statistical characteristics[23] of staff are shown in Table 1. The network of staff is sparse, where the clustering coefficient is low, the average degree of nodes is about 7, and the intermediary centrality is low.

The degree distribution is shown in Fig. 7. The curve is similar to a line under the log-log scale, indicating

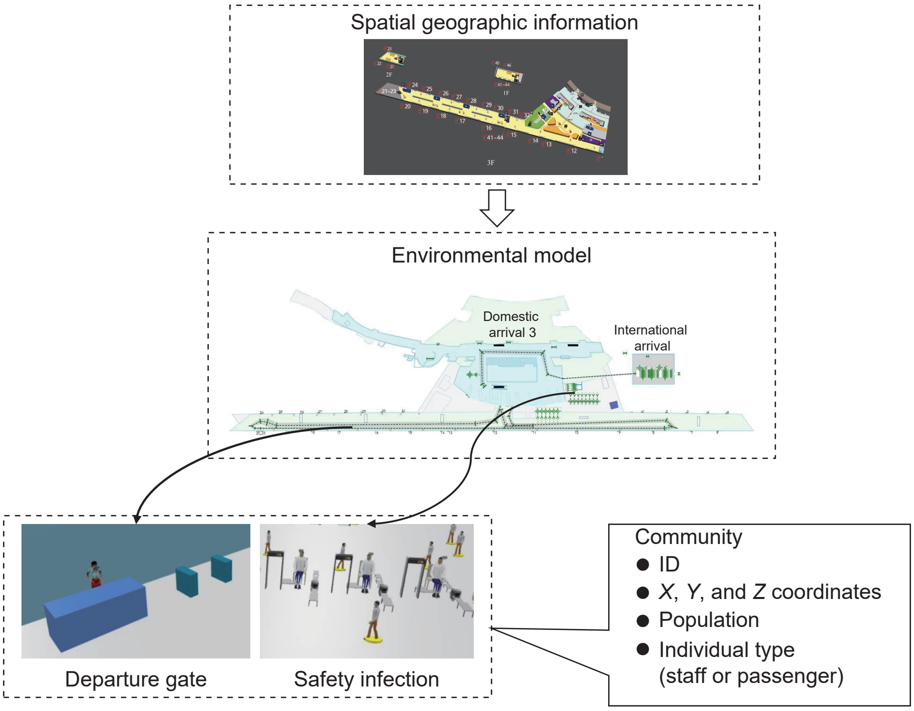

Fig. 5 Environmental model.

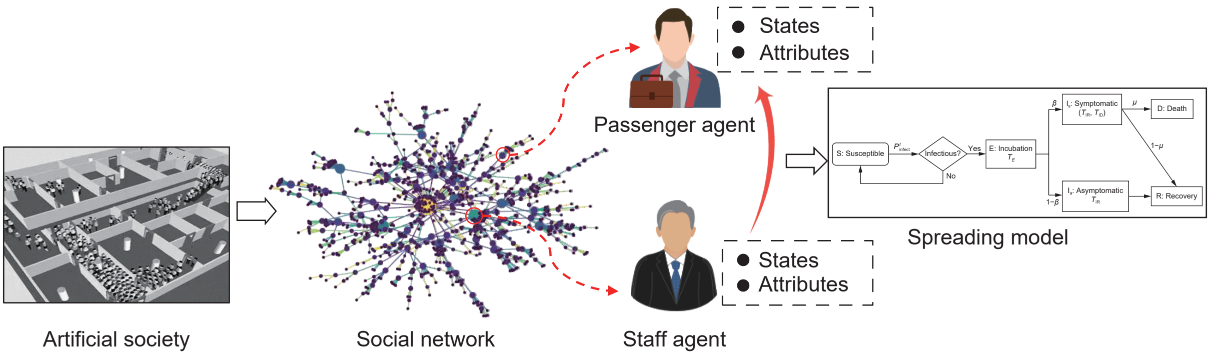

Fig. 6 Computational model based on the agent.

Table 1 Statistical characteristics of the static network of staff.

Statistical characteristics	Value
Number of nodes	1112
Number of edges	2897
Density	0.0047
Clustering coefficient	0.15
Degree centrality	0.0064
Betweenness centrality	0.0032

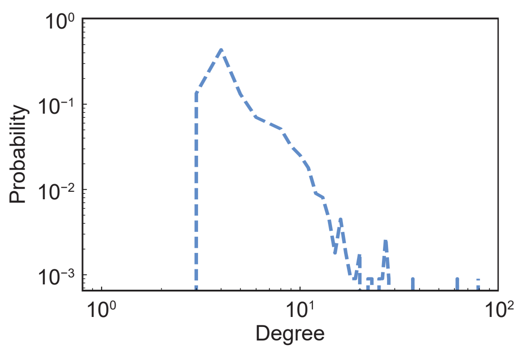

Fig. 7 Degree distribution of the static network of staff.

that the degree distribution approximately obeys the power-law distribution. The characteristics correspond with most of the networks in the real world. On the contrary, the degree distribution of the mobile contact of passengers shows obvious randomness and irregularity due to the random selection of functional areas based on probability. In addition, the average degree of staff is much larger than that of the passengers since staff connect the passengers whose flight is not in the same period.

3.4.2 Dynamic degree distribution of the contact networks

The aggregate network contains connections from the beginning to the end of the epidemic in Nanjing Lukou Airport, and we can observe the diurnal variation of degree distribution from Fig. 8.

The degree distribution at first obeys the power-law distribution from July 10 to July 21, but it changes on July 22 because of the sharp decline in flights. On July 23, the average degree is much lower and the network is sparser than that at the beginning. Generally, the contact networks model is constructed based on the real data of Nanjing Lukou Airport, so the variation of the degree distribution reflects the dynamic development of the artificial society to some extent.

3.5 COVID-19 spread and intervention strategy model

The disease spread is the main event in the artificial society. The disease course is the evolutionary process of health conditions experienced by patients, and we depict the spreading process based on the SEIR model[24] as well as the course characteristics of the patients infected by COVID-19.

As shown in Fig. 9, there are six states of individuals, susceptible (S), incubation (E), symptomatic infection (I_s), asymptomatic infection (I_a), recovery (R), and death (D). If the susceptible contact patients (E, I_s, or I_a), their state will become E with the probability of P^t_{infect}, the duration of the incubation is T_E. Then, they will enter the asymptomatic infection state with the probability of β, otherwise, they will enter the symptomatic infection with $1-\beta$ probability. Symptomatic patients may be dead with the probability of μ or recovery with the probability of $1-\mu$, while asymptomatic patients will inevitably enter the recovery state. T_{IR} is the duration from the infected state to the recovery state and T_{ID} is the duration from the infected state to the dead state.

As shown in Fig. 9, if a susceptible person is infected and not quarantined, the person will spread the virus to other susceptible persons. If the throat swab test result is positive, this person will be quarantined, otherwise, this person will continue spreading the virus.

According to our previous study[4], the intervention strategy can be represented by a six-tuple model, as shown in Eq. (7).

$$m^t = \left\langle N^t_{\text{con}}, P^t_{\text{infect}}, L^t_{\text{swab}}, \text{Qua}^t, \text{Rdtst}^t, T \right\rangle \tag{7}$$

where m^t is the quantitative strategy from time t to the next change in the intervention strategy. The specific meanings of the six elements in the tuple are shown in Table 2.

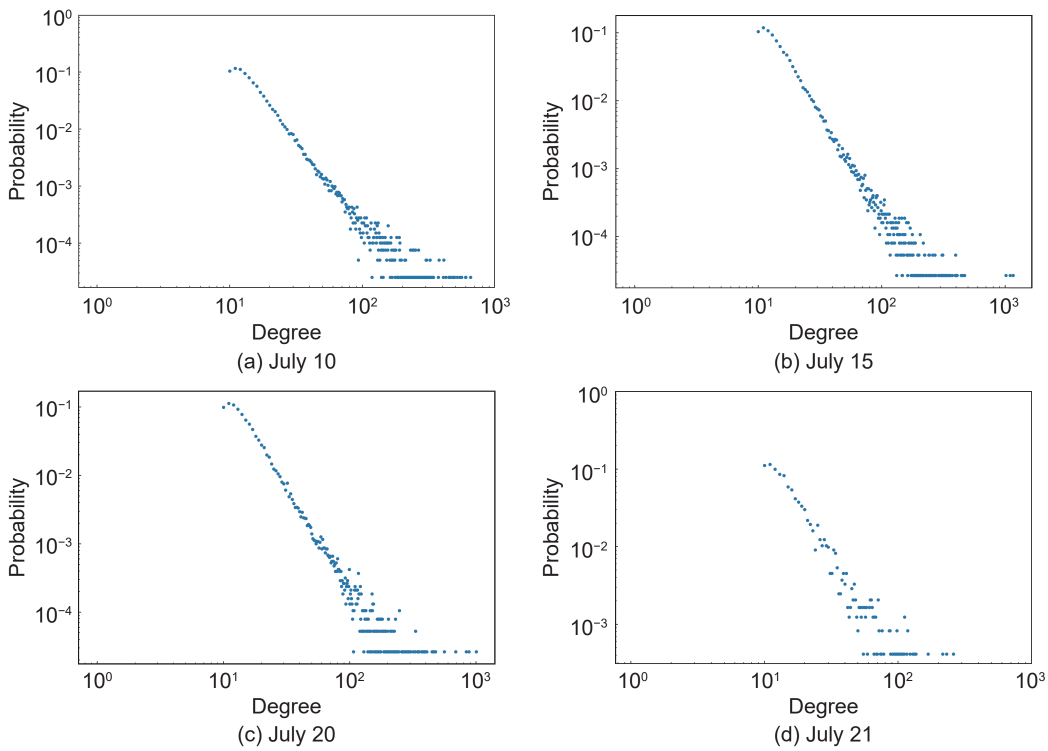

Fig. 8 Dynamic variation of degree distribution in the network.

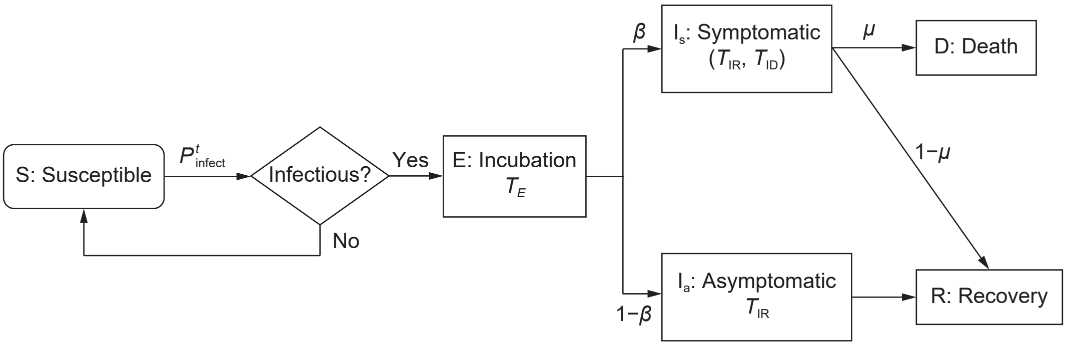

Fig. 9 SEIR model.

Table 2 Parameters of the intervention strategies.

Parameter	Meaning
N^t_{con}	Average number of contacted persons during the day
P^t_{infect}	Probability of infection
L^t_{swab}	Capability of throat swab testing
Qua^t	Quarantine patients or suspected patients
$Rdtst^t$	Test for the suspected patients
T	The time of executing

According to the notification issued by the Nanjing Municipal Health Commission (http://wjw.nanjing.gov.cn), we sorted out the main epidemic intervention policies during the outbreak at Nanjing Lukou Airport (Table 3).

4 Experiment

4.1 Statistical data of the epidemic in Nanjing Lukou Airport

The development of the epidemic in Nanjing is shown in Fig. 10, from which it can be observed that the new cases are concentrated in the 10 days after July 20th.

Based on the constructed artificial society, we can conduct propagation simulations of COVID-19 to reproduce the outbreak in Nanjing Lukou Airport, and compare the effect of different intervention strategies.

Table 3 Policies of Nanjing Lukou Airport.

Date	Policies description
2021-07-10	Mixed duties of cleaning staff for international and domestic flights.
2021-07-12	Regular weekly nucleic acid testing.
2021-07-20	Airport-related personnel were centrally isolated and re-tested for nucleic acid.
2021-07-22	Increase staff nucleic acid testing frequency to every other day.
2021-07-26	1. Nanjing Lukou Airport suspended operations. 2. The airport and related staff were closed-off management. 3. Strengthen the centralized isolation site reserves and standardized management.
2021-08-28	Nanjing Lukou Airport restarted operations.

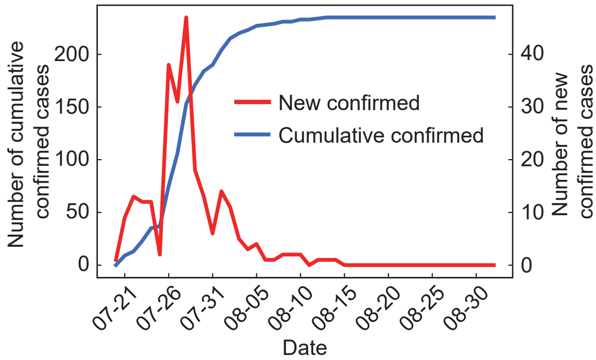

Fig. 10 Development of the real epidemic in Nanjing.

4.2 Parameters setting

According to the sensitivity analysis of the model parameters in our previous study in city, our spreading model is robust to the change in input parameters[4, 13]. To validate the proposed models, we set the parameters by comparing the simulation data with the real epidemic data and taking the new cases and cumulative cases as the indicator[25]. The simulation experiments run 1000 times to alleviate the influence of random factors. In Table 4, we show the parameter configurations.

Table 4 Experimental parameters for the reproduction of epidemic.

Parameter	Value
P^t_{infect}	0.15
α	0.69
μ	0.98
T_E	4 days (average)
T_{ID}	14 days (average)
T_{IR}	9.3 days (average)

4.3 Simulation of the epidemic in Nanjing Lukou Airport

We conducted a linear fitting between the simulation new cases and real new cases. The fitting results in Fig. 11 show that the slope of the fitting curve is 0.8444. The results of the simulation experiment validate the artificial society of Nanjing Lukou Airport that we constructed. On this basis, we next conduct computational experiments to explore the effect of different intervention strategies in the artificial society.

4.4 Effects of intervention strategies

We formulated four intervention strategies: environmental distinction, strict personnel management, frequent tests, and combined measures. The effects of the four strategies are shown in Fig. 12. Except for the combined measures, strict personnel management is the most effective intervention compared to the other two strategies. The cumulative cases decline obviously and maintain steady at a low level if combined intervention is adopted.

5 Discussion

From the experimental results of the outbreak simulation in Nanjing Lukou Airport, we found that the spreading characteristics differ considerably between static networks and dynamical networks. In a traditional static network, the growth pattern of the cumulative cases shows an S-shape[26]. However, it is more similar to a linear increase in dynamic contact networks. Correspondingly, the curve of the new case keeps a stable rate of rising without a peak. Compared with the real cumulative cases of Nanjing city, there existed a timestamp when the curve of real data was gradually separated from the simulated curve, and the deviation between the two curves becomes larger and larger with time increased, as shown in Fig. 13. The deviation represents the level where the COVID-19 overflowed from the airport to the urban area in Nanjing. Base on the finding, it is recommended that we should take actions to put off the separation timestamp and reduce the deviation once the epidemic breaks out in a transportation hub.

The reason why the cumulative cases show the linear increase is closely related to the dynamic update of the passenger. All edges of the dynamical network have an existing temporal interval, and only in the interval, the

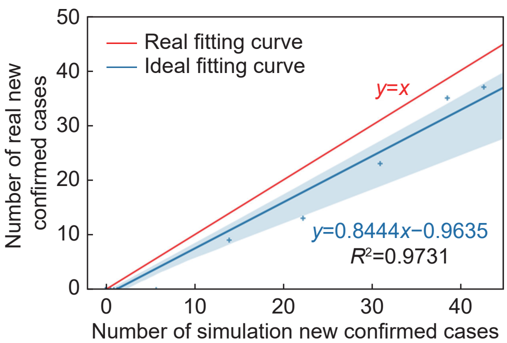

Fig. 11 Linear fitting between the numbers of simulation new confirmed cases and real new confirmed cases.

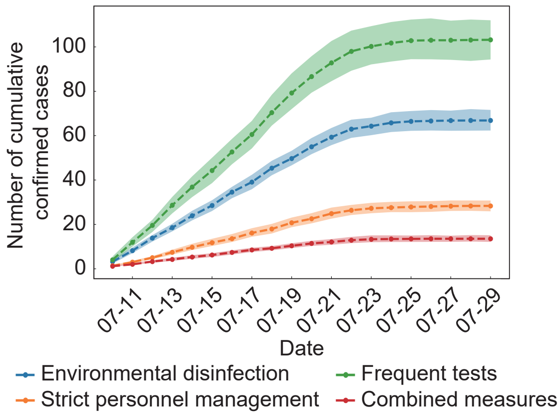

Fig. 12 Cumulative cases under four intervention strategies.

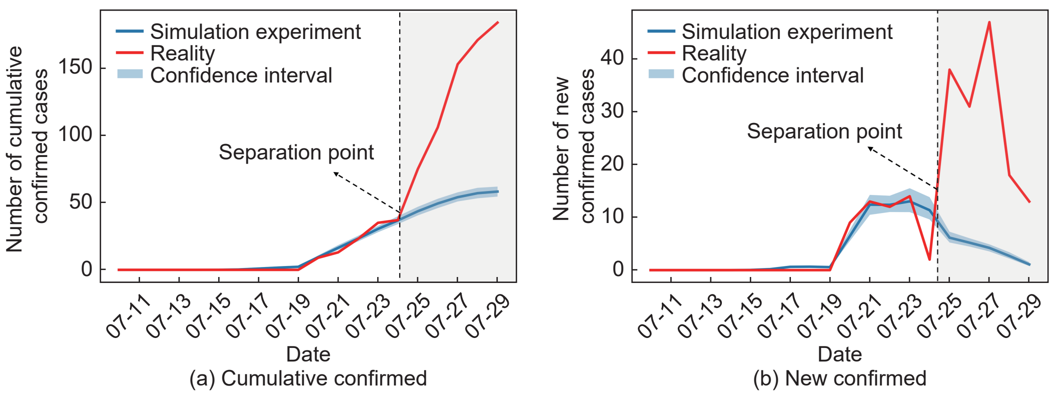

Fig. 13 Reproduction of epidemic in Nanjing Lukou Airport.

contact between the nodes of the edge can transmit the virus. Passengers who entered the terminal on the first flight had left when a new batch of passengers entered, so the individuals are not the same as in the past. Therefore, the virus spreads at a steady speed if the number of passengers is kept stable.

In terms of intervention strategies, the frequency of contact is a vital effective factor to mitigate the epidemic in airports. It is recommended that the administrators could promote unmanned security checks and boarding in the terminal to reduce contact behaviors between staff and passengers. And the flights should be halted as soon as possible once an outbreak breaks out.

6 Conclusion

Based on the continuous-time dynamical network, this paper proposed an algorithm for constructing a complex dynamical network and constructed an artificial society for epidemic simulation in Nanjing Lukou Airports. We reproduced the outbreak of COVID-19 in Nanjing Lukou Airports and studied the effects of four intervention strategies.

The most important finding of the paper is that the growth of cumulative cases is linear in a dynamic social system. In addition, it is effective for mitigating the epidemic to decrease the frequency of contact in airports.

Our research provides some reference for the construction of artificial society in complex dynamic social systems and simulation of disease spread on complex dynamical networks. Some remaining problems need further research, for instance, the artificial society can be improved by more elaborate modeling of environment, population, and contact behaviors.

Acknowledgment

This study was supported by the National Natural Science Foundation of China (Nos. 62173337, 21808181 and 72071207), the Hunan Key Laboratory of Intelligent Decision-Making Technology for Emergency Management (No. 2020TP1013), and Humanity and Social Science Youth Foundation of Ministry of China (No. 19YJCZH073).

References

[1] COVID-19 dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU), https://coronavirus.jhu.edu/map.html, 2022.

[2] Y. Li and C. Wei, Network public opinion crisis management based on the outbreak in Nanjing, (in Chinese), *Modern Business Trade Industry*, vol. 43, no. 11, pp. 151–153, 2022.

[3] W. Broniec, S. An, S. Rugaber, and A. K. Goel, Using VERA to explain the impact of social distancing on the spread of COVID-19, arXiv preprint arXiv:2003.13762, 2020.

[4] H. Chen, Z. Zhu, C. Ai, Y. Zhao, C. He, M. He, and B. Chen, Evaluating the mitigation strategies of COVID-19 by the application of the CO_2 emission data through high-resolution agent-based computational experiments, *Environmental Research*, doi: 10.1016/J.ENVRES.2021.112077.

[5] L. Wang and S. Wang, Epidemic and research trends of several major infectious diseases worldwide, (in Chinese), *Foreign Medicine*: *Epidemiology Infectious Diseases*, no. 1, pp. 5–9, 2000.

[6] J. Legrand, C. Viboud, P. Y. Boelle, A. J. Valleron, and A. Flahault, Modelling responses to a smallpox epidemic taking into account uncertainty, *Epidemiology and Infection*, vol. 132, no. 1, pp. 19–25, 2004.

[7] M. Morris and M. Kretzschmar, Concurrent partnerships and the spread of HIV, *Aids*, vol. 11, no. 5, pp. 641–648, 1997.

[8] S. Chang, E. Pierson, P. W. Koh, J. Gerardin, B. Redbird, D. Grusky, and J. Leskovec, Mobility network models of COVID-19 explain inequities and inform reopening, *Nature*, vol. 589, no. 7840, pp. 82–87, 2021.

[9] Q. Li, H. Chen, Y. Li, M. Feng, and J. Kurths, Network spreading among areas: A dynamical complex network modeling approach, *Chaos*: *An Interdisciplinary Journal of Nonlinear Science*, vol. 32, no. 10, p. 103102, 2022.

[10] S. Cheng, C. C. Pain, Y. K. Guo, and R. Arcucci, Real-time updating of dynamic social networks for COVID-19 vaccination strategies, arXiv preprint arXiv: 2103.00485, 2021.

[11] W. Li, Virus propagation model and simulation based on multi-agent dynamic complex network, MEng dissertation, Faculty of Information Engineering and Automation, Kunming University of Technology, Kunming, China, 2012.

[12] M. Peng, J. Yang, Q. Shi, L. Ying, H. Zhu, G. Zhu, X. Ding, Z. He, J. Qin, J. Wang, et al., Artificial intelligence application in COVID-19 diagnosis and prediction, *SSRN Electronic Journal*, doi: 10.2139/ssrn.3541119.

[13] Z. Zhu, C. Ai, H. Chen, B. Chen, W. Duan, X. Qiu, X. Lu, M. He, Z. Zhao, and Z. Liu, Understanding the necessity and economic benefits of lockdown measures to contain COVID-19, *IEEE Transactions on Computational Social Systems*, doi: 10.1109/TCSS.2022.3194639.

[14] Z. Zhu, B. Chen, H. Chen, S. Qiu, C. Fan, Y. Zhao, R. Guo, C. Ai, Z. Liu, Z. Zhao, et al., Strategy evaluation and optimization with an artificial society toward a Pareto optimum, *The Innovation*, vol. 3, no. 5, p. 100274, 2022.

[15] F. Y. Wang, Toward a paradigm shift in social computing: The ACP approach, *IEEE Intelligent Systems*, vol. 22, no. 5, pp. 65–67, 2007.

[16] G. H. Nguyen, J. B. Lee, R. A. Rossi, N. K. Ahmed, E. Koh, and S. Kim, Continuous-time dynamical network

embeddings, in *Proc. the Web Conference*, Lyon, France, 2018, pp. 969–976.

[17] T. Zhou, W. Bai, B. Wang, Z. Liu, and G. Yan, A brief review of complex networks, (in Chinese), *Physics*, vol. 34, no. 1, pp. 31–36, 2005.

[18] T. Xiao, Research on transportation planning of integrated passenger hub-rail station at the micro level, MEng dissertation, School of Civil Engineering, Xi’an University of Architecture and Technology, Xi’an, China, 2013.

[19] A. -L. Barabási and R. Albert, Emergence of scaling in random networks, *Science*, vol. 286, no. 5439, pp. 509–512, 1999.

[20] J. Truscott and N. M. Ferguson, Evaluating the adequacy of gravity models as a description of human mobility for epidemic modelling, *PLoS Computational Biology*, vol. 8, no. 10, p. e1002699, 2012.

[21] K. Rakić, M. Rosić, and I. Boljat, A Survey of agent-based modelling and simulation tools for educational purpose, *Tehnicki Vjesnik*, vol. 27, no. 3, pp. 1014–1020, 2020.

[22] X. Qiu, B. Chen, and P. Zhang, *Emergency Management Oriented Artificial Society Construction and Computational Experiments*, (in Chinese). Beijing, China: Science Press, 2017.

[23] R. Albert and A. -L. Barabási, Statistical mechanics of complex networks, *Reviews of Modern Physics*, vol. 74, no. 1, pp. 47–97, 2002.

[24] Q. Nie, Y. Liu, D. Zhang, and H. Jiang, Dynamical SEIR model with information entropy using COVID-19 as a case study, *IEEE Transactions on Computational Social Systems*, vol. 8, no. 4, pp. 946–954, 2021.

[25] N. Samieefar, R. Rashedi, M. Akhlaghdoust, M. Mashhadi, P. Darzi, and N. Rezaei, Delta variant: The new challenge of COVID-19 pandemic, an overview of epidemiological, clinical, and immune characteristics, *Acta Bio-Medica*: *Atenei Parmensis*, vol. 93, no. 1, p. e2022179, 2022.

[26] J. Sanz, L. M. Floría, and Y. Moreno, Spreading of persistent infections in heterogeneous populations, *Physical Review E*, vol. 81, no. 5, p. 056108, 2010.

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