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Urban Hierarchical Open-up Schemes Based on Fine Regional Epidemic Data for the Lockdown in COVID-19 ☼ ☾

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ARTICLE INFO

Article history:
Received 31 July 2020
Received in revised form 6 April 2021
Accepted 31 May 2021
Available online 15 June 2021

Keywords:
Fine urban governance
Urban open-up scheme
COVID-19
Non-epidemic residential communities
Epidemiological analysis
Economic cost analysis

ABSTRACT

During the COVID-19 outbreaking, China’s lock-down measures have played an outstanding role in epidemic prevention; many other countries have followed similar practices. The policy of social alienation and community containment was executed to reduce civic activities, which brings up numerous economic losses. It has become an urgent task for these countries to open-up, while the epidemic has almost under control. However, it still lacks sufficient literature to set appropriate open-up schemes that strike a balance between open-up risk and lock-down cost. Big data collection and analysis, which play an increasingly important role in urban governance, provide a useful tool for solving the problem. This paper explores the influence of open-up granularity on both the open-up risk and the lock-down cost. It proposes an SEIR-AL model considering the effect of asymptomatic patients based on propagation dynamics, and offered a model to calculate the lock-down cost based on the lock-down population. A simulation experiment is then carried out based on the mass actual data of Wuhan City to explore the influence of open-up granularity. Finally, this paper proposed the evaluation score (ES) to comprehensively measure schemes with different costs and risks. The experiments suggest that when released under the non-epidemic situation, the open-up scheme with the granularity refined to the block has the optimal ES. Results indicated that the fine-grained open-up scheme could significantly reduce the lock-down cost with a relatively low open-up risk increase.

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1. Introduction

COVID-19 refers to pneumonia caused by 2019 new corona-virus infection, which is highly infectious. The World Health Organization believes that the current outbreak of the new crown pneumonia can be called a global pandemic. With the epidemic developing, more than 60 countries have declared a state of emergency, and some of them have taken measures to “lock down the country” and “lock down the city.” The action of lock-down has been proved to control the epidemic effectively, but it also causes massive economic loss to the cities and countries [1–4], therefore, keeping risk at a deficient level, and opening up early becomes the demand of each city. Therefore, constructing an open-up scheme considering the trade-off between the risk and the cost is in need. Recent studies have made significant contributions to the simulation of virus transmission. For example, some researchers focus on finding out the factors affecting the transmission of viruses and how they affect the infection [5–8]. Some works focus on estimating the virus transmission, including transmission parameters, mortality rate, diagnosis rate, etc. [9,8,10,11]. Many studies concentrate on lock-down measures taken to prevent COVID-19. On the one hand, some studies try to estimate the effects of lock-down actions in mitigating the spread of COVID-19 [12–16]. On the other hand, many researchers focus on the economic impact of lock-down [17–19]. It can be seen that although the lock-down measures alleviate the spread of the epidemic, they also have a severe impact on the economy of many regions. Reducing the risk of epidemic transmission and reducing economic losses have both become the needs of the people, regions, and countries.

In recent years, big data collection and analysis plays an increasingly important role in urban governance [20–24]. Some experts have also studied the urban governance problems brought
about by the COVID-19 [24,25]. Some studies hope to help to put forward some more reasonable lock-down schemes. E.g., Alvarez et al. studied the optimal lock-down policy for a scheme who wants to control the fatalities of a pandemic while minimizing the output costs of the lock-down [25].

However, there are few studies on the impact of open-up schemes. This paper focuses on open-up schemes of different granularity. It explores the effects of granularity on economic cost and risk. Considering that Wuhan is the city with the earliest outbreak of the epidemic, the most rapid implementation of lock-down actions, and the quickest recovery from the epidemic situation, we did a simulation open-up experiment based on Wuhan epidemic data, from which the impact of granularity is detected. Finally, the optimal scheme suggestions are given by comprehensively analyze these open-up schemes.

The contribution of this paper includes:

1. We explored the impact of open-up granularity on both risk and economic costs. With higher granularity, the risk increases slightly, and the cost reduces significantly. We verified this rule by a simulation experiment based on the actual data of Wuhan;
2. We introduced the regional epidemic risk calculation model under the isolating state based on the epidemiological model;
3. We proposed the simplified calculation formula of urban lock-down cost;
4. Finally, through the comprehensive analysis of risk and cost, we introduced the scheme evaluation model, based on which to suggest Wuhan’s optimal multi-granularity open-up scheme (MGOS);

Section 2 describes the basic relative concepts in this paper. The Multi Granularity Open-up Scheme is illustrated in Section 3; the lock-down cost formulation and risk model are presented in Sections 4 and 5. The comprehensive analysis model is presented in Section 6. Section 7 includes the simulation experiment on Wuhan City and results analysis. The paper concludes with a brief conclusion in Section 8.

2. Relative concepts

Lock-down. Residents are required to isolate at home, restrict outdoor activities, close public transport, and strictly control urban external traffic. These restrictions are lock-down control. The specific forms include but are not limited to setting up checkpoints at the exit of residential areas, setting up roadblocks at critical intersections, and stopping public transport.

Open-up. As the epidemic gradually subsides, the production and life of residents are required restoring. The process of releasing these lock-down measures is called open-up, and the conditions that each region must meet to be allowed opening up are called open-up conditions.

Lock-down cost. When a city is in the state of lock-down, many economic activities are stagnant, so the lock-down measures bring significant economic loss, which is lock-down cost. In reality, the calculation of lock-down cost is very complicated. However, there is a highly positive correlation between economic growth and the employment [26]. Therefore, this paper proposes a simplified expression of lock-down cost, which uses a function constructed by the free population. In Section 4, we will present the details of the calculation formula.

Open-up risk. Open-up allows residents to have social contact again, which may provide conditions for the epidemic’s resurgence. Therefore, open-up brings about risk, which refers to the risk of virus re-spreading in the population. In Section 5, we will study the factors that affect the risk.

Open-up scheme. For a city, an open-up scheme includes a specific open-up schedule for every region. Usually, there are many possible open-up schemes at the beginning. The optimal one would be chosen after the evaluation of these schemes’ risk and cost.

3. Multi-granularity open-up scheme

The open-up time of a region has an impact on both its lock-down cost and epidemic risk. Because the epidemic severity is usually different in different parts of a city, a fine-grained open-up scheme can reduce the interaction between regions. It makes the low-risk areas can be open-up as soon as possible without being bounded by high-risk areas, therefore reduce the lock-down cost. It also makes the high-risk areas can maintain the lock-down status to ensure that the urban risk is staying at a low level. Therefore, in this paper, we propose the multi-granularity open-up scheme (MGOS) based on the urban management structure.

Hypothesis 1. Within a specific range, the lock-down cost would reduce effectively while the open-up granularity was refining. At the same time, the risk would increase slightly but still maintains at a low level. Therefore, it is an optimal choice to choose a fine-grained open-up scheme.

A clear definition of MGOS is as follows. MGOS: Firstly, the object city’s management structure is divided into a tree-like-structure with a depth of L (L-tree). MGOS refers to a scheme using some nodes (regions) selected from the L-tree. If only when the respective non-epidemic situation (NES) of a node reaches open-up condition (OC) could the people inside move freely in the city. Here NES is defined as the proportion of uninfected people in the total local population; OC is the value of NES, which must be satisfied when an area is open-up. Under the requirements for risk minimization, it is 100%. Notice that the selected nodes are independent of each other, and they cover the whole city. A set of node selection represents an MGOS. The number of selected nodes is defined as granularity. Before filtering, there are usually multiple MGOSs constructed.

Section 7 will build MGOSs based on the Wuhan city’s actual data and compare their lock-down cost and risk to verify the hypothesis in simulation experiments. Next, we will introduce the model used to calculate the lock-down cost and risk.

4. Lock-down cost calculation

There are few pieces of researches on economic cost (lock-down cost) under the open-up process. The lock-down cost contains very complex factors, so it is difficult to calculate accurately. Therefore, we can only use a very simplified model to express the lock-down cost.

As mentioned in the second Section, the Lock-down cost C is highly correlated with the population under lock-down. Therefore, it is simplified as a linear function of the number of lock-down population U: C=K’U. K is the average economic value a person brings in a day. When the area is under completely lock-down, C=K’N (N is the total population of the region).

\[
C = k \times \sum_{t=1}^{TW} \sum_{i=1}^{n} U_{i,t}
\]

(1)

In Eq. (1), \(U_{i,t}\) represents the lock-down population of the i-th area on day t, and \(\sum_{t=1}^{TW} U_{i,t}\) represents the total population under control in the city on day t, and TW represents the selected time window.
5. Risk measurement

While opening up the city, the risk of the open-up scheme lies in the probability that the virus may spread between the un-blocked people. At the beginning of the open-up process, a certain number of infected people existed, which constituted the initial risk of each open-up plan. Transmission from the infected to the healthy will increase the total risk, and isolation and cure of the infected will reduce the total risk. A decrease of or at least no increase in the number of infected people after a city has been open for a while means that the epidemic is under control, which is what the city’s open-up process hopes to achieve. There also exists a harsh situation that the infected population keeps growing, leading to the second outbreak.

SEIR-CAL, an SEIR model considering activity limitation, was applied to simulate the progress of the virus spreading. Given the open-up scheme, the model could generate a time series of the infected population, as a measurement of risk.

5.1. Description of the model

The well-known Susceptible-Exposed-Infectious-Removed (SEIR) model was modified to a hierarchical version with consideration of activity limitation to determine the effect of open-up. In a basic SEIR model, the total human population at time t is \( N(t) \), which is divided into four sub-classes: Susceptible \( S(t) \), Exposed \( E(t) \), Infectious \( I(t) \), Removed \( R(t) \). Further, each sub-class could be divided into two statuses: closed and not-closed. Thus there would be eight sub-classes in total. The descriptions of these sub-classes are given in Table 1.

| Variables  | Description                                                                 |
|------------|------------------------------------------------------------------------------|
| \( SN(t) \) | The same description with \( S(t) \) in the basic model                      |
| \( EN(t) \) | The infectors who are not self-aware, including the presymptomatic infectors |
| \( IN(t) \) | The infectious people who are free to move                                   |
| \( RN(t) \) | The same description with \( R(t) \) in the basic model                      |
| \( SC(t) \) | The susceptible people who are isolating at home                            |
| \( EC(t) \) | The exposed people who are isolating at home                                |
| \( ICH(t) \) | The asymptomatic infectors who are isolated in a particular facility, such as a hotel |
| \( ICM(t) \) | The Infectious people who are isolating in hospitals and being treated      |
| \( RC(t) \) | The Recovered people who are isolating at home                              |

**Assumption 1**: the city would only be opened up when the epidemic begins to subside in its later stages.

**Assumption 2**: all detected patients and asymptomatic infected persons would be quarantined in a particular facility, but not at their homes.

**Assumption 3**: neither new births nor death citizens affect the total urban population significantly.

**Assumption 2** and **3** are two minor assumptions which help to simplify the model without loss of generality. With assumption 2, the transfer path from \( EC \) to \( EN \) is irreversible, as Fig. 1 illustrated, which insulated the possibility that those infectors in the opened up population may infect those still closed. With assumption 3, the effects of newborns and dead people are not reflected in the model. The total population in the model remains constant.

A schematic diagram of the full system is given in Fig. 1. Let the number of districts that are opened up at date \( t \) be \( A_t \), and the population in these districts are \( N_i(t) \), \( i = 1, 2, \ldots, A_t \). \( N_i(t) = SC_i(t) + EC_i(t) + RC_i(t) \). When an area of the city is opened up, its population was added to the disease transmission dynamics, \( SC_i(t) \) turns to \( \Delta SN(t) \), \( EC_i(t) \) turns to \( \Delta EN(t) \), and \( RC_i(t) \) turns to \( \Delta RN(t) \).

\[
\Delta SN(t) = \sum_{i=1}^{A_t} SC_i(t)
\]

\[
\Delta EN(t) = \sum_{i=1}^{A_t} EC_i(t)
\]

\[
\Delta RN(t) = \sum_{i=1}^{A_t} RC_i(t)
\]

The total free population at date \( t \) is represented as below. The schedule of open-up determines its value.

\[
M(t) = \sum_{j=1}^{t} [\Delta SN(t) + \Delta EN(t) + \Delta RN(t)]
\]

Because \( SN(t) \), \( EN(t) \), and \( RN(t) \) are irregularly supplemented by \( \Delta SN(t) \), \( \Delta EN(t) \), and \( \Delta RN(t) \), a model in the form of a dif-
ferential equation may not express those variables accurately. We choose the iterative style to represent our SEIR-CAL model.

Let $\beta_1$ and $\beta_2$ and represent the infection rates of EN and IN respectively; we may have:

$$SN(t + 1) = SN(t) + \Delta SN(t + 1) - \frac{\beta_1 SN(t) EN(t)}{M(t)} - \frac{\beta_2 SN(t) IN(t)}{M(t)}$$

(6)

There are three possible paths for EN to transform: the symptom may onset ($EN \rightarrow IN$) with a probability of $k$; getting positive in nucleic acid testing and being quarantined ($EN \rightarrow ICH$) with a possibility of $\sigma$, and recover naturally ($EN \rightarrow RN$) with a probability of $\theta$. We may have:

$$EN(t + 1) = (1 - k - \sigma - \theta) EN(t) + \Delta EN(t + 1) + \frac{\beta_1 SN(t) EN(t)}{M(t)} + \frac{\beta_2 SN(t) IN(t)}{M(t)}$$

(7)

$$ICH(t + 1) = (1 - k - \theta) ICH(t) + \sigma EN(t)$$

(8)

Assuming that those infected persons with typical symptoms would be taken to hospital for treatment ($IN \rightarrow ICM$) within D days of the onset of symptoms:

$$IN(t + 1) = \max[IN(t) - IN(t + 1 - D), 0] + k EN(t)$$

(9)

In Eq. (9), $D \geq 1$. When $D \geq (t + 1)$, then $IN(t + 1 - D) = 0$. Finally, with treatment rate $\gamma$, ICM, and RN could be represented as:

$$ICM(t + 1) = (1 - \gamma) ICM(t) + IN(t + 1 - D) + k ICH(t)$$

(10)

$$RN(t + 1) = RN(t) + \gamma ICM(t) + \theta ICH(t) + \theta EN(t)$$

(11)

Eq. (6)-(11) constitute the main framework of the SEIR-CAL model. In the actual calculation, we set the initial state of the model as follows:

$$SN(0) = \Delta SN(0)$$

(12)

$$EN(0) = \Delta EN(0)$$

(13)

$$IN(0) = ICH(0) = ICM(0) = RN(0) = 0$$

(14)

There is no exact analytic solution of an SEIR model has yet been found. Once the initial status of the model is given as input, and the parameters are determined, results in numerical form could be output. In the case of a city open-up, the schedule of open-up is given as input, leading to a time series of the infectors (EN and IN in the model) in an observing window.

In other words, the output of the model is highly dependent on the value of parameters, which may vary with the specific application scenario. We will discuss the valuation of the settings in Section 5.2 and then validate the model with simple simulation data in Section 5.3.

### 5.2 Discussion of parameters

All parameters in the model are listed in Table 2. Some parameters reflect several inherent characteristics of the COVID-19, which can be verified by other epidemiological studies; the other parameters may vary with different locations or the epidemic stage, and we estimate these parameters based on the epidemic actual data in Wuhan.

In Table 2, $R_0$ and $\theta$ are obtained from fitting the nucleic acid test data of Wuhan from April 1st to May 13th; $\beta_1$ and $\beta_2$ are derived from $R_0$; $\sigma$, $d$ and $\gamma$ are derived from official statistics, public news reports or other references; the values of $D$ and $K$ are assumed.

The estimation of was widely discussed, with values ranging from 1.4 to 5.7 [32–35], which reflected the rapid spread of the disease in the early stage of the epidemic and could not simply fit the scenario of city open-up. On the other hand, there are not many pieces of research focused on the asymptomatic infectors, thus the value of $\theta$ (equals the multiplicative inverse of the average recovery period of the asymptomatic patients) lacks strong reference support. The above two reasons suggest the necessity of data fitting.

Article [12] investigated the Epidemiological case data at Ningbo, Zhejiang Province from January to March in 2020, and concluded that the transmissibility of an asymptomatic case equals about 0.65 times of a general infecter. Considering Ningbo has abundant medical resources, which is not significantly different from the case in Wuhan on the process of open-up, thus we can set $\beta_1 = 0.65 \beta_2$ in our case;

Our method to compute $\beta_2$ or the transmission rates of general infectors is the same with $\beta_3 = R_0/\delta$ [29]: where $d = \delta + D$. Here $d$ represents the length of the time window in which a virus carrier has a chance to infect susceptible people, and $\delta$ represents the average asymptomatic infectious period, which equals 4.5 days [29]. We assume $D = 1$, therefore, $d = 4.5 + 1 = 5.5$.

Assuming that $k$ represents the transmission rate from EN to IN and $k = w + ip$, where $w$ represents the proportion of the latent infectors in the total exposed human (EN), and $ip$ represents the length of the incubation period. Throughout the month of April, the Wuhan government had reported 741 new cases of asymptomatic infection, but only 1 new confirmed case [30]. It could be assumed that after excluding the influence of imported cases, the vast majority of the virus carriers in Wuhan would be the asymptomatic infectors, it would be possible that the value of is much smaller than 1/741, we choose $w = 1 ÷ 10000$ and $ip = 5.6$ [29], and $k = 1/56000$. The estimation of is based on the daily number of nucleic acid tests reported in Wuhan, from April 1st, 2020 to May 13th, 2020, an average of 41,740 cases of nucleic acid were tested and which was equivalent to 0.327% of the total population of Wuhan, so we choose $\sigma = 0.00327$. At last, we choose $\gamma = 1/24.7$ [31].
Under the assumptions above, an SEIR-CAL model was settled up, parameters $R_0$ and $\theta$ were taken as variables to calculate the time series of EN and fitted to the actual data of asymptomatic infectors reported in Wuhan between April 1st, 2020 to May 13th, 2020, to find the value of $R_0$ and $\theta$ that minimized the RMSE. Fig. 2 demonstrates the data and Fig. 3 shows the result of data fitting.

5.3. Experiments to verify properties

An SEIR-CAL model was verified on MATLAB (version: R2019b). Assuming that the total population is 10 million and 20,000 exposed cases at the initial time of opening, we listed ten opening schemes. We ran the model to observe the trends of the critical variables EN, IN, and IC. As Table 3 demonstrates, we assumed that the same number of people are opened at a time under each scheme. By adjusting the batches (1 to 4) and the length of the opening operation period (7 days, 11 days, and 14 days), we can obtain ten different schemes.

Fig. 4 demonstrates the trend of the critical variables EN, IN, ICH and ICM. These four key variables represent four groups of potentially at-risk people. It can be seen that the blue line was describing the most radical opening scheme, which opened all the population on the first date, is on the top in each of the figures. The black line with the cross representing the most conservative opening scheme is on the bottom, which shows that these two correspond to the highest risk and the lowest risk.

Take Fig. 4a for an example: the variable EN under each scheme almost shows a monotonous downward trend (which reflects that the epidemic is subsiding under our parameter setting). At the day 30, there would be 4,681 exposed cases remain under the most radical scheme (open all, scheme 1), the number of remaining exposed cases at day 30 was only 3,380 under the second most radical opening scheme (2batches+7days, scheme 2), and 2,423 under the most conservative scheme (4batches+14days, scheme 10).

In scheme 1, the number of exposed cases would be reduced to below 2,000 on day 47, compared with 34 days for scheme 10.

Fig. 4b shows the change in the number of confirmed cases, Fig. 4c for the asymptomatic infectors being observed in isolation and Fig. 4d for hospitalized patients. Table 3 demonstrates only a rough simulation of a city’s opening-up schedule. Nevertheless,
Table 3
Settings of 10 opening schemes.

| Schemes   | Batch 1             | Batch 2             | Batch 3             | Batch 4             |
|-----------|---------------------|---------------------|---------------------|---------------------|
| open all at the first one | \(\Delta S(N(0)) = 980000\) | \(\Delta S(N(0)) = 2000\) | \(\Delta S(N(0)) = 0\) | \(\Delta S(N(0)) = 0\) |
| 2 batches + 7 days | \(\Delta S(N(0)) = 4990000\) | \(\Delta S(N(0)) = 10000\) | \(\Delta S(N(0)) = 0\) | \(\Delta S(N(0)) = 0\) |
| 2 batches + 11 days | \(\Delta S(N(0)) = 4990000\) | \(\Delta S(N(0)) = 10000\) | \(\Delta S(N(0)) = 0\) | \(\Delta S(N(0)) = 0\) |
| 2 batches + 14 days | \(\Delta S(N(0)) = 4990000\) | \(\Delta S(N(0)) = 10000\) | \(\Delta S(N(0)) = 0\) | \(\Delta S(N(0)) = 0\) |
| 3 batches + 7 days | \(\Delta S(N(0)) = 3326667\) | \(\Delta S(N(0)) = 666667\) | \(\Delta S(N(0)) = 0\) | \(\Delta S(N(0)) = 0\) |
| 3 batches + 11 days | \(\Delta S(N(0)) = 3326667\) | \(\Delta S(N(0)) = 666667\) | \(\Delta S(N(0)) = 0\) | \(\Delta S(N(0)) = 0\) |
| 3 batches + 14 days | \(\Delta S(N(0)) = 3326667\) | \(\Delta S(N(0)) = 666667\) | \(\Delta S(N(0)) = 0\) | \(\Delta S(N(0)) = 0\) |
| 4 batches + 7 days | \(\Delta S(N(0)) = 2495000\) | \(\Delta S(N(0)) = 5000\) | \(\Delta S(N(0)) = 0\) | \(\Delta S(N(0)) = 0\) |
| 4 batches + 11 days | \(\Delta S(N(0)) = 2495000\) | \(\Delta S(N(0)) = 5000\) | \(\Delta S(N(0)) = 0\) | \(\Delta S(N(0)) = 0\) |
| 4 batches + 14 days | \(\Delta S(N(0)) = 2495000\) | \(\Delta S(N(0)) = 5000\) | \(\Delta S(N(0)) = 0\) | \(\Delta S(N(0)) = 0\) |

Comparing the results in Fig. 4 with the actual figures in Wuhan\(^1\), there is not significantly different between them in order of magnitude. In the real situation, the number of asymptomatic infectors and hospitalized patients in Wuhan was not zero, partly explains the discrepancy between the simulation results and the actual figures.

6. Schemes evaluation

Given an opening-up scheme, its cost value and risk value can be drawn according to the methods proposed in Sections 4 and 5. Reducing cost or risk is both the improvement to the scheme; however, these two goals often conflict, which is a typical multi-objective optimization problem. We establish an evaluation score to measure the risk and cost comprehensively and transform the multi-objective optimization problem into a single-objective problem.

Since risk and cost have different physical meanings and cannot be added together, they need to be normalized\(^2\). We denote the scheme as \(P_i (i = 1, 2, \ldots, n)\), then denote its normalized cost value as \(C_{p_i}\), and its normalized risk value as \(R_{p_i}\). The evaluation score of a scheme \(P_i\) can be represented as:

\[
ES(P_i) = w_1 R_{p_i} + w_2 C_{p_i}
\]  

In Eq. (15), \(w_1\) and \(w_2\) are the weights of risk and cost, respectively. \(w_2 = 1\) is set to simplify the model:

\[
ES(P_i) = w_1 R_{p_i} + C_{p_i}
\]  

According to Eq. (16), the evaluation score for an open-up scheme, comprehensively measures the cost and the risk, and it was chosen as the reference index we used to evaluate and select the schemes. The lower ES, the better the scheme.

The output of the cost model in Section 4 is a scalar. However, the risk model in Section 5 generates a time series of the population of those asymptomatic infectors (and the confirmed cases). Both the average value and the peak value in the series should be taken into consideration.

Given an opening time window \(T\), the average risk \(\bar{R} = \sum_{t=1}^{T} R_t/T\) measured the overall risk of scheme \(P_i\), and \(R_{p_i}\) is the normalization of \(R\).

The peak of the risk sequence measures the severity of the scheme, which is related to \(w_1\). The capacity of medical resources in a city has an upper limit. The closer the peak risk is to the ceiling, the higher \(w_1\) will be. In extreme cases, the risk may exceed the city’s medical resources’ capacity, and then \(w_1\) would rise sharply. However, since we assume that the city would only open on the late stage of the epidemic, this extreme scenario should be avoided while formulating an opening-up scheme.

We choose the total number of hospital beds \(Z\) as the indicator of the total amount of medical resources in the city, and we assume that one patient corresponds to one bed. Based on Wuhan’s practice, our model pays attention to the risk of asymptomatic patients. The government department of Wuhan would actively carry out nucleic acid testing on the public, then put the detected asymptomatic patients into medical quarantine, which is taking up

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\(^1\) The city of Wuhan has a population of around 11 million. It was closed down since January 20, 2020, and opened up on April 8, 2020. As of May 8, 2020, there were 610 asymptomatic infectors in observing, and no confirmed case was reported in the first month after opening up. Also, refer to [30].

\(^2\) For the variable \(z_i \in X\), its Min-Max normalized value \(z_i\) can be written as:

\[
z_i = \frac{z_i - \min(z)}{\max(z) - \min(z)}
\]
medical resources. Generally, an asymptomatic patient consumes fewer medical resources than a "normal" patient. The consumption will even be lower if some regions do not actively test and treat asymptomatic infected patients like Wuhan. We assume that the average amount of medical resources consumed by an asymptomatic patient is $k$ times of a confirmed patient, $0<k<1$. The value of $k$ will increase with the attention and the number of medical resources invested in asymptomatic patients.

Another factor that affects the value of $w_1$ is the detection rate of an asymptomatic case $\sigma$, which is one of the parameters in the risk model. The higher $\sigma$ means that asymptomatic patients are more likely to be identified and quarantined, thus increasing the consumption of public medical resources and increasing $w_1$.

Based on the above discussion, the risk weight value $w_1$ is a variable closely related to the number of patients, local medical resources, the detection capacity, and other factors. The value varies in different places and different stages of epidemic progression. The formula is given as follows:

$$w_1 = \frac{\text{max}(ICM_P) + \text{max}(EN_P)}{Z} \cdot \sigma \cdot k \cdot T$$  \tag{17}$$

In Eq. (17), $\text{max}(EN_P)$ is the peak in the series of ICM for opening scheme $P$, and $\text{max}(EN_P)$ is the peak in the series of EN, both $\text{max}(EN_P)$ and $\text{max}(EN_P)$ are output by SEIR-CAL model introduced in Section 5. $T$ is the length of the observing window.

7. Experiments

7.1. Experiment design

To verify the hypothesis 1 and to suggest the optimal scheme, the experimental design is as follows:

1. According to the management structure of Wuhan City, we design a set of different granularity open-up schemes. (the granularity ranged from 3 to 172, and the NES was simulated using the proportion data of the non-epidemic residential communities. OC is set to 100%);
2. When the NES of the node in the scheme reaches OC, open-up the node;
3. Calculate the daily lock-down cost and risk of the city in the simulation situation: in the observing period, according to the open-up nodes of the city every day, calculate the daily lock-down cost, and get the daily risk value according to the risk model;
4. Comparing the average risk and the total lock-down cost of each scheme to verify whether the hypothesis is satisfied. If the schemes with higher open-up granularity have significantly lower lock-down cost, while its risk value is relatively higher but still staying at a low level, hypothesis 1 would be proved to be valid in this experiment;
5. Through the comprehensive analysis model, the optimal scheme suggestions are given among the above open-up schemes.

7.2. Experiment settings

Based on the management structure of Wuhan City, as Fig. 5 demonstrated, three multi-granularity open-up schemes are constructed. The epidemic free status (NES) of each district is simulated based on the data of non-epidemic residential communities released by the Wuhan novel coronavirus pneumonia prevention command headquarters. According to the actual data, the NES is generally close to 100%. Thus, OC is set as 99% in this experiment as an approximation.
The number of asymptomatic patients is difficult to be observed without performing nucleic acid testing. On the other hand, existing studies generally do not pay attention to the pattern of changes in the number of asymptomatic patients. Therefore, we adopted a simplified treatment method: since April 1, 2020, the Wuhan Health Commission has announced a daily amount of nucleic acid tests and the number of asymptomatic patients detected. We obtain the detection rate of asymptomatic patients by quoting these two values. Then multiply the total population of Wuhan to get the estimated number of asymptomatic patients totally in Wuhan.

We functionally fitted the estimated number of asymptomatic patients in Wuhan during April 1, 2020, and April 30, 2020, and extrapolated forward for one month.

**7.2.2. Open-up schemes setup**

Select time window (TW): according to the non-epidemic proportion of the city from 10% to 95%, TW is set as period 03/08-04/10/34 days. Select MGOS: The management structure of Wuhan city is: Wuhan City - towns(3) - districts(15) - Blocks(172) - residential communities(7102), based on the settings above, three open-up schemes are constructed as follows:

**Scheme B1:** City - town - residential community.

**Scheme B2:** City - district - residential community.

**Scheme B3:** City - block - residential community.

For comparison, a unified scheme(A) that the whole city is open-up on April 10 is set as the benchmark scheme.

**7.3. Results and analysis**

**7.3.1. Analysis of cost**

The daily lock-down cost of each scheme is shown in Fig. 7. The figure shows that for the scheme B1, B2, B3, the time when the lock-down cost begins to decrease becomes earlier in turn, which indicates that with the refinement of the open-up granularity, the time of open-up in some areas is advanced. It also shows that the distribution of the epidemic situation is not balanced in different districts of Wuhan city. Moreover, daily blocking cost: B3 < B2 < B1, which indicates that with the refinement of open-up granularity, the daily lock-down cost decreased. In other words, the daily open-up population of the scheme with high granularity is higher than that of the low granularity scheme. It also suggests that in the relatively coarse-grained scheme B1, more low-risk sub-regions are trapped by the relatively high-risk areas every day, thus delaying their open-up time.

Fig. 8 shows that the total lock-down cost (C) decreases with the increase of granularity. Scheme B1, B2, and B3 reduce C by 17%, 27%, and 44%, respectively, compared with the benchmark scheme A. This shows that the fine-grained open-up scheme can significantly reduce the lock-down cost.

In conclusion, in the simulation experiment based on the actual data of Wuhan City, with the refinement of open-up granularity,
The lock-down cost can be significantly reduced, which is consistent with hypothesis 1.

7.3.2. Analysis of risk
Since we assume that only the exposed and infectious person who can move freely constituted the source of risk in the open-up, we set $T=120$ under the operation parameter setting shown in Section 5.2 and run the risk model to work out the EN and IN sequences of each scheme of A, B1, B2, and B3.

We concluded that the amount of IN has no significant impact on the value of risk, based on the following findings: 1) the daily amount of IN is always less than 1, and 2) since the assumption that $D=1$, which means that all IN will be effectively isolated in only one day after the onset of symptoms, thus losing the ability to infect other people. Fig. 9 shows the EN quantity change of each scheme during the observation period of 120 days. It can be found in Fig. 9 that the earlier the scheme is beginning to open, the higher the EN peak value, and the slower it converges to close to zero. When a scheme does not have any free population on a specific date, EN would be zero for that date, which significantly affects the measurement of the schemes’ overall risk. To allow all schemes to be compared on a relatively fair basis, the asymptomatic patients that have not yet been opened-up are also be factored into risk consideration. These asymptomatic patients, or the “frozen” risk carriers, are not capable of infection and recover overtime at the self-healing rate theta, which is defined in the SEIR-CAL model. The variation trend of the total risk value of each scheme is shown in Fig. 10.

The schemes in Fig. 9 and Fig. 10 have the same risk ranking. The benchmark scheme A, the strictest plan with the latest opening date, has the lowest risk. However, when the open-up granularity is gradually refined, the scheme's opening time is progressively advanced, and the risk value is also steadily increased.

Scheme B3 (with the street as management node) has the highest amount of risk.

The whole risk sequence of each scheme is summed daily and divided by the length of the observation period. The average risk value obtained is taken as the risk value indicator of the scheme, as shown in Fig. 11.

The difference in risk value between schemes is less than the difference in cost value. Scheme B3, with the highest risk, only increased the risk value by around 17% compared to scheme A, while B1 only increased the risk by about 31% compared with A. This can be explained as follows: under the setting of 99% OC in the experiment, the risk of epidemic infection has significantly been reduced, and the effect of early opening caused by refining the open-up granularity is very limited in enhancing the risk, which suggests the possibility that, by improving the open-up granularity, a higher cost reduction can be obtained while bearing a lower amount of risk increase, consistent with hypothesis 1.

7.4. Schemes comparison
Base on the actual data in Wuhan, we determined the values of parameters in Eq. (17) and applied them in the experiment: $k$: Wuhan is cautious about the risks carried by asymptomatic patients. It has implemented large-scale nucleic acid testing cooperated with the medical isolation for asymptomatic patients. Nevertheless, there is an order of magnitude difference in the number of medical resources consumed by an asymptomatic patient compared to a confirmed case. The conservative estimate is that $k=1/10$. $Z$: According to public news, by the end of January 2020, Wuhan would have more than 10,000 beds available for COVID-19 patients [10]. Wuhan still has the potential to expand the number of beds in its hospitals; furthermore, considering that the epidemic is at a later stage, the number of confirmed cases is small, and the
isolation and monitoring requirements for asymptomatic patients are relatively low. Therefore, the Wuhan city’s actual medical resource capacity should be more significant than this number, and our estimate Z=10000 is still conservative. T: Finally, we set T=120, consistent with the length of the observation window set in the experiment. According to Eq. (17), we calculated the risk weight $w_1$ of each scheme, and substituted it into Eq. (16) to calculate the evaluation score, ranked the evaluation score, and selected the lowest one as the recommended. Table 4 shows the normalized C, R, and the calculation of w and ES, according to Eq. (16) and Eq. (17). It can be seen that when the open-up granularity increases from 3 to 172, ES decreases from 0.6349 to 0.2082. In other words, with the refinement of open-up granularity, the value of ES reduces significantly, consistent with our expectation. Within a specific range of granularity, the fine-grained open-up scheme has a better risk-cost benefit. The reason lies in that a fine-grained open-up scheme brings significant cost reduction with slightly risk increasing, as we have analyzed earlier.

The OC set in the above experiments reflected that the city is close to the status of no epidemic when beginning to open-up, which is in line with Wuhan’s actual practice. To further study the regularity of risk and cost, we also tried to set up multi-granularity open-up schemes under different OCs and carried out some simulation experiments. Fig. 12 shows EN trends for a total of 19 schemes, and Table 5 demonstrates the evaluation score of them. Under each OC, those fine-grained open-up schemes performed better on ES. However, when the OC is loosening to below 99%, it also means that the underlying assumption of this paper - the city will only open-up when it is nearly free from the epidemic - is loosening. In this case, the setting of OC and the open-up granularity may have complex cross-influences on the scheme’s risk and cost. Although in the experiments we have done so far, the more granular schemes show better ES scores, it has not been proved that this rule would be valid under any OC.

### Table 4
Comparison of schemes A, B1, B2, and B3.

| Schemes | Normalized Cost C | Normalized Risk R | Weight of Risk $w$ | Evaluation Score ES = $C + wR$ |
|---------|-------------------|-------------------|-------------------|-----------------------------|
| A       | 1                 | 0                 | 0.0448            | 1                           |
| B1      | 0.6175            | 0.1862            | 0.2082            | 0.6349                      |
| B2      | 0.3839            | 0.5091            | 0.1454            | 0.4580                      |
| B3      | 0                 | 1                 | 0.0935            | 0.2082                      |

### Table 5
Comparison of schemes with different OC.

| OC=99% | Schemes | Normalized Cost C | Normalized Risk R | Weight of Risk $w$ | Evaluation Score ES = $C + wR$ |
|--------|---------|-------------------|-------------------|-------------------|-----------------------------|
| Standard | 1       | 0                 | 0.0448            | 1                 |
| -block | 0.4938  | 0.3958            | 0.2082            | 0.5762            |
| -district | 0.6882 | 0.2015            | 0.1454            | 0.7175            |
| -town | 0.8064  | 0.0737            | 0.0935            | 0.8133            |
| OC=90% | -block | 0.2492            | 0.6707            | 0.3949            | 0.5141                      |
| -districts | 0.2818 | 0.6454            | 0.4348            | 0.5625            |
| -town | 0.2880  | 0.6313            | 0.5142            | 0.6126            |
| OC=80% | -block | 0.1743            | 0.7832            | 0.4824            | 0.5521                      |
| -district | 0.1766 | 0.7823            | 0.5398            | 0.5989            |
| -town | 0.1788  | 0.7850            | 0.6342            | 0.6767            |
| OC=70% | -block | 0.1207            | 0.8518            | 0.5593            | 0.5971                      |
| -district | 0.1247 | 0.8506            | 0.5751            | 0.6139            |
| -town | 0.1024  | 0.8877            | 0.7226            | 0.7438            |
| OC=60% | -block | 0.0831            | 0.8997            | 0.6242            | 0.6447                      |
| -district | 0.0822 | 0.9046            | 0.6683            | 0.6867            |
| -town | 0.0467  | 0.9538            | 0.7721            | 0.7831            |
| OC=50% | -block | 0.0587            | 0.9294            | 0.6710            | 0.6824                      |
| -district | 0.0512 | 0.9410            | 0.7123            | 0.7214            |
| -town | 0      | 1                 | 0.7990            | 0.7990            |

**Fig. 12.** The trend of EN in those opening schemes with 50%-99%OC
8. Conclusion and discussion

Based on the scenario that the city has gradually quit the lockdown while the epidemic is in its later stages, this paper studied the relationship between the open-up granularity of urban open-up scheme and its risk and economic cost, then designed a simulation experiment to explore the variation rule of them, based on the actual data of Wuhan city. In order to make a quantitative analysis of the risks and costs in the process of opening-up, this paper designed a risk model based on epidemiology, and a simplified cost model based on the population. We found that when the city was nearly free from the epidemic, and an open-up scheme with finer granularity would have significantly lower costs and slightly higher risks. Results suggested that the multi-granularity open-up scheme would reduce 17% - 44% of the cost compared with the benchmark scheme, which would open all the population once at all, while the risk would increase by 3.1% - 17%. This paper also proposed ES, an evaluation indicator to measure the risk and cost of a scheme comprehensively, and then put forward the proposal of Wuhan city's multi-granularity opening scheme. The results showed that the scheme with the granularity of "the block" is optimal, and its ES score is 0.42 lower than the benchmark. Furthermore, based on some of the results of this study, the research team put forward the proposal of residential community open-up in Wuhan, and submitted it to the community prevention and lock-down group of Wuhan epidemic prevention headquarters on March 18. More than two weeks later, Wuhan city started the process of urban open-up on April 8.

The work of this paper also has its limitations. Firstly, due to the limited amount of available data, the schemes' granularity coverage is not extensively enough. Secondly, the concept of "the cost" in the progress of opening-up includes various and complex notations. This paper did not carry on the detailed discussion from the perspective of sociology and economics; it only conducts a simplified model for a preliminary simulation, in which the population in the locking-down status was taken as the calculation basis of costs.

In the future, we hope to study further the influence of other factors (such as opening conditions) in the open-up scheme on risk and cost and explore the law of cross-influence among factors.

We hope that our work may help develop more comprehensive solutions and attract more research on the sight of solutions to help cities recovering safely and economically from the epidemic.

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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