RESEARCH

A network-based model to explore the role of testing in epidemic control

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Abstract

Background: Testing is one of the most effective means to deal with epidemics. However, there is an upper bound on daily testing volume due to the limited healthcare staff and working hours, and different testing methods may also be adopted such as random testing and contact-tracking testing.

Methods: In this paper, a network-based epidemic transmission model combined with testing mechanism is proposed to study the role of testing in epidemic control. We simulate the epidemic spread process on complex networks and introduce testing preference to describe different testing strategies.

Results: Through a series of numerical simulations, we find that testing can flatten the infection curve and delay the outbreak of epidemics. In addition, the higher the priority for testing individuals in close contacts with confirmed cases, the smaller the infection scale. Compared with the increase speed of daily testing volume, the upper bound of daily testing volume plays a more important role in epidemic control. We also discover that when testing combined with other measures is adopted, the daily testing volume required to control epidemics (i.e., control infection scale below 5%) will be reduced by more than 40% even if other measures only reduce individuals’ infection probability by 10%.

Conclusions: In short, although testing can effectively inhibit the spread of infectious diseases, it requires a huge amount of daily testing volume. It is highly recommended that testing be adopted combined with other measures such as wearing masks and social distancing to deal with infectious diseases. Our research contributes to understanding the role of testing in epidemic control and provides useful suggestions for the government and individuals in response to epidemics.

Keywords: testing; infectious disease control; complex networks; numerical simulation

Background

Epidemics have been one of the major threats to human society. According to statistics from the World Health Organization (WHO), as of August 28, 2020, there have been over 24 million confirmed cases of coronavirus disease (COVID-19), including more than 820,000 deaths worldwide[1]. The International Monetary Fund (IMF) predicted that the global economic growth was −4.9% due to the COVID-19 pandemic[2]. In order to reduce the losses caused by COVID-19, testing has been adopted by many countries as an effective response measure. The WHO has also called for more tests in response to COVID-19[3]. Researchers have found that testing plays an important role in controlling the spread of infectious diseases [4, 5, 6, 7, 8, 9]. Testing can identify individuals infected but undiagnosed, which
makes it possible to protect others from infection by quarantining the infections [10, 11, 12, 13]. Scholars also found that testing data could provide accurate estimates of epidemic trends and help governments distinguish whether an outbreak is increasing or past its peak[14]. Testing is so important for controlling epidemics that it has attracted increasing attention of scholars.

A subset of previous research on testing focused on trials and clinical statistics, which is mainly in the field of HIV. In the HIV Prevention Trials Network (HPTN) 071 community-randomized trial[15], participants were divided into three groups: combination prevention intervention with universal testing and antiretroviral therapy (ART), the prevention intervention with ART provided according to local guidelines, or standard care. The HIV incidence of the three groups suggested that universal testing and treatment reduced the population-level incidence of HIV infection. The timing of testing was also found important for controlling HIV[16]. Grinsztejn et al. studied the effects of early versus delayed testing on HIV infection and the clinical results indicated that early testing could reduce the HIV transmission[13]. Cohen et al. found that early testing and implementation of ART treatment can reduce HIV infections[12]. Researchers also discovered that the effectiveness of testing may be greatly reduced if high-frequency transmitters are not tested or linkage to care is inadequate[17, 18]. In addition, some scholars were also concerned about testing strategies. For example, Lightfoot et al. reported that using a social network strategy to distribute HIV self-test kits could reduce the undiagnosed infections[19]. Factors such as age, residence and education level should also be taken into consideration to develop more targeted promotion testing strategies[20, 21].

Another subset of the previous research explored the impact of testing on the epidemic transmission by mathematical models. A series of established mathematical models showed that universal testing could control the epidemic[22, 23, 24, 25, 26]. Granich et al. proposed a mathematical model to simulate the spread of HIV and they found that universal voluntary testing and treatment could drive HIV transmission to an elimination phase within 5 years[22]. A compartmental model was proposed by Aronna et al. to study the impact of testing and an explicit expression for the basic reproduction number $R_0$ in terms of testing rate was obtained. From the expression of $R_0$, conclusion was drawn that testing among asymptomatic cases are fundamental to control the epidemics[27]. Kolumbus and Nisan have established a SEIR model to study the effect of tracking and testing on suppressing epidemic outbreaks and found that testing can reduce both economic losses and mortality, but it requires a large testing capacity[28]. According to the report of Imperial College London, weekly testing healthcare workers (HCWs) and other at-risk groups could reduce their contribution to transmission by 25-33%[3]. Priyanka and Verma adopted the SIR model to compare the effectiveness of testing and lockdown measure and found that testing even performed better than lockdown[29]. The effect of specificity and sensitivity of testing has also been studied[30].

In previous studies, infectious diseases such as HIV have a slow transmission process, so the number of infected cases is relatively small in a short period. As a result, the upper bound of testing volume does not need to be considered. However, when epidemics such as SARS and COVID-19 occur, infected persons will accumulate
rapidly in a short time and a large number of individuals need to be diagnosed through testing. In this case, the upper bound of daily testing volume cannot be ignored and the impact of testing on suppressing epidemic transmission requires in-depth research. In mathematical models, it is often simply assumed that individuals are tested and quarantined with a certain probability. However, in real life, the daily testing volume will gradually increase as the understanding of the epidemic deepens and an individual will not be tested again within a certain period (such as two incubation periods) after being tested negative considering the limited testing resources. In order to bridge the gap, an epidemic transmission model combined testing mechanism was proposed to study the role of testing in epidemic control.

Methods
In this paper, we propose a model to study the impact of testing on epidemic transmission. The model consists of two parts: epidemic transmission model and testing mechanism. The former simulates the epidemic transmission process in the population, and the latter models the testing process implemented by the government.

Epidemic transmission model
An extended SEIR model[31, 32] is introduced to describe the epidemic transmission process. Complex networks, where nodes represent individuals and edges represent the social contact, are used to depict the contact structure among individuals. In our model, an individual can be in one of the six states: susceptible (S), latent (L), asymptomatic infectious ($I_a$), symptomatic infectious ($I_s$), recovered (R) and dead (D). Specifically, the infection process is as follows. Initially, an individual is randomly chosen as the infection source (i.e. set it in state $I_s$) and others are susceptible (S). At each time step, a susceptible (S) individual $i$ will randomly contact one of his/her neighbors. Individual $i$ in contact with symptomatic or asymptomatic infectious individuals will be infected with probability $\lambda$ and $\gamma \lambda$ respectively. $\lambda$ represents the infection rate in contact with symptomatic infectious individuals and $\gamma$ measures the relative infectiousness of asymptomatic infections compared with symptomatic infections. Once individual $i$ is infected he/she will enter latent (L) state and when the latency period $1/\epsilon$ is over, he/she will become asymptomatic or symptomatic infectious with probability $p_a$ and $1 - p_a$ respectively. At the same time, infectious individuals (asymptomatic and symptomatic) will recover with probability $\mu$ and die with rate $\beta$. The whole process will evolve until there is no infected individuals (including latent, asymptomatic and symptomatic people) on the networks.

Testing mechanism
In real life, we cannot be aware of infectious diseases as soon as they occur, so there will be a delay between the start timing of testing and the time when infectious diseases begin. Therefore, in our model, only when the current time step is greater than $T$, the testing mechanism will be introduced into the epidemic transmission model. In addition, due to limited healthcare workers and medical resources, an upper bound exists in daily testing volume. At each time, the largest number of people who can be tested is $V$, which represents the daily testing volume. In this model, asymptomatic and symptomatic infectious individuals will be tested positive
and will be quarantined, so they cannot cause secondary infections by contacts with others. Given the limited testing resources, individuals who are tested negative will not be tested again within two incubation periods, which has been adopted by many countries as a testing strategy in response to COVID-19.

As the understanding of the epidemic deepens, the daily testing volume will gradually increase. Considering the limited medical staff and their working hours, there is also an upper bound on the daily testing volume. In this paper, the change of daily testing volume is described as equation (1).

\[ V = \max(V_{inc} \times (t - T), V_{limit}) \]  

(1)

where \( V_{inc} \) and \( V_{limit} \) indicate the increase speed and upper bound of the daily testing volume respectively. \( t \) is the current time step and \( T \) is the time when testing starts.

In addition, different testing strategies may be used when implementing testing, such as random testing (RT), contact-tracking testing (CT), or a combination of the both. In this paper, testing preference \( \alpha \), which measures the priority of testing individuals who are in close contacts with confirmed cases, is introduce to represent different testing methods. If \( \alpha = 1 \), individuals in close contacts with confirmed cases will be tested first (CT). While \( \alpha = 0 \) means random testing (RT). When \( 0 < \alpha < 1 \), a combination measure of RT and CT is adopted.

The testing process is performed as follows. We use \( M \) to represent the number of individuals who are in close contacts with confirmed cases and not tested. At each time step, if \( \alpha M \leq V \), \( \alpha M \) individuals in close contacts will be tested first and then \( V - \alpha M \) individuals will be tested randomly in the population. Otherwise, if \( \alpha M > V \), only \( V \) individuals in close contacts will be tested randomly. Table 1 presents a summary of parameters and variables, and respective descriptions as well as values used in our model.

**Results**

In this paper, Barabasi-Albert (BA) scale-free networks are generated and used to describe the contact structure of population in real life[33]. A series of epidemic spread simulations are conducted on these networks. All the results are averaged over 1000 simulations.

We first investigate the impact of the daily testing volume and the start timing of testing on the epidemic transmission. Two indicators are considered: the peak value of infections \( v_p \) and the time when the peak arrives \( t_p \) because these two indicators are the most concerned by the government in response to epidemics. From Figure 1(a), we can see that the greater the daily testing volume and the earlier the testing starts, the lower the infection peaks. To make \( v_p \) less than 0.5\%, the daily testing volume should be at least 2\% and testing should start within 70 time steps (see region I in Figure 1(a)). Figure 1(b) shows that \( t_p \) will first increase and then decrease as the daily testing volume grows. This can be explained as follows. Increasing the daily testing volume can suppress the spread of infectious diseases and delay the outbreak. However, if the testing volume continues to increase, the infectious disease can be controlled to a great extent and will end in advance because
almost all infections are identified and quarantined, leading to a smaller $t_p$. $t_p$ will reach the maximum when the daily testing volume is between 1% and 4%, and testing starts within 25 time steps (see region I in Figure 1(b)). Larger $t_p$, which means more time to prepare before the outbreak, is very meaningful for us to control epidemics. We found that the impact of testing on the spread of infectious diseases lies in flattening the infection curve, delaying the arrival of the outbreak or ending the epidemics in advance.

In real life, the daily testing volume will gradually increase as the understanding of the epidemic deepens. Therefore, we study the impact of changes in the daily testing volume on epidemic transmission. The impact of $V_{inc}$ and $V_{limit}$ is shown in Figure 2. It can be seen that as $V_{limit}$ increases, the infection scale decreases significantly. However, the infection scale is hardly changed with the increase of $V_{inc}$, which means that in terms of controlling infectious diseases, it is more important to break through the limitation of daily testing volume. The solid line in Figure 2 represents the contour line where the infection scale is 5%, which requires the upper bound of daily testing volume to reach at least 5%.

We then investigate the impact of testing preference $\alpha$ on the epidemic transmission, which is shown in Figure 3. When the start timing of testing $T$ and the daily testing volume $V$ are fixed, the larger the test preference $\alpha$, the smaller the final infection scale, which means that the higher priority testing for individuals in contacts with confirmed cases indicates the better control of infectious diseases. The five curves in Figure 3 can be divided into two groups according to the values of $T$ and $V$: Group A includes solid square, solid circle and solid triangle curves and Group B includes hollow, semi-solid and solid triangle curves. From groups A and B, we can see that the earlier to start testing and the larger the daily testing volume, the smaller the infection scale. However, comparing group A and B, it can be found that the testing volume $V$ has a greater impact on the curve, which means that the testing volume plays a greater role in controlling the spread of infectious diseases than the start timing of testing.

In order to control infectious diseases just through testing (S0), a huge daily testing volume is required (see Figure 1). Assuming that a city has a population of 10 million, daily test volume of 5% means that 500,000 individuals need to be tested every day, which is too difficult to implement. In order to reduce the testing volume while achieving the goal of controlling infectious diseases, we have introduced other control measures such as wearing masks and social distancing. Another two scenarios are considered where other control measures can reduce individuals' infection probability by 10% and 30% (S10 and S30). From Figure 4 we can see that even if the infection probability is reduced by only 10%, the infection scale will be greatly reduced. When the infection probability is reduced by 30%, the infection scale will be less than 2%. In the inset of Figure 4, the three different scenarios are compared in detail. To control the infection scale below 5%, if no other measures are taken, the daily testing volume needs to reach 5.1%. However, if other measures are taken to reduce the infection probability by 10%, the daily testing volume will reduce more than 40% and only needs to reach 3%. Once other measures are taken to reduce the infection probability by 30%, the infection scale will be about 1% even if the daily testing volume is 1%.
We further explore how testing affects the epidemic transmission when the infectiousness of the epidemic changes. With different basic reproductive number $R_0$ and daily testing volume $V$, a series of simulations are conducted. The results under scenario S0 and S10 are shown in Figure 5(a) and (b) respectively. S10 means that other measures are adopted to reduce individuals’ infection rate by 10% and S0 indicates that only testing measure is taken. We find that regardless of scenarios S0 and S10, the infection scale always increases with the basic reproductive number $R_0$, and decreases with the daily testing volume. The solid line in Figure 5 is the contour line where the infection scale is 5%, which means the change of minimum daily testing volume required to control the infection scale below 5%. It can be seen that regardless of whether other measures are taken, the required daily testing volume almost increases linearly as the basic reproductive number grows. However, in scenario S0, when $R_0$ is relatively large ($R_0 > 3.6$), the required daily testing volume will increase sharply (see Figure 5(a)), which means that when the infectiousness of the epidemic is strong, the daily testing volume required to control the epidemic will be extremely large if only testing measure is taken. Comparing Figure 5(a) and (b), we also find that the required daily testing volume will be greatly reduced once other measures are taken at the same time.

Finally, we study whether the network scale has an impact on the results. From Figure 6, it can be figured out that although the number of nodes in the network is different, the trend of the infection scale with the daily testing volume is almost the same, which indicates that our results are useful for understanding the epidemic transmission process on a larger scale although they are obtained in a small network.

Discussion

In response to epidemics, different testing strategies may be adopted by governments, such as random testing, contact-tracking testing or the combination of both. Moreover, as the understanding of epidemics deepens, the daily testing volume will gradually increase. However, considering the limited medical staff and their working hours, there is an upper bound to the daily testing volume. Therefore, in this paper, an epidemic transmission model combined with testing mechanism is proposed to study the role of testing in epidemic control, which incorporates different testing strategies as well as the increase speed and upper bound of daily testing volume.

Through a series of simulations, we discover that testing can inhibit the spread of infectious diseases. In addition, the priority testing for individuals in close contacts with confirmed cases can enhance the effect of testing on infectious diseases. However, in order to control the epidemic (i.e., control the infection scale below 5%), the daily testing volume needs to reach 5.1%. When the urban population is relatively large, 5.1% means a huge amount of testing every day. Our results are consistent with previous studies, that is, only large-scale testing can effectively control epidemics[3, 28]. Fortunately, effective algorithms such as group testing have been proposed by scholars[34, 35, 36], which make it possible to greatly increase the daily testing volume.

We also find that when other measures such as wearing masks and social distancing are adopted, the daily testing volume required will be greatly reduced. Assuming that other measures can only reduce individuals’ infection probability by
10%, the daily testing volume required will be reduced by more than 40%, which further emphasizes the importance of taking comprehensive measures in response to epidemics. We conduct simulations on networks with different scale and obtain the same results, which indicates that our results are also meaningful for the epidemic control on a large scale.

In this study, we focus on the impact of testing on the spread of infectious diseases. Therefore, the impact of testing specificity is not considered. For example, how an infected individual can affect the spread of infectious diseases after being tested negative, which is worthy of further study.

Conclusions
In this paper, an epidemic transmission model combined with testing mechanisms is proposed to study the impact of testing volume, start timing of testing and testing preference on the spread of infectious diseases. Through extensive numerical simulations, some conclusions are obtained as follows.

1. The infection peak decreases with the increase of daily testing volume. Early testing can also reduce infection peak. Increasing the upper bound of daily testing volume can greatly reduce the infection scale, but the increase speed of daily testing volume hardly impacts the infection scale.

2. The higher priority for testing individuals in close contact with confirmed cases, the smaller the infection scale. However, when the daily testing volume is large, testing preference has little impact on the infection scale.

3. When testing combined with other measures are adopted in response to epidemics, the daily testing volume required will be reduced by more than 40% even if other measures can only reduce the infection probability by 10%. We also find that the daily testing volume required increases almost linearly with the basic regeneration number $R_0$.

4. The scale of the network has little effect on the results. Although the nodes of the networks are different, the trend of infection scale with the daily testing volume is basically the same.

Based on this research, testing can reduce the infection peak and delay the outbreak of epidemics. This is very important for governments to deal with epidemics because it means that we have more time to prepare medical resources. Testing has become one of the most effective measures to deal with infectious diseases. According to our results, we have provided some suggestions for dealing with epidemics. It is the most important to increase the daily testing volume because larger testing volume means that more infected people are identified and then treated, thereby reducing the infection scale and saving more lives. Starting testing as early as possible is another way to suppress the epidemic transmission. In addition, comprehensive measures can greatly reduce the daily testing volume required, so it is recommended that testing be combined with measures such as wearing masks and social distancing. In summary, our research contributes to understanding the role of testing in controlling epidemics and provides useful suggestions for governments and individuals in response to infectious diseases.

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**Figures**

Figure 1 The impact of testing volume $V$ and start timing of testing $T$ on epidemic transmission. (a) shows the impact on the infection peaks and (b) shows the impact on the arrival time of infection peaks. In region I of (a), the peak values are smaller than 0.005. In region I of (b), the peak time are larger than 130 time steps. Starting testing early and increasing daily testing volume can suppress the epidemic transmission.

Figure 2 The impact of changes in daily testing volume on infection scale. Breaking through the limitations of daily testing volume can greatly suppress the epidemic transmission but promoting the increase speed of daily testing volume hardly changes the infection scale.

Figure 3 The impact of testing preference on epidemic transmission. Square, circle and triangle curves are obtained under $T = 30$ (Group A) and solid, semi-solid and hollow triangle curves are obtained under $V = 0.06$ (Group B). The priority testing for individuals in contacts with confirmed cases can suppress the epidemic transmission.

Figure 4 The effect of testing on epidemic transmission under different scenarios. S0 means that no other measures are taken except testing. S10 and S30 indicate the scenarios where other measures are taken to reduce individuals’ infection probability by 10% and 30% respectively. Combined with other measures such as wearing masks and social distancing, the daily testing volume can be significantly reduced while the epidemic will still be controlled.
Figure 5 The effect of basic reproductive number $R_0$ and testing on infection scale under different scenarios. The results of scenario S0 where only testing measure is adopted are shown in (a), and (b) describes the results of scenario S10 where other measures are implemented to reduce individuals’ infection rate by 10%. The solid line is the contour line where the infection scale is 5%. The daily testing volume required to control epidemics increases almost linearly as $R_0$, but when other measures are adopted the required testing volume will decreased.

Figure 6 The impact of network scale. The square, circle and triangle curves represent the simulation results on networks with 5000, 8000, and 10000 nodes, respectively. Even if the network scale is different, the trend of the infection scale with the daily testing volume is almost the same.

Table 1 Model parameters, variables and respective descriptions

| Parameters | Description | Value |
|------------|-------------|-------|
| $N$        | The number of nodes (population size) | Different values |
| $\lambda$  | Infection rate in contact with symptomatic individuals | Different values |
| $\gamma$   | Relative infectiousness of asymptomatic individuals | 0.5 |
| $\epsilon$ | Reciprocal of latency period | 0.2 |
| $p_a$      | Transmission rate from state $E$ to $I_a$ | 0.4 |
| $\mu$      | Recovery rate | 0.2 |
| $\beta$    | Death rate | 0.03 |
| $T$        | Start timing of testing | Different values |
| $V$        | Daily testing volume (normalized by population $N$) | Different values |
| $\alpha$   | Contact-tracking testing preference | Different values |
| $V_{inc}$  | Increase speed of daily testing volume | Different values |
| $V_{limit}$| Limit of daily testing volume | Different values |