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Epidemic modeling for the resurgence of COVID-19 in Chinese local communities

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ARTICLE INFO

Keywords: COVID-19, Mutation, Resurgence, SEIQR model, Quarantine

ABSTRACT

COVID-19 is a constantly challenging global health issue due to its strong intensity, rapid mutation and high infectiousness. The new Delta and Omicron variants have triggered massive outbreaks worldwide. Even China, which has done a good job in outbreak prevention, is still heavily affected by the virus. The long-term fight against multiple COVID-19 outbreaks is ongoing. In this study, we propose an SEIQR model that considers the incubation period and quarantine measurement. We verified our model using actual outbreak data from four Chinese cities. Numerical simulations show that a five-day delay results in a double resurgence scale. Our model can be used as a tool to understand the spread of the virus quantitatively and provide a reference for policymaking accordingly.

1. Introduction

It has been reported that COVID-19 has infected more than 380 million people and killed more than five million people till January 2022. The resurgence of the pandemic in India was extremely severe in the first half of 2021. There are many reasons for the outbreak, such as the virus mutating to become more infectious, lax prevention or quarantine policies, and the disruption of medical systems. As early in February 2021, India had limited new cases to 8000 per day, but the virus was still mutating into a stronger more contagious phase Delta. India has had more than 400,000 new cases in a single day [1]. Even in China, there were several local small-scale outbreaks caused by the Delta variant during the summer of 2021. China has successfully controlled the spread of the disease and avoided a nationwide outbreak.

It is believed that the isolation of confirmed cases, restriction on group gatherings, effective tracing of close contacts, and enhancement of medical allocation would help to effectively control the epidemic [2–4]. Therefore, it is crucial to provide more precise models that consider these factors. It was found that factors such as the incubation period and delay from onset to isolation have significant impacts on the spread and combat of COVID-19. In this study, we present a detailed simulation analysis of these factors and find that if prevention and control are properly conducted, spreading can be controlled quickly.

Researchers have done much work on the modeling of epidemic dynamics, especially the incubation period, transmission rate from close contact to infection, and properties of multi-generation transmission of the epidemic [5,6]. The duration between departure and symptom onset was discussed ahead of time to reduce the recall bias [7]. Distance is considered an important factor that affects the spread of an epidemic. A response system based on enhanced testing and contact tracing can play a major role in relaxing social distancing interventions [8]. Transmission on complex networks has provided significant help in our study [8,9]. To describe the transmission characteristics of COVID-19, dynamic models have been established to analyze the transmission rules and characteristics, predict the transmission process of the epidemic, and propose a hypothesis of heterogeneity to restore the propagation process [6,10,11].

In the Susceptible-Exposed-Infected-Removed (SEIR) model, susceptible refers to those who are not infected and healthy, which includes most people. Exposed refers to those in the latent period of this infectious disease. Infected refers to the confirmed population. Removed refers to the recovered and dead population. People can transform from one category to another. Combining the SEIR model with Wuhan’s actual situation, Yang et al. achieved a good fitting and prediction of the epidemic in Hubei [12].

The Susceptible-Exposed-Infectious-Quarantine-Recovered (SEIQR) model of COVID-19 considers discrete-time transmission of imported cases for an assessment and risk analysis [13]. A compartmental epidemic model with intervention strategies shows the importance of quarantine measures [14]. However, the discussion of quarantine measurements is insufficient. This study aims to provide a thorough analysis of data-driven epidemic prevention and control through simulation. In this study, an SEIQR model was built to simulate the epidemic process in local communities, in which prevention and control factors are considered. In addition to the SEIR model, isolated ones are represented in the Q (quarantine) state to simulate prevention and control measures.

Starting with the data related to three resurgences in local communities of China in the summer of 2021, we built an SEIQR model to reveal the mechanism of resurgence with strict control measures. The param-
2. Data description

The data used in this study were collected from three local communities: Nanjing, Yangzhou, and Zhengzhou. The first reported local case in Nanjing was found on July 20, 2021, at Lukou International Airport, which was imported from an international flight. The resurgence in Yangzhou came from Nanjing after the first local case was traced on July 28, 2021. The epidemic in Zhengzhou was caused by a breakthrough in hospitals. The data came from the public media from the first to the last reported case. There were 255 confirmed cases in Nanjing from July 20, 2021, to August 12, 2021. A total of 570 individuals were confirmed in Yangzhou from July 28, 2021, to August 26, 2021, and 138 individuals were diagnosed in Zhengzhou from July 30, 2021 to August 26, 2021.

3. Model building

Based on the characteristics of the mutated COVID-19 virus and control measures during local resurgence, an SEIQR model was established in this study to explain the intrinsic mechanism considering the whole process of resurgence and strict quarantine measures. Moreover, the impacts of the virus and quarantine measures were established based on our SEIQR model.

In our model, Susceptible (S) represents vulnerable populations. Exposed (E) indicates that patients have been infected but show no symptoms (such as fever, cough, etc.), which may infect others with a smaller probability. Infectious (I) represents those with characteristic symptoms and will infect susceptible with a larger probability. Quarantine (Q) represents patients who have been traced and isolated, which can infect susceptible people with mild probability in situations where breaking through the defense line occurs. Recovered (R) represents people who have recovered or died, which are non-infectious and will not be reinfected. An illustration of the proposed model is shown in Fig. 1.

It was assumed that the first infected person, Case A, was confirmed after n days of incubation. Case A was isolated in the hospital and recovered after proper treatment. Once a confirmed case was reported or a positive nucleic acid test was found by normal testing, immediate tracing for contacts of Case A was conducted, and nucleic acid tests were implemented for the close and second close contacts as well as the whole community in which Case A lives. All individuals who tested positive were immediately isolated in hospitals and traced further.

The confirmed Case A contacted the nearby susceptible ones, with probability \( \beta_2 \), transforming the latter ones into asymptomatic infected, that is, E.

The asymptomatic infected individuals were in contact with the nearby susceptible individuals, with probability \( \beta_1 \), making the latter transform into asymptomatic infected individuals.

Asymptomatic cases were confirmed after incubation. The rate of this transmission was set to \( \sigma \).

It is difficult for these isolated strains to infect susceptible strains. However, when a breakthrough of the defense line occurs, such as in a hospital, the Q state has the possibility to infect others, with probabilities of disease transmission of \( \beta_3 \) and occurrence of breakthrough of \( \beta_4 \).

With proper prevention and control, asymptomatic and confirmed cases can be traced and isolated with probabilities \( \delta_2 \) and \( \delta_1 \), respectively, to cut off their contacts with the susceptible in time. As long as the transmission chain is completely blocked in time, the outbreak will end within a couple of weeks.

Individuals who were quarantined at the hospital recover at different rates due to symptoms. Most cases are mild or common, with few severe and critical illnesses. Therefore, recovery rates differ based on their symptoms [15–18]. Patients with mild symptoms recover quickly at rate \( r_1 \), ordinary patients recover at rate \( r_2 \), and patients with severe symptoms recover at rate \( r_3 \).

The system of ordinary differential equations for SEIQR based on the above assumptions is as follows:

\[
\frac{ds}{dt} = -\beta_1 S_e(t) - \beta_1 MS_e(t) - \beta_1 MS_t(t) - \beta_2 M(t) - \beta_2 M(t) S_t(t) - \beta_3 M(t) Q(t)
\]

\[
\frac{dE}{dt} = \beta_1 S_e(t) + \beta_1 M(t) S_t(t) + \beta_2 M(t) S_t(t) - \delta_1 E(t) - \delta_1 E(t)
\]

\[
\frac{dI}{dt} = \delta_1 E(t) + \delta_2 E(t) - \gamma I(t)
\]

\[
\frac{dQ}{dt} = \delta_3 I(t) + \delta_4 I(t) - \gamma Q(t)
\]

where \( S(t), E(t), I(t), Q(t) \) and \( R(t) \) represent the proportions of the SEIQR states in the system as a function of time. Parameter \( \beta_1 \) represents the probability that the infected population will transmit the disease to the susceptible population, and \( \beta_2 \) represents the probability that the exposed population will transmit the disease to the susceptible population. \( \beta_3 \) represents the probability that the quarantined population will transmit the disease to the susceptible population. \( \beta_4 \) stands for the probability of occurrence of the event in which the quarantined broke through the defense line. \( M \) is the maximum number of people each infected person is exposed to daily. \( m \) was set as the maximum daily contact area of the quarantined population. \( \sigma \) is the probability of transformation from the exposed to the infected state, which is the reciprocal of the mean incubation period. \( \delta_1 \) represents the probability that an infected person is quarantined. \( \delta_2 \) represents the proportion of an asymptomatic infected person being quarantined, and \( \gamma \) represents the probability that a quarantined person will recover or die.

4. Model validation

The first result provides a match between the simulation and actual local resources in China. The simulation results for the three regions considered in this study are shown in Figs. 2, 3, and 4. The parameters were selected based on empirical data and related references [19]. The curves for the simulation were averaged over 50 trials.

The imperfect match at an early stage between the real situation and our model is due to the delay in the official reports when resurgence occurred. When the resurgence of COVID-19 first occurred, there were no strict control measures until the first confirmed cases were reported. Therefore, the official report of confirmed cases postponed the real development of the epidemic, which would merge into later stages of the spreading process. Although the free propagation stage is observed, our simulation can revive not only the early stage, but also the whole progress. The match between the data and the model is shown in Figs. 2, 3, and 4.

Moreover, as soon as the infected cases are reported, contact tracing and isolation are implemented immediately to cut off the transmission
Fig. 2. Modeling for resurgence in Nanjing. Parameters are chosen as follows: \( N = 250; n = 10; n_2=15; n_3=5; \beta_1=0.3; \beta_2=0.2; \beta_3=0.01; \beta_4=0.001; \sigma=1/N; \gamma=0.01; \gamma_1=0.02; \gamma_2=0.03; \gamma_3=0.04; \gamma_4=0.01; \delta_1=0.3; \delta_2=0.3; \sigma=1/5; M = 6; m = 2. \)

Fig. 3. Modeling for resurgence in Yangzhou. Parameters are chosen as follows: \( N = 600; n = 8; n_2=18; n_3=3; \beta_1=0.5; \beta_2=0.3; \beta_3=0.01; \beta_4=0.001; \sigma=1/N; \gamma=0.03; \gamma_1=0.04; \gamma_2=0.05; \gamma_3=0.07; \gamma_4=0.15; \gamma_5=0.01; \delta_1=0.5; \delta_2=0.1; \sigma=1/7; M = 4; m = 2. \)
chain effectively. As can be seen from the right parts of Figs. 2, 3, and 4, the Q-curve exhibits a marked increase, coinciding with the real processes. For the R-curve, the fit is performed by piecewise recovery rates, depending on their symptoms.

5. Parameter analysis

A parameter analysis considers three aspects: the intrinsic character of the virus, prevention and control measures, and breakthrough of the defense line.

To analyze the effects of some parameters, only one or a few parameters were changed, and the others were fixed as the baseline. The baseline parameters are chosen as follows: $N = 200$; $n = 8$; $n_2=15$; $n_3=4$; $\beta_1=0.5$; $\beta_2=0.3$; $\beta_3=0.01$; $\beta_4=0.001$; $\gamma=1/N$; $\tau=0.06$; $\gamma_1=0.05$; $\gamma_2=0.05$; $\gamma_3=0.07$; $\gamma_4=0.1$; $\delta_1=0.8$; $\delta_2=0.7$; $\sigma=1/5$; $M = 4$; $m = 2$.

5.1. Intrinsic character of the virus

Intrinsic parameters determine the characteristics of the virus. In our model, three parameters are utilized to quantify the transmission of COVID-19: $\beta_1$, $\beta_2$, and $\sigma$. These represent the asymptomatic transmission probability, disease transmission probability of the confirmed person, and probability of transition from the latent to infected state, respectively. Here, we demonstrate the effects of $\beta_2$ and $\sigma$. It is apparent that the larger the two parameters, the more severe the spreading, as shown in the simulation results in Fig. 5 and 6.

5.2. The prevention and control measures

Prevention measures were taken as soon as the first diagnosis of exposure or infection was reported. The number of days delayed from the reported day to the isolation day is of crucial importance and is set as $n$ in our model. Moreover, the strength of the prevention and control policy are presented by the following factors and parameters: the days staying in hospital ($n_2$), probability of transmission from infected to isolated ($\delta_1$), probability of transmission from asymptomatic to isolated ($\delta_2$), maximum number of contacts per day ($M$), and probability of transmission from isolated into recovery ($\gamma$).

Effective and timely tracing and isolation of asymptomatic and infected individuals are important for controlling the resurgence of COVID-19, as shown in Fig. 7 and 8. A small rate of transmission from asymptomatic or infected to isolated indicates the weakness of preven-
Fig. 6. Effect of the probability of latent state converted into the infected state, the baseline value is $\sigma = 1/5$.

Fig. 7. Effect of the probability of transmission from infected into isolated, the baseline value is $\delta_1 = 0.8$.

Fig. 8. Effect of probability of transmission from asymptomatic into isolated, the baseline value is $\delta_2 = 0.5$.

Fig. 9. Effect of the number of contact per day, the baseline values are $M = 1$; $n = 5$; $\delta_1 = 0.8$; $\delta_2 = 0.5$.

Transmission measures, resulting in a higher infection rate and longer time period before the end of local resurgence.

During the resurgence period, public gatherings were canceled to reduce contact. However, during normal daily life before reported cases, crowded places such as airports, schools, and factories possess a larger number of contacts each day, resulting in more severe resurgence. The more contacts per person per day ($M$), the later the discovery of prevention and control, and the more difficult the prevention and control work is. Therefore, the time $n$ for starting control and isolation probabilities $\delta_1$ and $\delta_2$ will also change. The interactions among the four parameters are shown in Fig. 9. The parameters associated with prevention are adjustable along with $M$. Our simulation shows that as long as the control is carried out in a timely and effective manner, the resurgence can be controlled within one or two incubation periods.

5.3. The breakthrough of the defense line

Transmission may occur during the isolation period, particularly in hospitals. The parameters related to this situation are the probability of a breakout event ($\beta_3$), transmission probability from isolated to exposed ($\beta_2$), and number of contacts per day when isolated ($m$). As shown in Fig. 10, even with larger values of these three parameters, the effect was negligible because the occurrence was sufficiently rare.

6. Conclusion

In this study, we collected confirmed case data from resurgence regions of COVID-19. An SEIQR model was built to simulate the dynamics of resurgence and quarantine in the local areas of China. The simulation results were highly consistent with the actual data. The virus characteristics, such as incubation, infectiousness, transmission rate, prevention and control measures (isolation transmission rate, maximum contact volume, etc.), and potential breakthroughs were considered in our model. By changing these parameters, we can simulate the virus intensity and adjust the control strength.

The SEIQR model was used for the numerical simulation of a small range of outbreaks in some areas of China. It can also be used to analyze the impact of latency, transmission rate, tracking degree, and isolation measures on epidemic development. This study provided a more suitable model for local epidemic simulations with higher accuracy. However,
Fig. 10. Effect of breakthrough the defense line, the baseline parameter, the baseline values are $\beta_4=0.001; \beta_5=0.01; m = 2$.

population heterogeneity and mobility were not considered, which are planned for further investigation.

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 study.

Acknowledgement

This work was jointly supported by the National Natural Science Foundation of China (Grant No. 11971074).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jnlssr.2022.03.005.

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