

## Article

# Study of COVID-19 Epidemic Control Capability and Emergency Management Strategy Based on Optimized SEIR Model

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**Abstract:** Due to insufficient epidemic detection and control, untimely government interventions, and high epidemic prevention costs in the early stages of the epidemic outbreak, the spread of the epidemic may become out of control and pose a great threat to human society. This paper optimized and improved the traditional Susceptible-Exposed-Infectious-Removed (SEIR) model for investigating epidemic control and public health emergency management. Using the Corona Virus Disease 2019 (COVID-19) outbreak as an example, this paper simulates and analyzes the development of an epidemic outbreak during various periods with the optimized SEIR model, to explore the emergency control capacity of conventional medical control measures, such as large-scale outbreak testing capacity, hospital admission capacity, or daily protection of key personnel, and analyze the government's emergency management strategies to achieve low-cost epidemic control. The model developed in this study and the results of its analysis demonstrate the differences in outbreak emergency control capacity under different conditions and different implementation strategies. A low-cost local outbreak emergency management strategy and the timing of the government's resumption of work and school are discussed on this basis.

**Keywords:** SEIR model; epidemic control; public health emergency management; COVID-19

**MSC:** 62P10; 92B99; 92D25



**Citation:** Wang, W.; Xia, Z. Study of COVID-19 Epidemic Control Capability and Emergency Management Strategy Based on Optimized SEIR Model. *Mathematics* **2023**, *11*, 323. <https://doi.org/10.3390/math11020323>

Academic Editors: Hung-Lung Lin and Yu-Yu Ma

Received: 7 December 2022

Revised: 29 December 2022

Accepted: 3 January 2023

Published: 8 January 2023



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## 1. Introduction

Infectious epidemics are a potential threat to the productive life of contemporary human society. In the early stages of an infectious disease outbreak, there is no effective drug for the virus in question, nor is there time to develop a vaccine for it, and the early spread of the disease will increase exponentially if there is no effective public health emergency management. Human society has been threatened by large-scale infectious diseases multiple times, with smallpox, plague, and cholera not far behind, followed by Spanish flu, AIDS, and SARS. Once the early exponential growth of a highly contagious disease with severe symptoms or high mortality is not controlled early, the rapidly increasing number of critically ill patients will quickly “damage” the capacity of the local health care system and may eventually cause a serious humanitarian crisis.

A large-scale outbreak of the Corona Virus Disease 2019, also known as COVID-19, occurred in Hunan and Hubei provinces of China and the surrounding areas in January 2020. The World Health Organization (WHO) declared the outbreak a Public Health Emergency of International Concern (PHEIC), and the Chinese government also considered the outbreak a major security threat affecting people's public health [1]. Emphasis was placed on how to contain the “exponential” growth of the epidemic at the start of an epidemic [2]. Many scholars have confirmed through different studies that taking effective blocking measures, targeted reduction in person-to-person contact, reduction in the frequency of area-to-area contact, etc., can effectively restrain the rate of increase. For example, Fu [2] conducted a

systematic comparison and analysis of the first wave of COVID-19 epidemic trends in China. With the government's "containment" measures, such as school closures, travel restrictions, cell-level lockdowns, and contact tracing, the local transmission within the country has been effectively reduced. Zeller et al. [3] investigated New Orleans with validated data during the first wave of the COVID-19 epidemic in Louisiana, USA, including population flow and genetic data. The results suggested that COVID-19 infections were present in New Orleans prior to Mardi Gras, and that the primary cause of the outbreak was the special festival with large crowd exposure and inadequate initial nucleic acid testing. Ghafari et al. [4] conducted a detailed analysis of the Iranian COVID-19 outbreak for 802 genetic samples, and identified 36 cases of extraterritorial migration that formed a large spread in different regions of the country. The results of the study indicate that the main outbreak of the epidemic is due to Iran's underestimation of the "tracking", "detection" and "blocking" of foreign travelers by border management, leading to the outbreak of the national epidemic. They also used the *SEIR* model to extrapolate the future prevalence of each region. In Taiwan, Hsieh and Hsia [5] studied government measures to restrict people's travel behavior by adopting public transportation services during the pre-, mid-, and post-outbreak phases of the COVID-19. In Italy, Cereda et al. [6] conducted a systematic retrospective survey for the state of Lombardy, and found that more than 500 cases had been reported before the first official case was reported which had spread in 222 of Lombardy's 1506 (14.7%) municipalities, with an average transmission interval of 6.6 days, and a basic regeneration number ranging from 2.6 to 3.3. The number of cases decreased after the government's initial "blocking" measures. Kwok et al. [7] used the Markov Chain Monte Carlo method to analyze COVID-19 case data in Hong Kong. Studies have shown that stopping transmission at the initial stage of the epidemic in Hong Kong is attributed to effective prevention measures taken by the government, such as wearing masks, hand hygiene, and social distance, and border control.

The establishment of epidemic system dynamics models can provide powerful prediction methods and decision-making tools for public health emergency management practices, by simulating the transmission pattern, disease evolution, and emergency management of epidemics [8]. The main common epidemic system dynamics models are the SIR model [9], the SIS model [10], and the *SEIR* model [11]. Chen and Ting [9] studied a SIR epidemic model with distributed time lags and saturated incidence, applied differential inequality theory to obtain a set of sufficient conditions to guarantee the permanence of the system, and obtained some sufficient conditions for global asymptotically stability of endemic equilibrium by constructing suitable Lyapunov functions. Yuan et al. [10] studied a class of SIS epidemic models containing finitely distributed time delays, obtained sufficient conditions for the global stability of the epidemic equilibrium point and the disease-free equilibrium point, and revealed the influence of time delays on the stability of the equilibrium point. Cha et al. [11] created an age-structured *SEIR* epidemiological model for both longitudinal and horizontal transmission epidemics, and the study confirmed the threshold results in the presence epidemiological status in most cases.

With the above-mentioned problems and methods, a mathematical optimization model of *SEIR* was proposed to numerically simulate and analyze a variety of factors related to the emergency prevention and control capacity of the epidemic, mainly including (1) daily prevention and control measures, such as wearing masks, washing hands frequently, maintaining social distance, and isolating infected individuals; (2) daily mass sampling; and (3) expansion of the admission capacity of the medical system. The model we developed and the results of its analysis demonstrate the differences in outbreak emergency control capabilities under different conditions and different execution strategies. In addition, a low-cost local outbreak emergency management strategy and the timing of the government's resumption of work and schooling are discussed. The models, methods, and results constructed in this paper are expected to provide an important reference for managers or decision makers in government health authorities in the future emergency management prevention and control mechanisms for responding to epidemic diseases.

Section 2 briefly introduces the application of the *SEIR* system dynamics model in epidemic public health emergency management, and present the modeling approach and case hypothesis of this paper. Section 3 shows the results and analysis of simulation based on the optimized *SEIR* model, and discussed the emergency control effect and strategy during different stage of COVID-19 epidemic. Section 4 gave a further discussion about the results and formulated future research directions and limitations of this study. Finally, Section 5 gathers the results of the research and presents the conclusions and suggestions of the analysis. The essential part of this paper will be discussed specifically in the following four sections.

## 2. Materials and Methods

### 2.1. Public Health Emergency Management during COVID-19

Emergency management provides a valuable theoretical approach and practical reference for the scientific management of public health emergencies. The methodological theory, system construction, and practical empirical evidence on public health emergency management have been hot research topics of long-term concern for scholars and active practice for governments [12]. Yang [13] introduced the United States to its advanced emergency management concept and system for public health emergencies, constructing an omnidirectional, tridimensional, and comprehensive emergency network that can effectively achieve coordination between horizontal government departments and vertical national, state, and regional public health departments. Wang [14] explored the ways to build emergency management systems in urban places that are prone to increasing and concentrating public health emergencies, and the progress and problems of local governments in establishing and improving urban public emergency management systems. Ying-Lian [15] argued that the system is the key to public health emergency management and introduced four types of emergency management institutions: emergency office, command headquarters, “joint defense and air defense”, and joint conference. Moreover, he also analyzed the effectiveness of different agencies in mobilization, decision-making, and coordination in comparison to public health emergencies. Sun et al. [16] adopted the risk analysis method based on the basic theory of risk management and conducted a risk analysis of emergency management of public health emergencies according to their characteristics. Cao et al. [17] discussed the development and problems of Chinese public health emergency management in the context of the major public health emergencies that occurred in the past decade. He concluded that China’s public health emergency system has been gradually established, the monitoring and early warning system has been significantly strengthened, and the material stockpile and transfer management system has been improved, yet there are still problems, such as the low operational efficiency of the command and decision-making system, the low number of professional emergency management personnel, and the insufficient investment in emergency management funds.

Emergency management is the main preventive and control measure of the COVID-19 epidemic, and its research has continued to increase this year with the continuous practical exploration of COVID-19 emergency management in various countries. Martinez et al. [18] described the experience of emergency management in a hospital in Barcelona, Spain, during a COVID-19 pandemic emergency, in which teamwork, emotional management, and orderly execution were among the capabilities that effectively protected good health and prevented the spread of the epidemic. Wang et al. [19] introduced the effectiveness of emergency management in a dental clinic in Beijing during the 2019 COVID-19 pandemic. The number of dental patients in this clinic has dropped dramatically due to public health policies and dental emergency management, which has been effective in controlling COVID-19 cross-infection in the dental clinic. Song [20] reviewed Japan’s experience in building public health emergency management system, including emergency management organizational system, operating mechanism, emergency plan system, laws and regulations, and emergency supply management system, and focused on China’s response to the

new crown pneumonia epidemic. During the process, the lack of emergency management capabilities for public health emergencies was exposed.

### 2.2. Application of SEIR System Dynamics Model in Epidemic Public Health Emergency Management

The SEIR system dynamics model is one of the basic mathematical models for the study of epidemics, mainly applied to the study of infectious disease transmission speed, spatial scope, transmission pathways, dynamic mechanism, and other issues. Bokler [21] compared the SEIR model with other infectious disease models based on epidemiological modeling of recurrent epidemics of measles in developed countries. He suggested that the SEIR model is more consistent with the epidemic transmission patterns of measles and influenza viruses than other models, and pointed out the necessity of establishing a SEIR measles model that includes age and spatial structure, which is an important guide for the effective prevention and control of infectious diseases. The SEIR model has recently been widely used for public health emergency management due to epidemic outbreaks, which can simulate and predict some characteristics of early outbreak behavior of epidemics and provide countermeasure reference for emergency management of government and medical institutions [22–24].

The SEIR model consists of an epidemiological evolutionary pathway that includes the Susceptible-Exposed-Infected-Removed equations [25]. Susceptible refers to people who have not been infected with the infectious disease and are so far healthy. The Exposed are people who are in the incubation period of the infectious disease. The Infected is a group of people who have been diagnosed. Removed is the removed population, including recovered and deceased people. The traditional SEIR model is designed with multiple spaces that can be modified for specific infectious disease characteristics [26]. Different scholars have adopted different model improvements and uses for the analysis of the development process of the COVID-19 outbreak. The SEIR model of hidden transmitters (SUEIR model) was developed in the study of Lin [22], which closely fits the characteristics of the means of dealing with the new crown epidemic in the country of prevention and control. The model fairly accurately describes the course of the epidemic in China and predicts rather precisely the inflection point of the spread of the epidemic, and the eventual cumulative number of confirmed cases. Ku et al. [23] analyzed the kinetic parameters of the epidemic's transmissibility using provincial transmission data within China at the beginning of the epidemic, with simple set-up modifications based on the SEIR model, and measured the impact of the correlation between the transmissions of the epidemic from province to province. They agreed that the virus is extremely transmissible and that vigilance is needed to prevent a possible second wave of infection outbreaks brought on by the resumption of work and school. Danon et al. [24] also modified the traditional SEIR model for the characteristics of the COVID-19 outbreak by adding another parameter for the number of people with infectious status without symptoms to the SEIR model setting to form the model. Furthermore, they used the dynamics of infectious disease data from China, England, and Wales, and concluded that in England and Wales, without human intervention, the epidemic would have reached its peak of transmission approximately four months after the onset of the epidemic.

### 2.3. Case Assumptions and Model Construction

The conventional SEIR system dynamics model assumes a total population of  $N$  and divides the study population into four states  $S$ ,  $E$ ,  $I$ , and  $R$  according to the specific states of the population regarding the course of the infectious disease, and  $N = S + E + I + R$ .  $S$  (Susceptible) represents the susceptible people, healthy people who have never been infected with infectious diseases;  $E$  (Exposed) refers to the latent people, people who have actually been infected with infectious diseases, but have not yet developed symptoms, and traditional models generally set the exposed as not yet having the ability to transmit;  $I$  (Infected) means the infected people, the one who have developed symptoms related to infectious diseases and have the ability to transmit.

The model further assumes that infected individuals are exposed to an average of  $r$  individuals per day, where the probability of encountering a person in state  $S$  is assumed to be  $S/N$  and the probability of achieving transmission after exposure is assumed to be  $\beta$ ;  $R$  (Removed) denotes the number of people who move out of the transmission loop, which specifically includes those who died after infection and those who were cured after infection, and the migration rate is usually labeled as  $\gamma$ , the sum of the cure rate and the mortality rate.

Evolutionary systems described in previous research, such as Lin's model [22], only simulated the natural transmission process of a disease without considering the impact of an intervention or assuming a government with unlimited capabilities that all  $E$  and  $I$  states will be treated properly and immediately. This paper introduces the government intervention factors into Lin's evolution model [22], and investigates the evolution process of the epidemic under the intervention of a government whose daily detection capacity is only  $K$ , and the total treatment capacity of the medical system is only  $G$ . More specific model modifications to the settings are as follows.

1. The exposed ( $E$ ) is also infectious, but because it does not have symptoms of an illness, the exposed is mixed in with the general susceptible population ( $S$ ). Identifying the exposed cases from the population through screening tests and isolating them to eliminate the problem of transmission is necessary. With the assumption of the transmission property of the latent person, the average number of contacts per day is  $r_E$ , where the probability of encountering a susceptible person is  $S/N$ , and the probability of successful disease transmission after contact is  $\beta_E$ . Meanwhile, the exposed individuals who are tested are able to be detected and switched to the symptomatic infected ( $I$ ) type. Or, the exposed spontaneously develops symptoms without testing and shifting to the infected ( $I$ ) type, and the probability of this spontaneous state shift is assumed to be  $\alpha$ .
2. The infected ( $I$ ) is someone with symptomatic manifestations of the disease. Due to the already clearly perceptible symptoms, and with adequate attention to the epidemic, it is assumed that infected individuals will be spontaneously or forcibly isolated, without additional testing, and without mixing into the social population. Nonetheless, even if quarantined, because of the imperfect nature of quarantine itself, it is assumed that the quarantined person may still come into contact with a small number of susceptible people. To distinguish between markers, the average number of people an infected person comes into contact with per day is assumed to be  $r_I$ , where the probability of encountering a susceptible person is  $S/E$ , and the probability of successfully achieving disease transmission after contact is  $\beta_I$ .
3. Assuming that strict official quarantine measures are not enforced, this corresponds to the period in the actual situation when governments do not take coercive measures at the beginning of the epidemic, or the period at the end of the epidemic when officials deregulate the epidemic, but continue to search for the infected and the exposed. It is presumed that the testing facility has a perfect capability to determine whether the virus has been transmitted, and that the false negative and false positive rates of the test are 0%, and that the facility has the capacity to perform multiple  $K$  tests per day. The test was performed on a mixed group of exposed ( $E$ ), and a general susceptible population ( $S$ ).
4. If the total capacity of the health care system in a region is  $G$  (the upper limit of the total number of patients that the health care system can receive at the same time), and assuming that the limit of the daily capacity of the health care system is a constant  $D$ . The prevention and control of the epidemic will be achieved by identifying the exposed ( $E$ ) through extensive sampling, isolating, and treating the infected ( $I$ ) and the exposed ( $E$ ) population, and controlling the proportion of the population with the virus so that the sum of the average daily number of infected persons in the population plus the number of infected persons tested on the same day will be lower than the assumed capacity constant ( $T$ ) of the healthcare system. Therefore, the model can

generate a threshold value for when the population base and the number of patients is adequately enough that the capacity of the given health care system (the total capacity  $G$  and the daily capacity  $D$ ) is no longer possible to contain the epidemic, and that value is the outbreak point at which the development of the epidemic is out of control.

Any one state has  $N = S + E + I + R$ . On this basis, the differential equation for the dynamics of the daily epidemic change is analyzed as follows:

$$\frac{dS}{dt} = -r_I\beta_IIS/N - r_E\beta_EES/N \tag{1}$$

$$\frac{dE}{dt} = r_I\beta_IIS/N + r_E\beta_EES/N - \alpha E - \min(K, S + E)E/(S + E) \tag{2}$$

$$\frac{dI}{dt} = \alpha E + \min(K, S + E)E/(S + E) - \gamma I \tag{3}$$

$$\frac{dR}{dt} = \gamma I \tag{4}$$

In the equation above, both  $E$  and  $I$  states are also contagious, the average number of contacts per day is  $r_E$  and  $r_I$ , and the probability of successful disease transmission after contact is  $\beta_E$  and  $\beta_I$ . Other parameters are the same as normal *SEIR* model, such as  $\alpha$  is the probability of  $E$  transmit to  $I$  without testing, and  $\gamma$  is the probability of  $I$  transmit to  $R$ .  $K$  is the maximum detection capacity of the relevant institution, the target testing people is  $S + E$ , thus, the actual number of people tested is  $\min(K, S + E)$ . When the testing capacity  $K$  has exceeded the total number of susceptible and the exposed patients remaining at that time, it is possible to test all of them at once on the same day. Transforming the above differential equation into a discretized difference equation yields the following results:

$$S_t = S_{t-1} - r_I\beta_I I_{t-1} S_{t-1} / N - r_E\beta_E E_{t-1} S_{t-1} / N \tag{5}$$

$$E_t = E_{t-1} + r_I\beta_I I_{t-1} S_{t-1} / N + r_E\beta_E E_{t-1} S_{t-1} / N - \alpha E_{t-1} - \frac{\min(K, S_{t-1} + E_{t-1}) E_{t-1}}{(S_{t-1} + E_{t-1})} \tag{6}$$

$$I_t = I_{t-1} + \alpha E_{t-1} + \frac{\min(K, S_{t-1} + E_{t-1}) E_{t-1}}{S_{t-1} + E_{t-1}} - \gamma I_{t-1} \tag{7}$$

$$R_t = R_{t-1} + \gamma I_{t-1} \tag{8}$$

With the above model, a community is assumed to have a relatively homogeneous mix of people, corresponding to real-world work or residential clusters that are relatively spatially close to each other. It is assumed that there is an initial population of 10,000 people in the region ( $N = 10,000$ ), where one person in the initial state is already infected but is still in the latent state because it is not tested ( $I_0 = 1$ ), and the number of people in the other conditions in the initial state are ( $E_0 = 0, R_0 = 0, S_0 = N - E_0 - I_0 - R_0 = 9999$ ). It is noted that Lin [22] has estimated the amount of people who carry the virus and will get sick within 14 days; thus, we assume the same approximate incubation period of 14 days, and the corresponding daily probability that the exposed ( $E$ ) turns to be infected ( $I$ ) would be about 7%. As normal contacts would vary very widely in different cities and different periods, we set  $\beta_E = 15$  (15 days for a person with no symptoms) and  $\beta_I = 3$  (3 days for a person with symptoms or infected), as an approximation for the imperfect prevention and control. The ability of the new coronavirus to infect both infected and exposed individuals is consistent with exposure to a susceptible population. From the parameter calibrated by Lin [22], the estimated successful transmission probability is about 3% to 80% (based on different period in the disease control by Chinese government), thus we assume that all people will wear masks and wash hands frequently, and we set a probability of 3% to be able to convert an infected individual to a latent individual. The infected individuals ( $I$ ) will be admitted to hospital for treatment, and the value of the removal rate is assumed to be 5%

based on the estimated duration of treatment for the outbreak from Lin [22]. All parameters can also vary to simulate different variants of COVID-19, different countries or different seasons, and this model can deduce the evolution characteristics of an infectious disease at this level under the action of large-scale control measures, changing a few parameters the characteristics still remains.

In addition, Lin's [22] model only examined how to estimate the parameters of the SEIR model based on real infection data. In order to further investigate the impact of large-scale infection control measures, we introduced two specific infection control measures, large-scale screening (assuming that the maximum daily screening capacity is  $K$ , and there is a perfect screening method without any false negatives or false positives) and large-scale admissions (the number of daily admissions is  $D$ ). While in the former dynamics,  $K$  is in the Formulas (2), (3), (5) and (6), and  $D$  is going to be tested how much will be needed or how high will it reach, which will be discussed later.  $K$  is the maximum detection capacity every day, and the testing target would be the susceptible and the exposed ( $S + E$ ), so the actual number of people tested every day would be  $\min(K, S + E)$ .

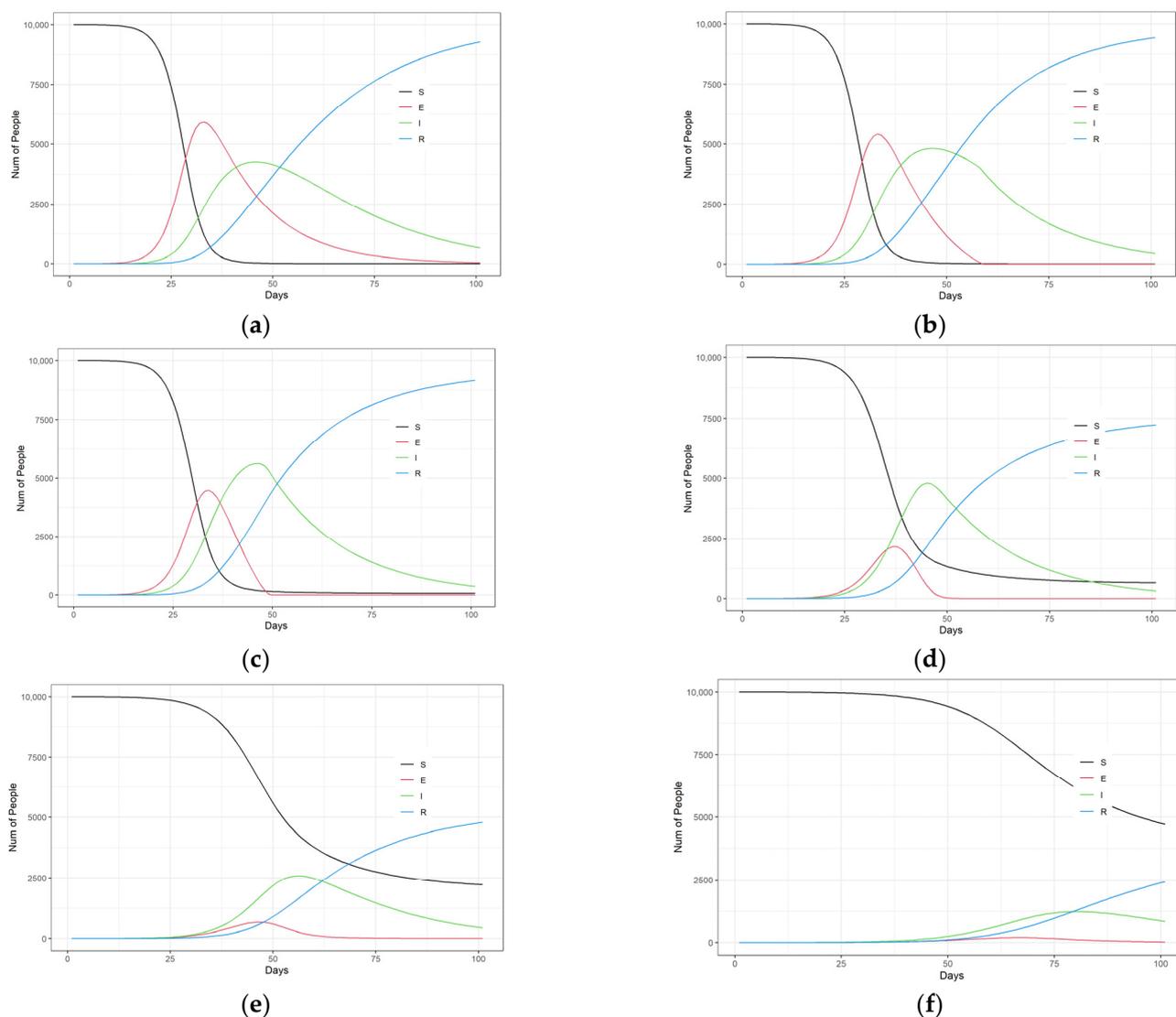
### 3. Results

#### 3.1. Simulation Analysis of the Emergency Control Effect of Daily Testing Capacity in the Early Stage of the Epidemic

Given the above model settings, if the daily testing capacity of the sampling agency is always  $K$  and testing starts just after the outbreak begins to spread, the obtained results of the evolutionary path of the outbreak are shown in Figure 1 (more details and amplified figures can be found in Appendix A, Figures A1–A6).

From Figure 1, it can be seen that, starting from the same initial state, the peak of the epidemic is rapidly delayed and the number of infected persons at the peak of the epidemic decreases as the testing capacity of the authorities increases. Once the outbreak sampling capacity reaches the more extreme level of being able to test 3000 people per day, the peak of the outbreak is delayed until about day 70 relative to a hypothetical initial local population of 10,000 people in total, while the peak number of infected people in the outbreak is suppressed to a level of less than 1000. It can be tentatively concluded that the higher the epidemic testing capacity of the authorities is, the better the emergency control of the epidemic and the lower the peak number of epidemics are.

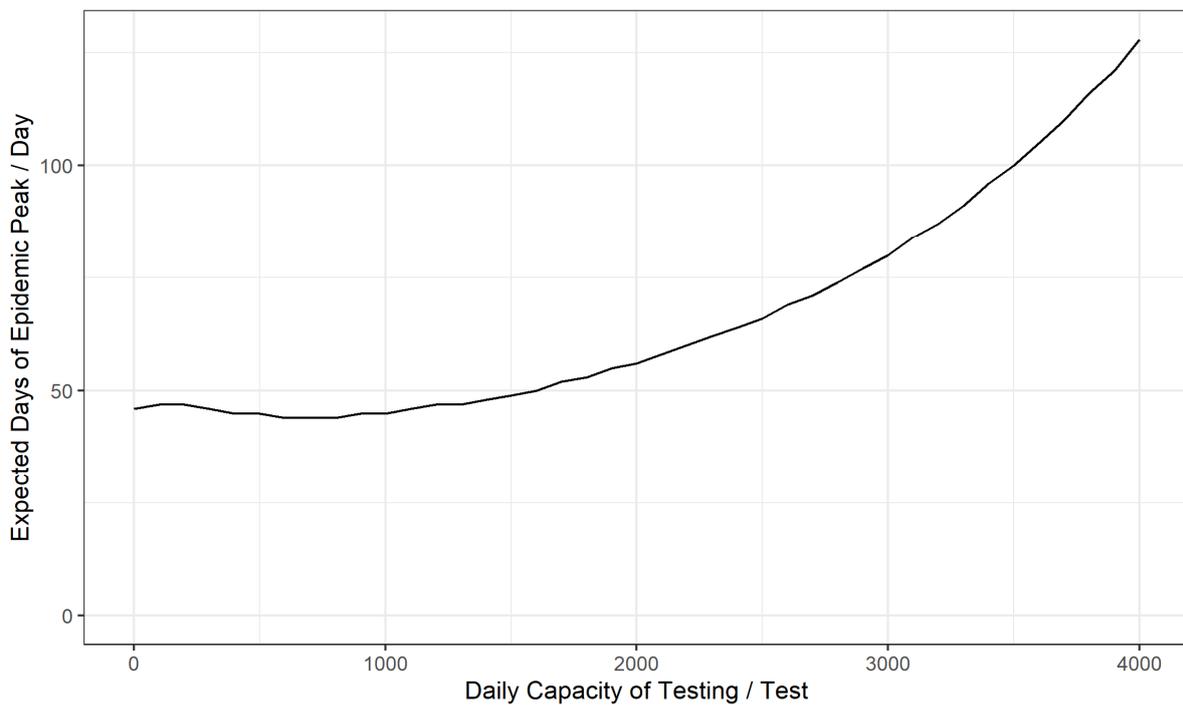
The model evolves by default in the absence of a vaccine and an effective drug, thus the model will always evolve to the point where everyone will eventually be "infected". However, the speed of infection is much slower with human interventions, thus ensuring that the number of patients never exceeds the capacity of the local health system. In Figure 1a shows the case without human intervention, the epidemic would have peaked at about 4300 and would have reached its peak in about 46 days. In Figure 1b–d, with daily testing capacity increasing from 0 to 100, 300, and 1000, the epidemic would have peaked at about 4800, 5600, and 4800, and would have reached its peak in about 47, 46, and 46 days, respectively. We see that with daily testing capacity slightly change, the peak number and the peak days will not be controlled greatly. While in Figure 1e,f, when the daily testing capacity grows to 2000 and 3000, the epidemic would have peaked at about 2500 and 1200, and would have reached its peak in about 55 and 80 days, respectively. We found that the peak day will change slowly at first, then quickly with the changing daily testing capacity. Thus, as for the daily testing capacity, we either not do it or should do a lot.



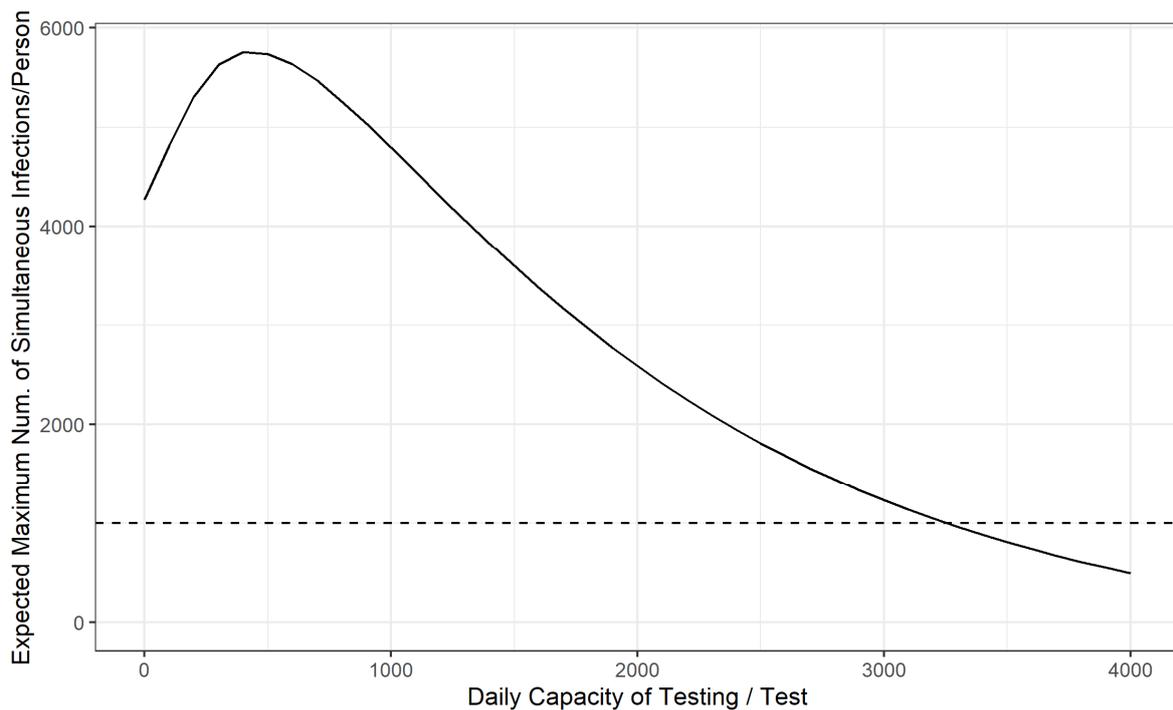
**Figure 1.** The influence of the daily testing capacity of the epidemic on the evolutionary process of the epidemic. (a) Daily testing capacity of 0; (b) Daily testing capacity of 100; (c) Daily testing capacity of 300; (d) Daily testing capacity of 1000; (e) Daily testing capacity of 2000; (f) Daily testing capacity of 3000.

Except regarding the progression of the epidemic evolution over the whole time, if only the time of the arrival of the epidemic peak is analyzed, the relevant numerical simulation results are shown in Figure 2.

It can be seen from Figure 2 that the time of peak arrival of the epidemic can vary significantly for different epidemic testing efforts, and the number of infections can also differ greatly at the time of peak arrival. As the testing capacity  $K$  increases, the time when the peak of the epidemic (which refers to the state where the infected ( $I$ ) reaches its maximum) appears, and the size of its number of infections at this time are shown in Figure 2a. As the testing capacity increases, the time of arrival of the epidemic peak is not even greatly affected when  $K < 2000$  people, but as  $K$  increases further, the time of arrival of the epidemic peak is promptly delayed. It is ultimately due to the fact that with increased testing capacity, the exposed mixed in with the general susceptible population can be tested more effectively, thus effectively containing the outbreak. When the testing capacity reaches about 3000 people per day, the peak of the epidemic can be delayed until the arrival of about 75 days while when the testing capacity reaches about 4000 people per day, the peak of the epidemic can be delayed until the arrival of about 151 days.



(a)



(b)

**Figure 2.** Effect of daily testing capacity on the timing and scale of the arrival of the epidemic peak. (a) Time of onset of the top of the outbreak; (b) Number of the infected at the onset of the peak of the epidemic.

Raising testing capacity can always postpone the occurrence of the peak of an epidemic, but the relationship between the number of people at the peak and testing capacity is complicated. In Figure 2b, the number of patients showed a trend of increasing, then decreasing when the peak of the epidemic arrived as the daily testing capacity  $K$  increased.

If the authorities had no epidemic detection capacity at all, the number of infected people at the peak of the epidemic under natural evolution would be about 4200. At this point, as the testing capacity increases, the exact number of patients at the peak increases at a fast rate. If the number of people tested daily reaches about 500, the number of infected people will reach about 6500 at the peak of the epidemic. Nevertheless, the number of infections at the peak will gradually decrease as the testing capacity is further enhanced for the outbreak. If it is possible to test 3000 people per day, the confirmed cases in the epidemic peak are only about 700. If 4000 people could be tested daily, the peak number of confirmed cases in the epidemic would be only about 550.

It is worth emphasizing that the efficiency of outbreak testing can be significantly improved by using “suspected patient tracking systems (e.g., China’s Epidemiological Survey Information System)”. In the above simulation, assuming that the susceptible ( $S$ ) and the infected ( $I$ ) are completely mixed together and cannot be traced, the efficiency of testing to detect the exposed can be significantly improved if the population to which the potentially infected individuals are exposed can be traced, thus enabling the delineation of the suspected infected individuals. Supposing that this efficiency can be increased by a factor of about 10, it is possible to postpone the peak of the epidemic by about three times (151 days) with a daily testing of 4% ( $=4000/10,000/10$ ) of the population.

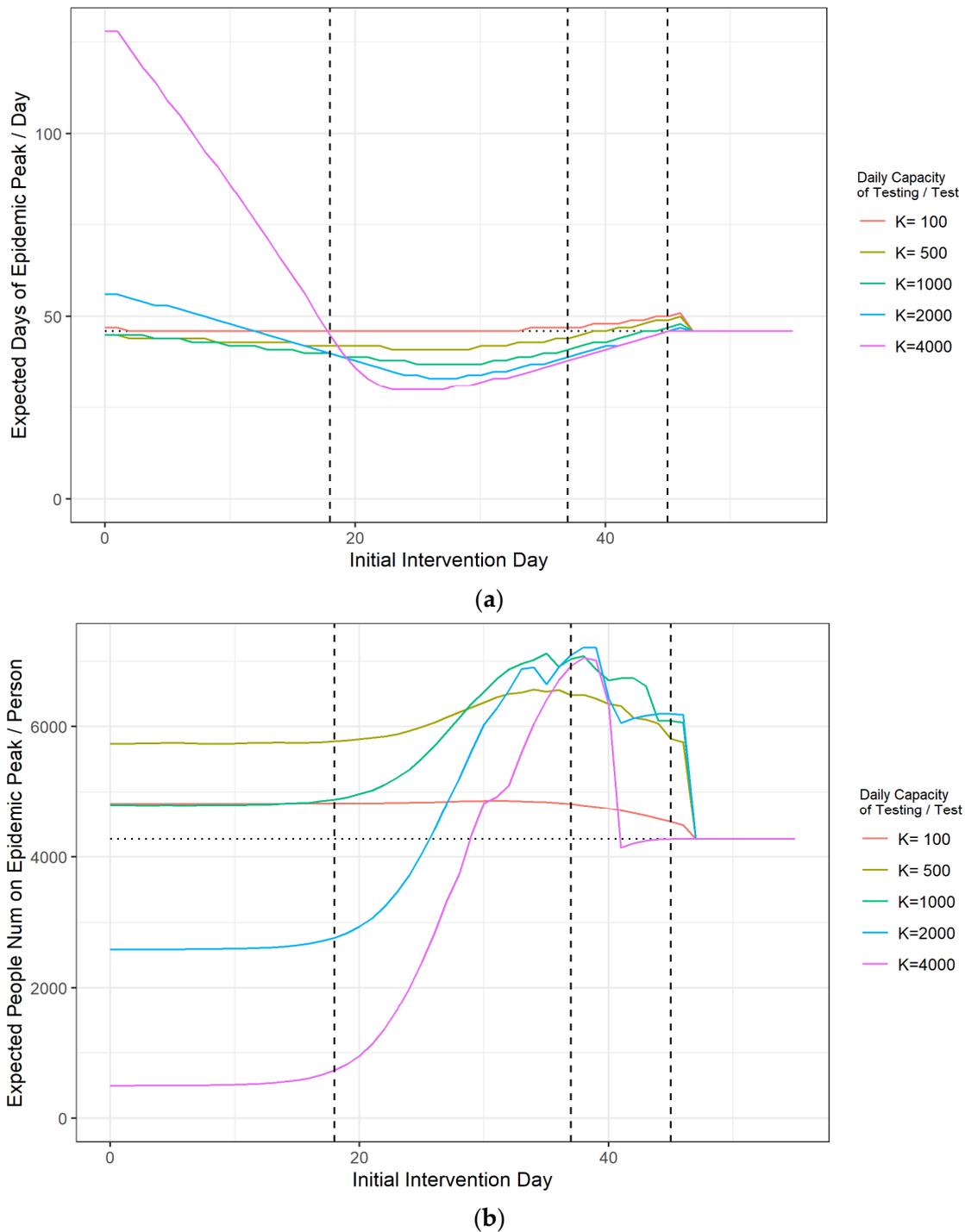
According to the indicator of the number of ICU beds per 10,000 people in the world [27,28], the current figures in the United States and Germany are the highest, reaching 3.47 and 2.97 beds per 10,000 people, respectively, while the number of ICU beds per 10,000 people in China is only 0.36. With an estimated serious illness rate of about 10–25% in the COVID-19 epidemic in each country, the capacity ( $G$ ) for COVID-19 epidemic in a community of 10,000 people in the real situation is less than 100 people in magnitude without expansion of the healthcare system. When further considering a 10-fold increase in the admission capacity ( $G$ ) of the local health system, the admission capacity is only in the order of 1000 people (as marked by the dashed line in Figure 2b). Accordingly, a daily testing capacity of 3500 people is required (taking into account that with the help of the suspected patient tracking system the testing capacity can be reduced by about 10 times, requiring only about 350 people per day), in order to be able to effectively cooperate in the total number of epidemic admissions and to ensure that the development of the epidemic itself does not penetrate the local medical system’s admission capacity.

### 3.2. Simulation Analysis of Timing Options for the Emergency Management of an Outbreak

In the following, an analysis of the impact of emergency management policies for large-scale testing at different stages of outbreak development on outbreak control is presented.

The same simulation was used to examine the effect of different outbreak testing capabilities ( $K$ ) and different starting emergency intervention timings ( $T$ ) on the peak of the outbreak, and the related results are shown in Figure 3a. Overall, the earlier the start of testing for different outbreak testing capacities, the easier it is to control the peak level of the outbreak and prevent it from exceeding the total capacity of the local hospital ( $G$ ). Regarding the transmissibility similar to COVID-19, the number of infections is relatively small during the initial period of nearly 18 days of the spread of the epidemic, and the premature implementation of emergency testing is not very effective. Rather, it is better to wait until the outbreak already has a significant local spread and start performing mass testing. Since about day 20 of the epidemic’s evolution, the epidemic has reached the rapid outbreak stage, when it is very critical to the starting intervention date. Even starting intervention a day earlier can lead to a very significant impact. If the epidemic is left to evolve for about 30–37 days (see Figure 3a), the effect on the increasing number of the infected at the peak of the epidemic is no longer significant, or the epidemic itself is out of control. However, if the epidemic is left unchecked for about 37–45 days, the epidemic is considered to have reached the middle stage of infection, when a high percentage of the population has already been screened for infection-recovery-immunization or infection-

death, and the remaining general susceptible population is already small. If mass testing of susceptible and latent populations (asymptomatic populations) is conducted at this time, a better control effect of reducing the number of infections at the peak of the outbreak can be achieved. Finally, when the outbreak has been uncontrolled for 45 days or more, when the population has acquired a significant degree of “herd immunity” and the peak of the epidemic has passed, it is no longer meaningful to start mass testing to control the number of infections at the peak of the epidemic.



**Figure 3.** Effect of daily testing capacity and initial intervention timing of the peak of the epidemic. (a) Time when the peak of the outbreak arrived; (b) Number of the infected at the peak of the epidemic.

To compare the effect of mass testing with different testing capabilities at the same intervention time, it can be found that starting to perform mass testing at the beginning of the outbreak (from around day 20 to day 30) is highly effective in controlling the number of infections at the top of the outbreak. Using no testing performed ( $K = 0$ ) as a comparison (dotted dashed line in the figure), it can be seen that a small amount of testing at this stage instead raises the number of infections at the peak of the epidemic. As the testing capacity increases further, the number of infections at the peak of the epidemic will rapidly decrease. If reasonable mass testing measures are not implemented at this stage, the increase in testing capacity will instead lead to an increase in the number of infections at the peak of the epidemic by around day 30 to 37. The last chance to significantly reduce the number of infections at the peak of the epidemic is if the mass testing measures continue to be implemented until the epidemic reaches around day 37 to 45. Once this opportunity is missed, an epidemic’s peak of infection has passed.

If the issue of the time of arrival of the epidemic peak is considered, as shown in Figure 3b, it is less affected when the testing capacity is relatively weak. With the increased testing capacity, the sampling department may need to reach a capacity of more than 2000 people per day to significantly impact the timing of the peak of the outbreak without the help of the “suspected patient tracking system”. It can be observed that the stronger the testing capacity and the earlier the start of large-scale testing, the better it is to control the arrival of the epidemic peak. For smaller outbreak testing capacity, once the outbreak enters the outbreak period, its peak must occur around day 45. In general terms, in times of weak mass detection capacity, unless the arrival of the epidemic peak can be delayed by a small amount in the very early or mid to late stages of the epidemic, the increase in epidemic testing capacity in the mid-stage will instead lead to the early arrival of the epidemic peak, although the advance will be roughly only about 7 days.

The timing of emergency management of an epidemic is a matter of cost–benefit trade-offs for the government to take emergency interventions. Clearly, an expansion of the government’s capacity to intervene in an outbreak, regardless of cost, will always help to strengthen the control of the outbreak. However, in the early stages of the epidemic, the number of infected and exposed individuals in the population is too small to justify the cost of performing daily testing of thousands of people. Second, the numerical simulation once again proved that the lack of guidance from the necessary “suspect information tracking system” resulted in slow changes in the effectiveness of the improved outbreak testing capacity.

### 3.3. Simulation Analysis of Outbreak Control Effectiveness and Emergency Management Decisions during the Peak of COVID-19

If the COVID-19 epidemic is not effectively controlled in emergency situations in the early stages, we can estimate the limitations imposed by the daily capacity limit  $D$  of the health care system aside from considering the limitation  $G$  of the total capacity of the health care system once it has developed into a high epidemic period.

In all virus-carrying populations, both the infected ( $I$ ) and the exposed ( $E$ ) are already carrying the virus and have the ability to infect others; therefore, disease control needs to focus on both the number of new infected and exposed individuals in order to achieve control of the growth in the number of the infected cases toward the next day. Under the current measures taken for the disease, we suppose that the infected are already well isolated and controlled, and that it is the exposed that pose the real risk of transmission, which is why we need to calculate the constraint between the proportion of the exposed and the testing capacity.

Considering different initial states, in order to control the number of next-day infections in one day without exceeding the daily admission capacity  $D$  of the health care system, then the screening capacity  $K$  that the community needs to be equipped with. If the total number of new infections in that community on that day is set to  $M$ :

$$M = \Delta E + \Delta I = r_I \beta_I IS/N + r_E \beta_E ES/N - \gamma I < D \tag{9}$$

The result is:

$$E < \frac{DN}{r_E \beta_E S} + \frac{\gamma N - r_I \beta_I S}{r_E \beta_E S} I \tag{10}$$

Or can be written in:

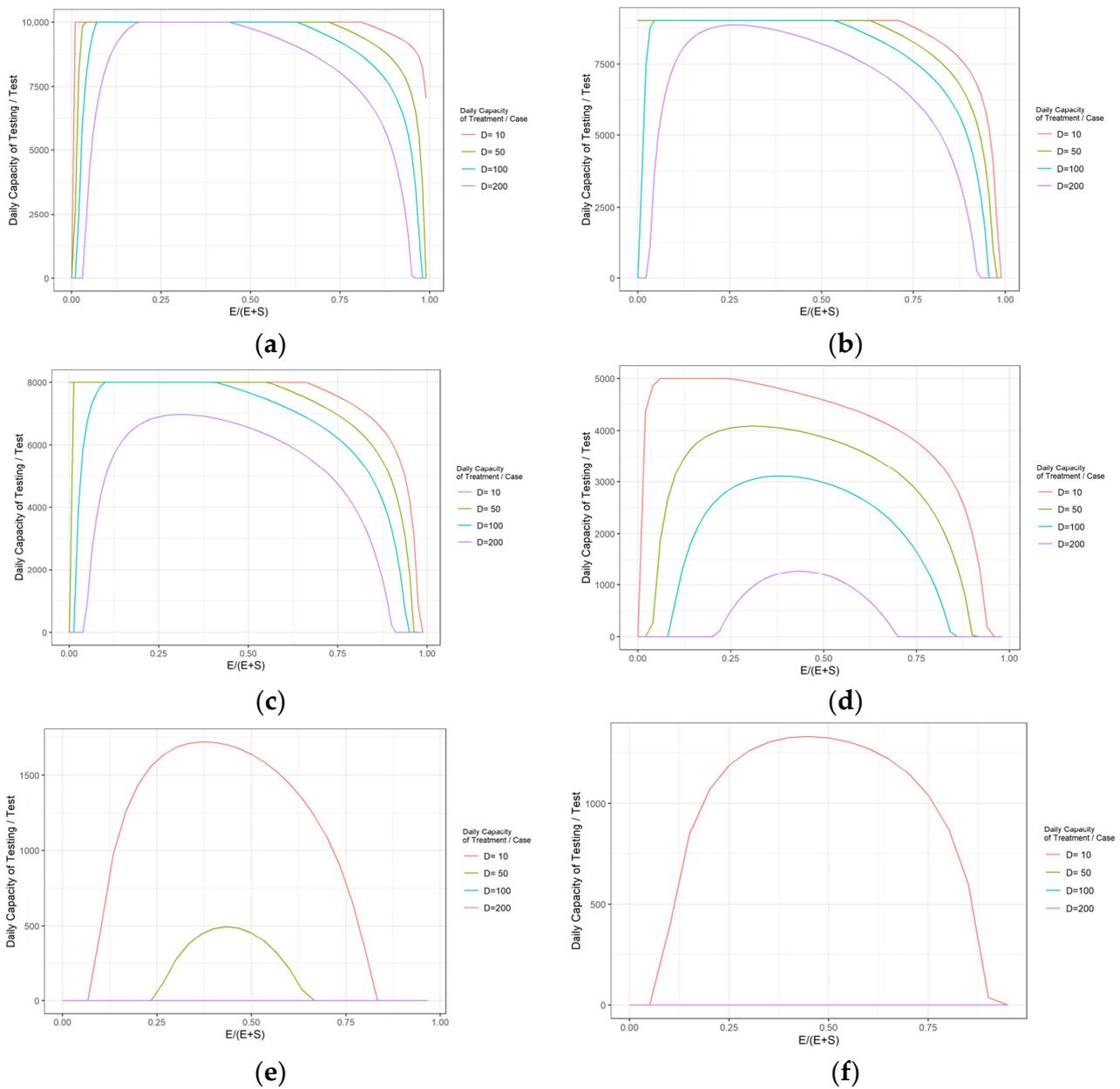
$$\frac{E}{N} < \frac{D}{r_E \beta_E S} + \frac{\gamma - r_I \beta_I S/N}{r_E \beta_E S} I \tag{11}$$

Making the critical value  $E^* = \frac{DN}{r_E \beta_E S} + \frac{\gamma N - r_I \beta_I S}{r_E \beta_E S} I$ , with respect to the single-day sampling problem, and letting the current initial state be  $(S_t, E_t, I_t, R_t)$ , so that, according to Equation (6), the number of infected persons  $E_{t+1}$  on the next day can be labeled as:

$$E_{t+1} = E_t + r_I \beta_I I_t S_{t-1}/N + r_E \beta_E E_t S_t/N - \alpha E_t - \frac{\min(K, S_t + E_t) E_t}{(S_t + E_t)} < E^* \tag{12}$$

It follows that the necessary testing capacity to control the number of new infections in the next day's outbreak should satisfy  $K < K^*$ , where  $K^*$  is the critical testing capacity (The expression for  $K^*$  is not concise enough, so numerical methods are used here to calculate it). If the authorities are unable to provide more than this capacity, the epidemic will exceed the hospital's daily capacity  $D$  on the next day, and this situation will result in an excessive ratio between mixed latent ( $I$ ) and susceptible ( $S$ ) individuals on one day, which will result in the number of new infections again exceeding the hospital's capacity on the next day. Consequently, calculating the daily critical testing capacity can help us understand the capacity requirements at different stages. The variation of  $(S_t, E_t, I_t, R_t)$  values with the current conditions in the environment is given in Figure 4 (more details and amplified figures can be found in Appendix A, Figures A7–A12). The critical testing capacity  $K^*$  that is currently required to guarantee that the admission capacity  $D$  of the healthcare system will not be exceeded on the next day.

In Figure 4, the options that can be compared with each other are listed. For example, Figure 4a,b represent the average required testing capacity for the initial spread phase of the outbreak, respectively. In Figure 4b, for example, the susceptible and the exposed populations are mixed together without discrimination, but the total number of people reaches  $S + E = 9000$ , while the number of people already infected and hospitalized reaches 1000. With the gradual increase in the proportion of  $E$  in the undifferentiated ( $S + E$ ) population from 0, the demand for the test all rises rapidly. However, if the ratio of  $E$  increases further and the extreme value is taken around  $E/(E+S) = 25\%$ , then even if the daily admission capacity of the health care system is 200, it will require a daily testing capacity of about 8300. For a community of 10,000 people, this is an almost "census" level of testing capability required. Even with the help of the "suspect information tracking system", it is necessary to sample about 10% of the population in the community every day, which is also a considerable pressure. However, if the proportion of  $E$  increases, the demand for testing will instead fall. This is mainly due to the decrease in the proportion of  $S$  in susceptible populations. In fact, when the percentage of  $E$  reaches about 90% or more, the test is no longer needed. Such situations correspond to a time when the admission capacity of the healthcare system is in extremely high demand. Assuming that the treatment period for the disease is 20 days, the daily admission capacity of the health care system at full capacity is  $1/20$  of the total admission capacity = 5% of the level; therefore, the daily admission capacity  $D = 200$  corresponds to the total admission capacity  $G = 4000$  people. A healthcare system of this size is clearly ambitious for this community.



**Figure 4.** The effect of daily testing capacity on the ability to control the potential development level of the epidemic. (a)  $S + E = 9999, I = 0$ ; (b)  $S + E = 9000, I = 1000$ ; (c)  $S + E = 8000, I = 1000$ ; (d)  $S + E = 5000, I = 1000$ ; (e)  $S + E = 3000, I = 1000$ ; (f)  $S + E = 2000, I = 1000$ .

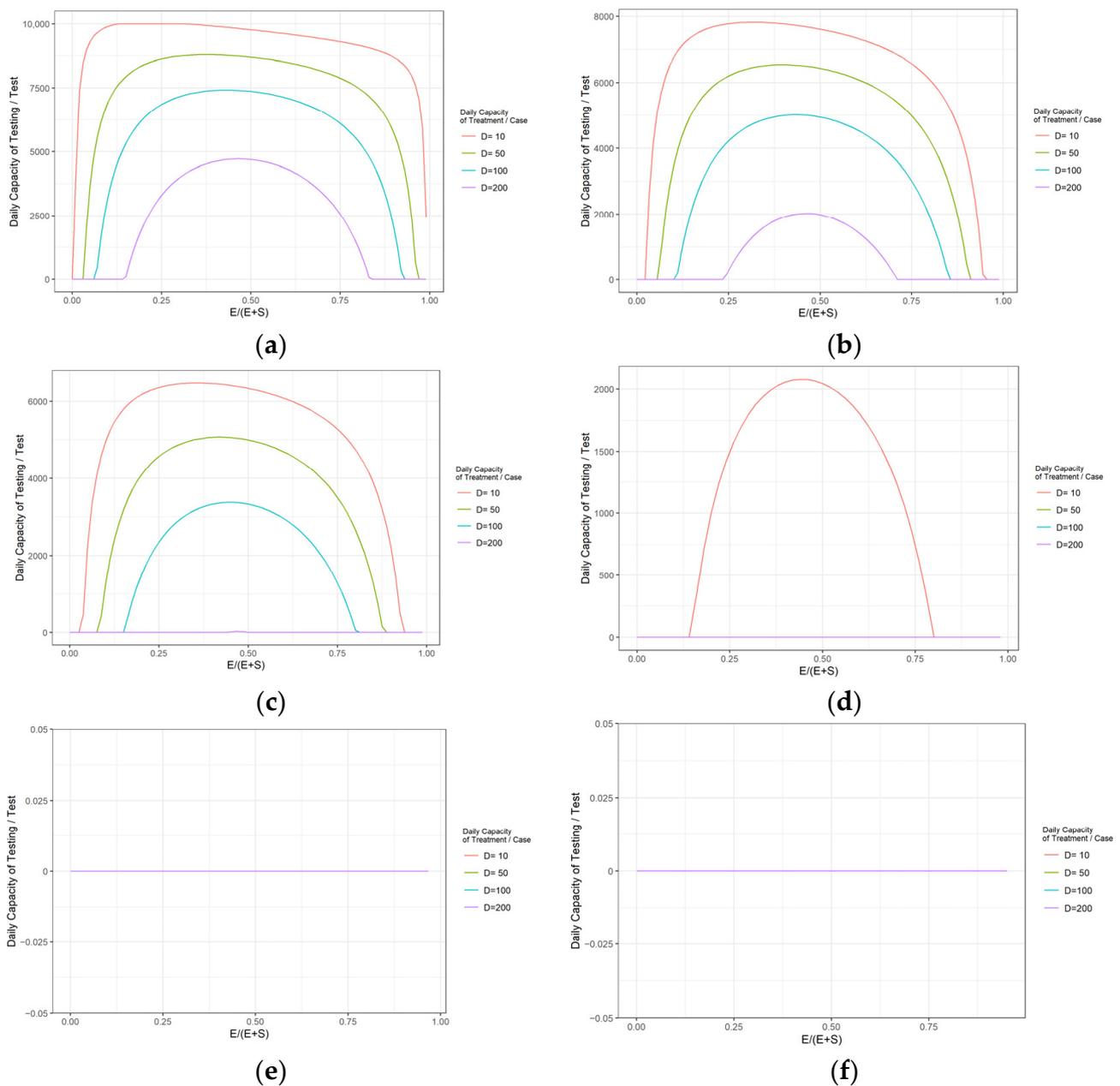
Furthermore, by comparing the subplots (c, d, e, f), it is observed that as the number of undiagnosed people ( $S + E$ ) decreases, the demand for testing capacity also decreases rapidly. When the epidemic has reached the middle stage of development ( $S + E = 5000$ ), the daily testing capacity requirement for the epidemic has been much smaller. For example, for the case of daily admission capacity  $D = 100$ , the corresponding daily testing capacity needs to meet around 2000 people. The strong contagiousness of the outbreak is evident in the fact that the testing capacity for that day was still an impressive 40~60% of the testing requirement relative to the total population of 10,000 people in that community during that period. If with the support of the “suspect information tracking system”, the scale of this daily testing capacity is acceptable, but still at a very high level.

When the outbreak has reached an advanced stage, for example, when the total number of undiagnosed people is only 2000 (accordingly, indicating that 80% of the community has

already been infected with the virus), there is still a need for a high capacity of the health system for patient admission. If the daily admission capacity is reduced to only about  $D = 10$  (corresponding to a total admission capacity of  $S = 200$ ), it is still necessary to examine approximately 800 to 1200 people per day. With the help of the “suspect information tracking system”, the testing capacity requirement can be adjusted downward to about 1% of the total community population.

Figure 4 demonstrates the striking transmissibility of the COVID-19 epidemic. At the level of the epidemic’s infectious capacity parameters, trying to contain the epidemic would require either building a medical system of staggering size or constructing a huge number of testing capabilities. For this reason, if effective emergency control of the epidemic is not accomplished in the early stages of the epidemic, it will be difficult to achieve actual control of the epidemic under the existing conditions in the middle and late stages of the epidemic. In addition to the above two means of expanding the medical system and improving the testing capacity, if we can enhance the awareness of epidemic prevention and control, both for the protection of the contacts of the infected ( $I$ ) and the self-protection of the susceptible and the exposed people (e.g., by wearing masks and washing hands regularly), the average daily number of contacts of the infected ( $I$ ) decreases from  $r_I = 3$  to  $r_I = 1$  and the average daily number of contacts of the latent people ( $E$ ) decreases from  $r_E = 15$  to  $r_E = 5$ . The same analysis method can significantly reduce the requirements in terms of expanding the health care system and improving the testing capacity, and the related results are illustrated in Figure 5 (more details and amplified figures can be found in Appendix A, Figures A13–A18).

Figure 5 shows that if the equivalent number of contacts in the infectious capacity factor for COVID-19 can be reduced to one-third of the original number by everyone wearing a mask and washing their hands regularly, the minimum number of tests corresponding to the capacity requirement of the health care system for a single day can be drastically reduced. Comparing subfigures in Figure 5 to the correspondence subfigures in Figure 4, we see that with the help of low-cost instructions, such as wearing mask and washing hand, in order to contain the peak infected number to half of the population, the critical daily capacity of testing based on the same admission capacity  $D$  to ensure that  $D$  of the healthcare system will not be exceeded on the next day has changed drastically. In subfigure (a), when the daily admission capacity  $D = 200$ , the raw system needs  $K^* = 10,000$  in Figure 4, but only needs  $K^* \approx 5000$  in the new system. The same situation also applies to other starting point of simulation. In subfigure (b), if set  $D = 200$ ,  $K^* \approx 8800$  in the raw system while  $K^* \approx 2000$  in Figure 5. In subfigure (c), if set  $D = 100$ ,  $K^* = 10,000$  in the raw system while  $K^* \approx 3200$  in Figure 5. In subfigure (d), if set  $D = 10$ ,  $K^* = 10,000$  in the raw system while  $K^* \approx 2000$  in Figure 5. In subfigure (e), if set  $D = 10$ ,  $K^* \approx 1700$  in the raw system while  $K^* = 0$  in Figure 5, which means this starting point ( $S + E = 3000$ ,  $I = 1000$ ), we do not need testing anymore, and only have to keep the daily admission capacity of treatment to 10, which is enough to control the disease. In subfigure (f), if set  $D = 10$ ,  $K^* \approx 1300$  in the raw system while  $K^* = 0$  in Figure 5, means that from this starting point, we do not need any testing, we only need to keep a small treatment capacity, as this is enough. If the outbreak is in the middle to late stages (more than half of the total population has already been infected), daily testing is no longer necessary by maintaining a daily admission capacity of only 0.5% of the total population. If the scale of the health care system is further reduced to a 0.1% intake capacity, only 1% of the population’s daily testing capacity will be required in the middle and late stages of the epidemic. With the help of the “suspect information tracking system” to improve the testing efficiency  $E$ , the outbreak of COVID-19 can be effectively controlled at a lower cost.



**Figure 5.** Relationship between the daily testing capacity of the epidemic and the potential level of the epidemic development. (a)  $S + E = 9999, I = 0$ ; (b)  $S + E = 9000, I = 1000$ ; (c)  $S + E = 8000, I = 1000$ ; (d)  $S + E = 5000, I = 1000$ ; (e)  $S + E = 3000, I = 1000$ ; (f)  $S + E = 2000, I = 1000$ .

### 3.4. Decision on the Timing of Resumption of Work and School under the Consideration of Epidemic Control Costs

In the first three sections, this paper analyzes the effectiveness of the main measures of emergency management of infectious diseases in terms of outbreak control in different states. It is important to note that the costs of different outbreak emergency management measures are not identical. The more affordable means, such as wearing masks and washing hands, are often cheaper if the local information infrastructure is already in place (e.g., cell phone use is widespread and can be tracked and located), and the cost of establishing a “suspected information tracking system” on top of that is often cheaper less expensive. If there is an inexpensive rapid testing reagents and detection means, the cost can be controlled even if the large-scale expansion of the local daily testing capacity. The most costly means in general is often to expand the capacity of the local health care system, as

this involves a large infrastructure, medical equipment, population of doctors and nurses, etc. Therefore, in the light of the cost elements of the resumption phase, it is necessary to consider, on the one hand, the need to ensure the safety of people's lives (the assumption in this paper is to ensure that the capacity of the local medical system is at least sufficient to meet the requirements of new patients) and, on the other hand, the need to consider the cost of epidemic control and to achieve reasonable control of the epidemic at the lowest possible cost under different realistic conditions. The cost of outbreak control is made up of the following four main components:

1. The cost of reducing the average number of contacts to one-third or less by reducing the probability of the infected and the exposed people coming into contact with susceptible people through daily preventive and control measures, such as wearing masks, washing hands frequently, reducing social contact between people, and isolating suspected infected persons.
2. The cost of establishing a "suspected information tracking system" to locate the exposed ( $E$ ) mixed in with the crowd.
3. The cost associated with expanding local capacity for routine testing.
4. The cost of the expansion of the local health care system's capacity to admit and treat patients, building more hospitals, hospital beds, supporting more equipment, such as ventilators, hiring more doctors and nurses, etc.

Based on the simulation results and conclusions of Figure 5 on the demand for health-care system size and daily testing capacity in the middle and late stages of the epidemic, it is evident that a daily admission capacity at the 0.5% level of the total community population (or a daily admission capacity at the 0.1% level of the total community population plus a daily testing capacity at the 1% level) can achieve low-cost epidemic control. The cost-optimal solution for effective epidemic control can then be derived by taking into account the price conditions of different countries, different time periods, and different infrastructure levels.

The price of daily prevention and control materials, for example, varies widely from country to country. For example, in China, the masks are generally around 5 RMB per piece, a hand sanitizer is around 20 RMB per bottle. The cost of isolation is relatively higher, for example, hotel accommodation costs up to 200 RMB a day. Additionally, it is easier to establish a "suspected patient tracking system" by means of China's telecommunication infrastructure. Through the relevant electronic information tracking system, it is feasible to track the activities of a wide range of people at a relatively low cost and to detect the possible population of suspected patients at an early stage, thus greatly improving the efficiency of virus nucleic acid testing. With these two major costs in mind, results similar to those in Figures 4 and 5 can be simulated to calculate the critical testing capacity  $K^*$  that can effectively control the outbreak based on the current intake capacity  $D$ . The corresponding costs for maintaining the testing capacity and for maintaining the admission capacity can then be accounted for. Among these, the unit testing capacity maintenance costs, such as nucleic acid testing reagents, varies widely in price around the world. The cost of testing in many countries ranges from 500–3000 USD, and the supply of testing reagents is severely inadequate. However, the price of nucleic acid testing in China has dropped to 30 USD or less, which is an important means of controlling the spread of the disease at low cost. The most costly means of outbreak control is to amplify the capacity of the local health care system. Referring to the relevant statements of the National Health Insurance Bureau, the per capita medical cost of patients hospitalized with confirmed cases of COVID-19 reached 21,500 RMB, the per capita treatment cost of seriously ill patients exceeded 150,000 RMB, and the treatment cost of a few critically ill patients reached hundreds of thousand dollars.

It can be calculated the minimum cost to resume work and school under the current epidemic conditions through the above scheme, and the reasonable decision of resuming can be made by examining whether the cost is already within the acceptable range. It is worth noting that the decision to resume work and school is the least costly way to control the development of the epidemic through the lowest possible means of epidemic

control in the absence of specific drugs *and* vaccines, while ensuring that the capacity of the health care system will not be knocked out by the epidemic. The specific situation and specific timing vary greatly from place to place. If effective drugs and vaccines have been discovered, these two means of epidemic prevention and control can also be added *in order* to find the least costly means. Alternatively, perhaps the large-scale adoption of both measures depends equally on cost; for example, if the cost of an effective drug is higher than the degree of acceptance, the optimal decision for outbreak control may still be to impose daily masking and hand washing on the entire population [29].

#### 4. Discussion

The results suggest that the presence or absence of control measures can contribute to large differences in the process of epidemic transmission and control effectiveness. Other studies using kinetic models, such as *SEIR*, to simulate the natural transmission process of COVID-19 have investigated only the characteristics of the virus itself without going further into the control measures; therefore, we believe that they are insufficient. Depending on the results of the model simulations in the previous section, it is shown that as the control capacity increases, the spread of the epidemic is contained not in a linear but in a non-linear relationship. We examined the characteristics of this nonlinear relationship and verified that for viruses of COVID-19's level of transmissibility, either no control at all or massive control beyond a critical threshold is required, otherwise they are barely effective. To this end, metrics such as critical sampling capacity were estimated, and the model revealed that virus spread is not managed under this sampling capacity.

In fact, since 2020, the Chinese government has adopted large-scale control exceeding the critical threshold that achieved effective epidemic control and has completely ignored control after December 2022 due to cost considerations, which have verified our conclusion. Therefore, the impact of large-scale control measures on infectious diseases must be taken into account if they are to be implemented in a strong governance scenario, which is the main contribution of this paper. The correlation simulation curves displayed in our previous section elucidate the differences in epidemic control capacity in terms of the magnitude, speed, and peak transmission number level of COVID transmission reflected by different transmission coefficients, different initial states, and different control instruments, which reveal the more complex characteristics of this dynamical system.

With the simulation results and analysis in the previous section, it is explained that there are some effective emergency control measures for common infectious diseases. For example, building mass testing capacity through strong government agencies to identify and isolate hidden asymptomatic, but infectious carriers at an early stage, and developing mass treatment capacity to quarantine and treat symptomatic and asymptomatic infected people in a timely manner. While effective outbreak control measures for the ordinary individual are to limit the range of activities, reduce the frequency of person-to-person contact, wash hands regularly, wear masks, and other measures that can drastically minimize the transmission coefficient.

Yet, different outbreak emergency management strategies and control measures have tremendous differences in cost. The government can use cost optimized emergency management strategies to achieve efficient and comparatively inexpensive outbreak control measures. For a virus, such as COVID-19, which is highly transmissible, the least costly and efficient control measure may be to reduce the transmission factor by two to three times by having everyone wearing a mask, washing their hands frequently, and reducing human contact. Constructing a comprehensive screening policy is also a more cost-effective control measure than constructing a mega treatment facility. The model simulation results led to the finding that screening measures must either not be done or must exceed the critical testing capacity matched by intake capacity to effectively contain the outbreak. The model simulation results led to the finding that screening measures must either not be done or must exceed the critical testing capacity matched by intake capacity to effectively contain

the outbreak. Otherwise, the epidemic will not only be suppressed, but also the health care system may be overwhelmed.

Epidemic transmission is a large and complex system that contains multiple parameters which are quite intricately entwined. Of all preventive and control measures, if the construction of one measure is significantly increased, the measures can often be appropriately reduced, which involves cost considerations. As a result, more expenses should be paid in the area of preventive and control measures with the highest marginal returns. This paper makes a kinetic analysis based on simple assumptions only, revealing the approximate substitution relationship between the relevant factors and discovering the nonlinear linkage characteristics among them.

Recently, some of the literature has adopted the *SEIR* evolution model to simulate the evolution process of viruses in nature. Nevertheless, few of them have considered introducing epidemic control methods into the *SEIR* model to simulate the control effects. For example, Berger et al. [30] added testing and conditional quarantine into the *SEIR* model, whose key setting is that a person in the period of asymptomatic infection can be tested to reveal infection or would be revealed later when symptoms develop, and patients in different states should have different quarantine policies. Especially the faster testing method can dampen the economic impact of the virus and reduce the peak infections. As the key calculation is still in a formula way, it might be not very easy to show the non-linearity relation clearly. Chen et al. [31] took constrained medical resources into consideration in a detailed way, to make more use of the three hospital admission policies (which are hierarchy, mixed, and Fangcang healthcare system) in different infectious stage. They found very different dynamic states based on different treatment policies, and the Fangcang system results in the largest reduction in infections and deaths, especially when the medical capacity is small. Berger et al. [32] took testing methods into consideration in detail with five kinds of testing methods, to control this disease in different transmission stages based on the *SEIR* model. It was indicated that if we can take virological testing every 2 weeks, the output loss would be cut in half and the death rate can be kept under the status quo. Based on this literature, this paper has expanded the application mode of the *SEIR* model with epidemic control methods taking into consideration and revealed some interesting non-linear features that cannot be captured by natural-state disease transmission models alone.

The limit of this paper lies in the applied cases without large-scale verification in other countries and regions except China, and lack of comparison with methods or models from other researches. In addition, a more detailed and specific discussion, and more general preventive and control measures against other viruses, and the marginal cost of each measure, are not fully considered. However, this paper pioneered the introduction of the marginal cost of prevention and control measures into the paradigm of thinking about epidemic prevention and control. This paradigm has excellent scope for expansion and is suitable for incorporating specific country regions, virus types, etc., into the comprehensive consideration, which is where such studies should be further pursued.

## 5. Conclusions

In this paper, the original *SEIR* model was developed to construct a mathematical model for simulating and analyzing the infectious disease transmission process in the specific case of COVID-19. Additionally, the model was applied to the COVID-19 epidemic transmission case to simulate and analyze the ability of emergency control of the epidemic using daily epidemic prevention, mass sampling, and hospital admission under different realistic conditions, respectively. On the assumption of lack of specific drugs and vaccines, we simulated and predicted the progress trend of epidemic prevention and control under various actual situations such as different initial conditions, different testing capacity, and different hospital admission capacity, and analyzed and optimized strategies for measures, timing, and cost selection for emergency management of the epidemic.

It is proven through numerical simulations that it is almost impossible to contain an outbreak without daily preventive measures, such as wearing masks and washing hands regularly on a large scale, with the infectious capacity demonstrated by COVID-19. Even if large-scale daily vaccination measures could reduce the infectious capacity parameter (average effective number of contacts) of COVID-19 to one-third or less of the previous level, outbreak control would still require a very large daily testing capacity to be contained. In addition, if the “suspect information tracking system” method can increase the efficiency of finding the exposed ( $E$ ) “mixed in” with the general susceptible population ( $S$ ) by a factor of 10, the difficulty of controlling infectious diseases can be significantly reduced. In other words, if the above “affordable” means of combating the epidemic were not employed, one would have to choose between large-scale routine testing or large-scale capacity of the health care system, and both would be very costly.

The results of the mathematical model simulations and analysis illustrated in this paper can provide scientific and effective recommendations for the authorities to implement emergency management strategies for the COVID-19 outbreak:

1. At the beginning of the COVID-19 epidemic, the increase in the number of outbreak testing can considerably enhance the emergency control capacity of the epidemic, which can significantly delay the arrival of the peak of the epidemic and reduce the number of infected people at the peak of the epidemic development. To conduct the test among approximately 3500 people per 10,000 people per day can effectively control the outbreak and protect the local health care system from being highly stressed.
2. For the timing of emergency outbreak interventions, mass sampling for example, the implementation of mass testing starting around the 20th to 30th day of the COVID-19 outbreak was most effective in controlling the number of infections at the peak of the outbreak. The final window for limiting the number of infections at the peak of the outbreak through emergency management measures is around day 37 to day 45 of the outbreak.
3. When the COVID-19 epidemic is in the middle and late stages of development (more than half of the total population has already been infected), it is no longer necessary to perform daily testing when routine protective measures, such as wearing masks and washing hands, are strictly enforced, as long as a daily treatment capacity of 0.5% of the total community population is maintained. Alternatively, reducing the daily treatment capacity to 0.1% of the total community population while maintaining a daily testing capacity at the 1% level of the total community population could achieve effective control of the COVID-19 outbreak at a lower cost.
4. The decision on the timing of resumption depends mainly on the magnitude of the total cost of community epidemic prevention and control. This paper summarizes the simulation results of the daily admission capacity and critical testing capacity of the healthcare system generated under different *SEIR* model parameters, which can be combined with the unit testing cost, unit treatment cost, and actual price level corresponding to different epidemic stages to derive the total cost of epidemic control, and thus decide whether to resume work and school at a particular time.

**Author Contributions:** Conceptualization, Z.X. and W.W.; methodology, Z.X.; formal analysis, Z.X.; investigation, W.W.; resources, Z.X. and W.W.; data curation, Z.X.; writing—original draft preparation, Z.X. and W.W.; writing—review and editing, W.W.; supervision, W.W.; funding acquisition, W.W. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by National Social Science Foundation of China, grant number 22CJY021. The APC was funded by Natural Science Foundation (General Program) of Fujian Province, China, grant number 2021J011126.

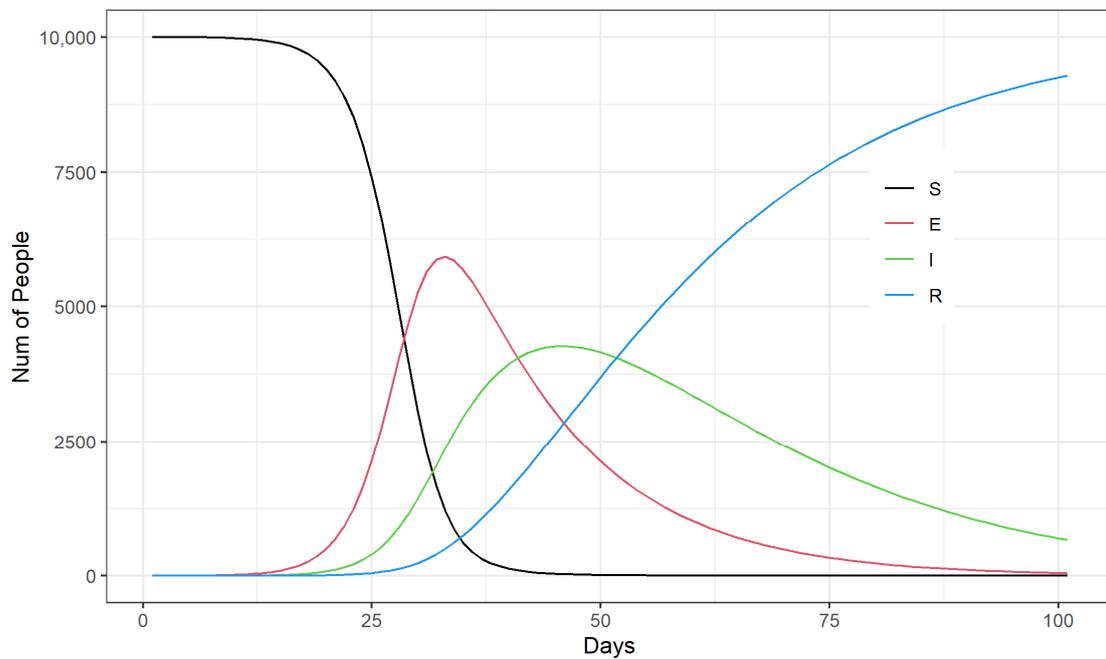
**Data Availability Statement:** No new data were created or analyzed in this study. Data sharing is not applicable to this article.

**Acknowledgments:** We thank Feng Gao for the helpful discussions on topics related to this work.

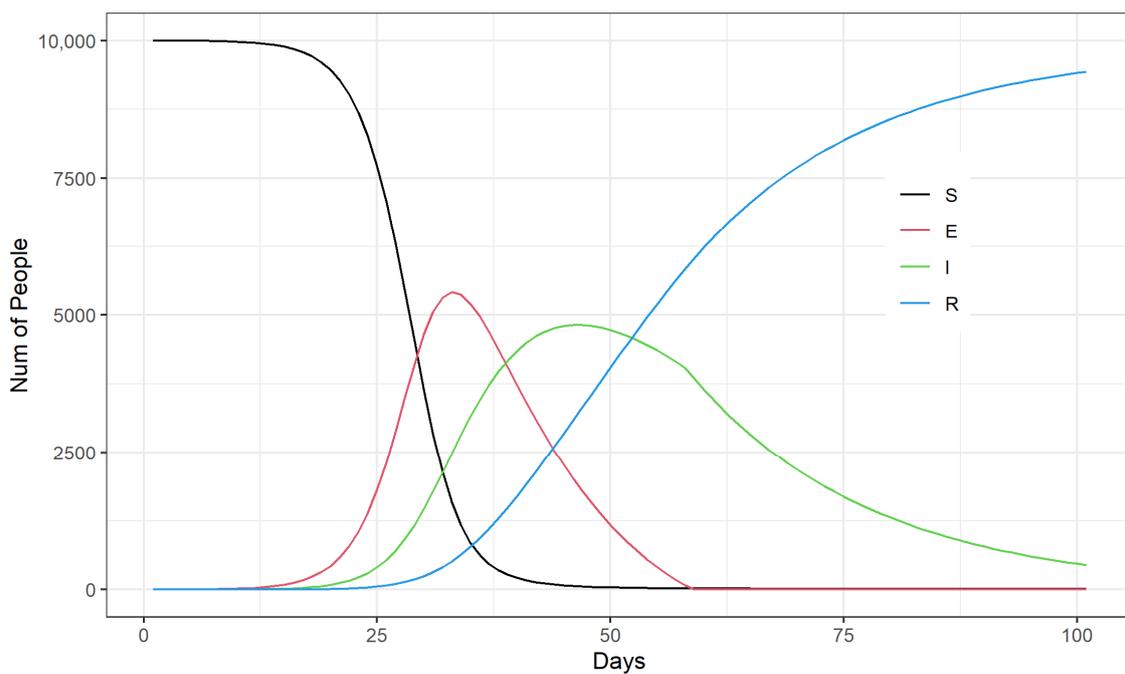
**Conflicts of Interest:** The authors declare no conflict of interest.

**Appendix A**

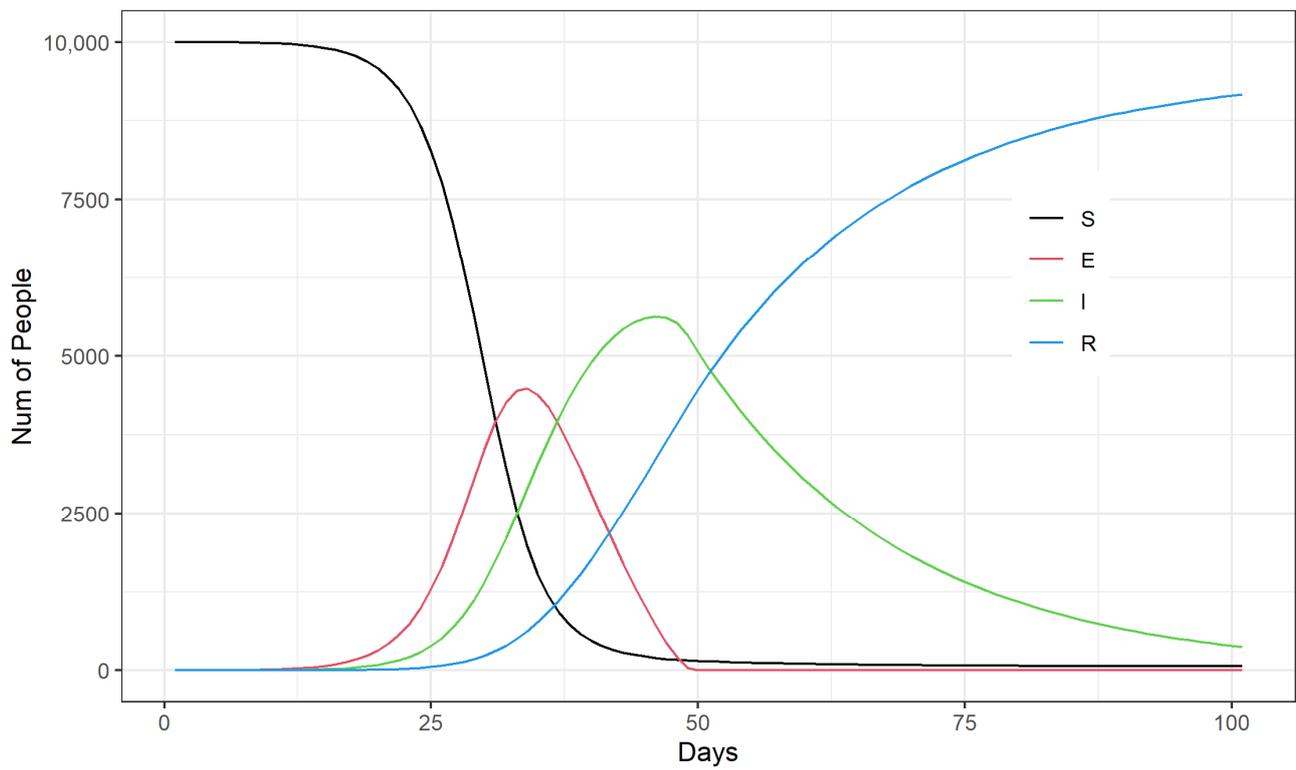
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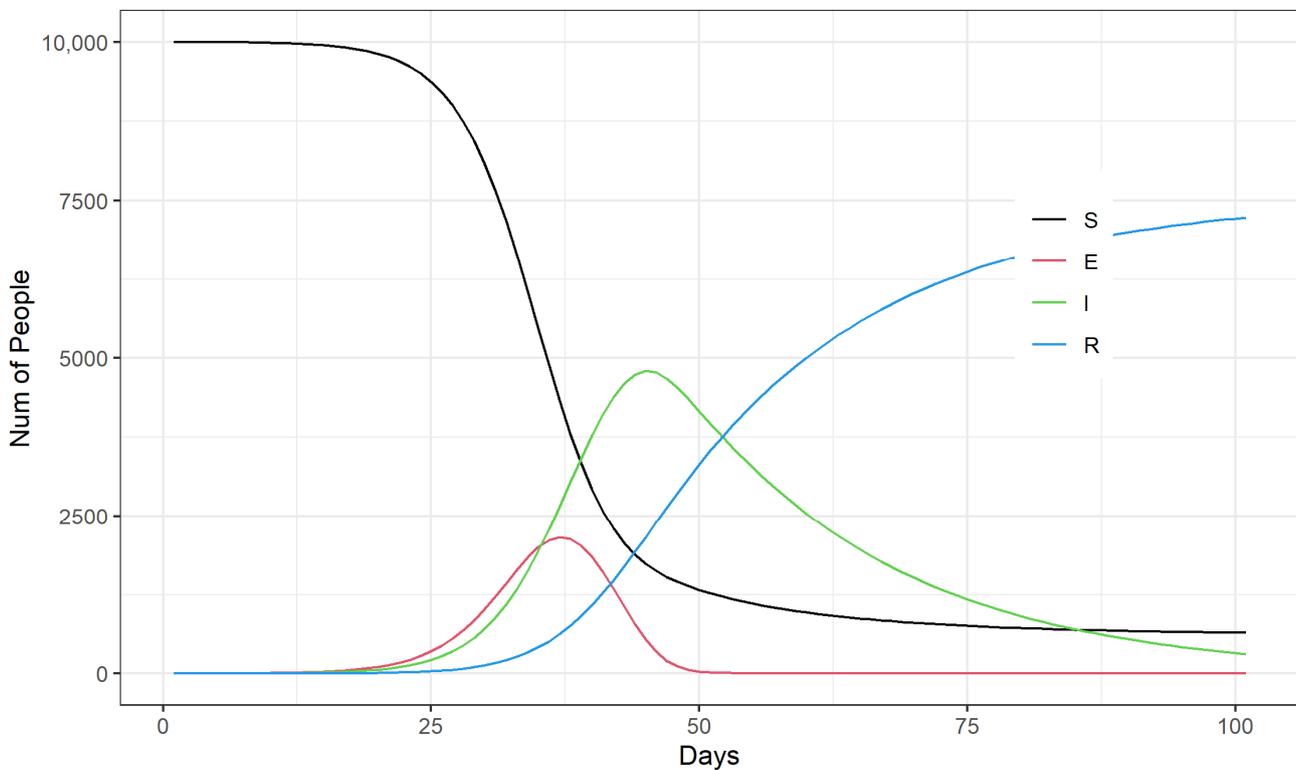
**Figure A1.** The influence of the daily testing capacity of 0 person on the evolutionary process of the epidemic; (The unit of the ordinate is “person”).



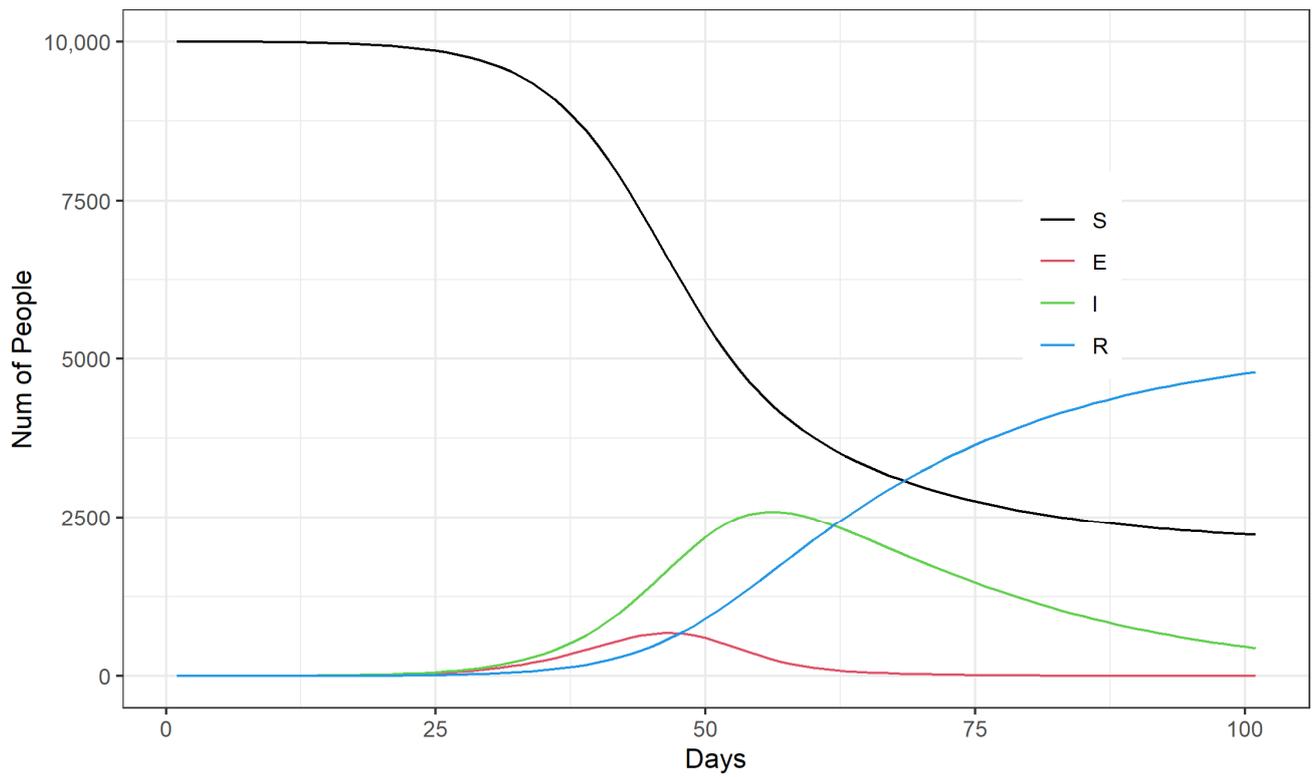
**Figure A2.** The influence of the daily testing capacity of 100 person on the evolutionary process of the epidemic; (The unit of the ordinate is “person”).



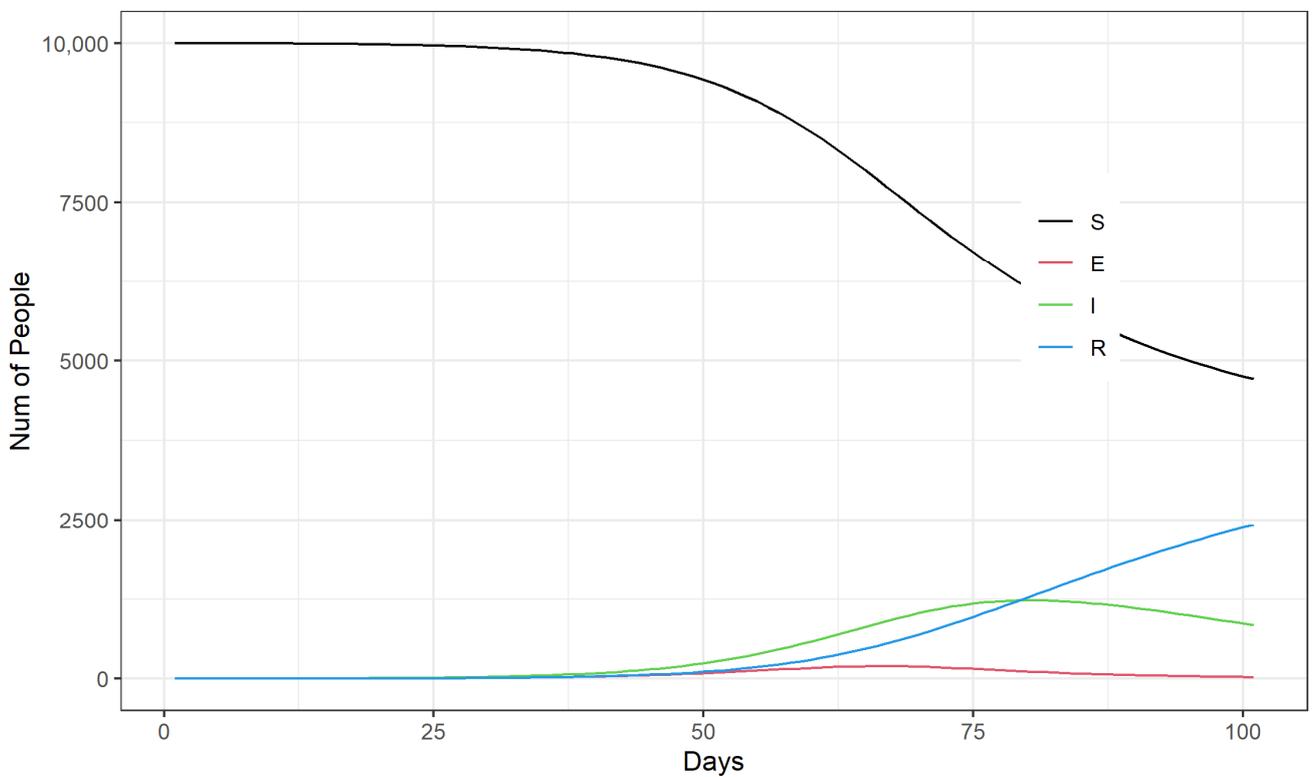
**Figure A3.** The influence of the daily testing capacity of 300 person on the evolutionary process of the epidemic; (The unit of the ordinate is “person”).



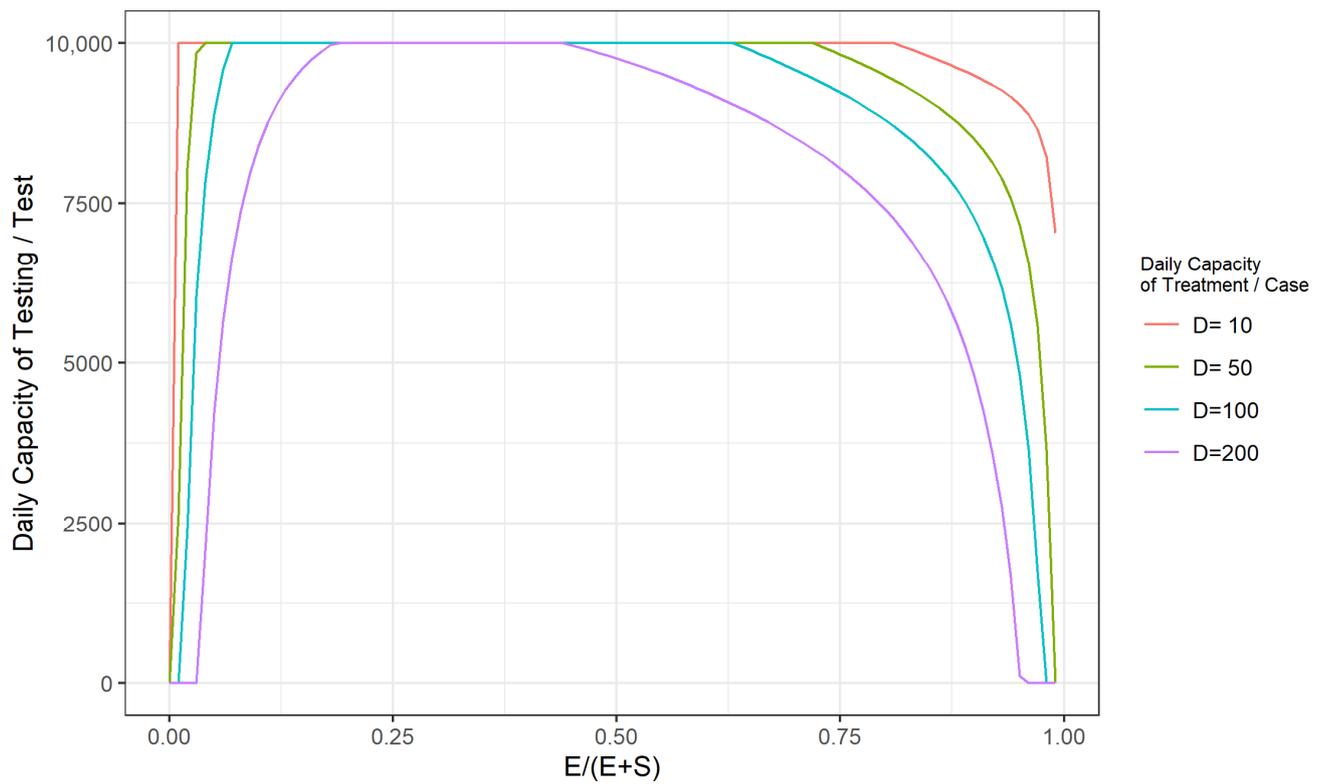
**Figure A4.** The influence of the daily testing capacity of 1000 person on the evolutionary process of the epidemic; (The unit of the ordinate is “person”).



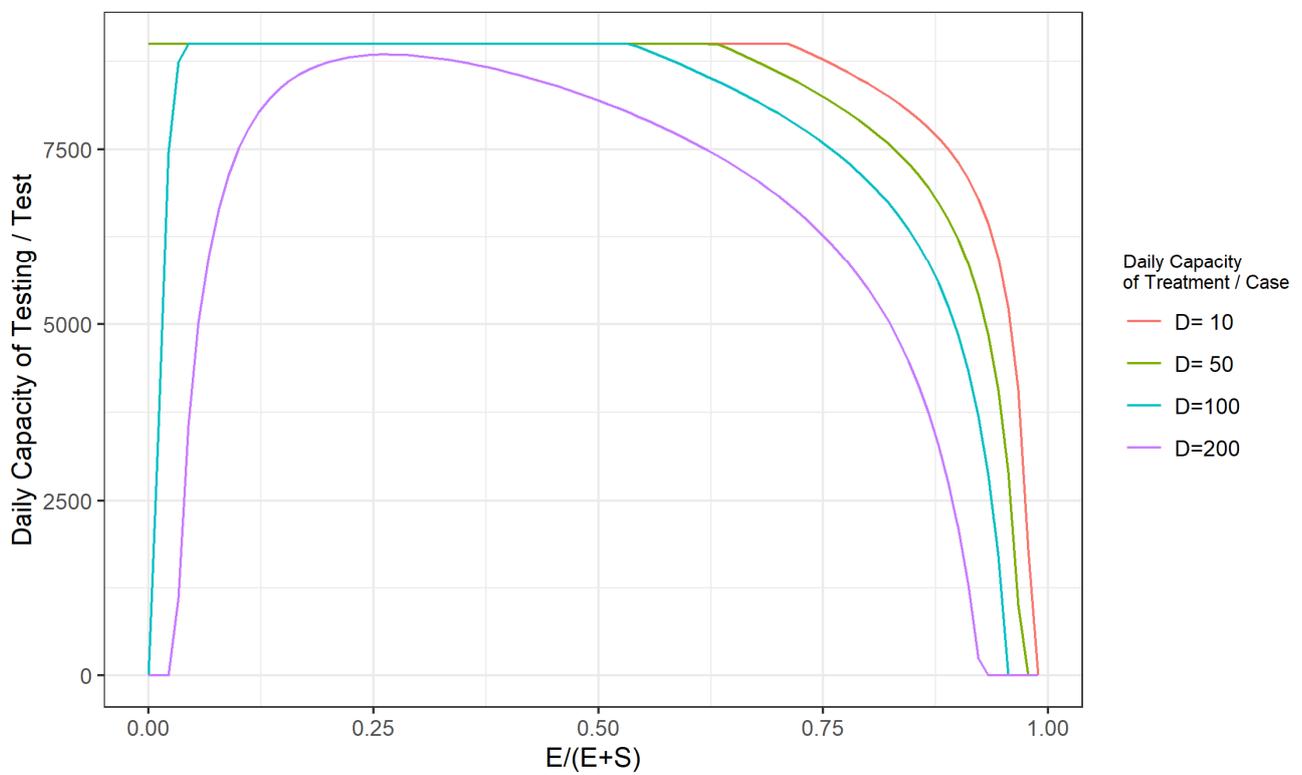
**Figure A5.** The influence of the daily testing capacity of 2000 person on the evolutionary process of the epidemic; (The unit of the ordinate is “person”).



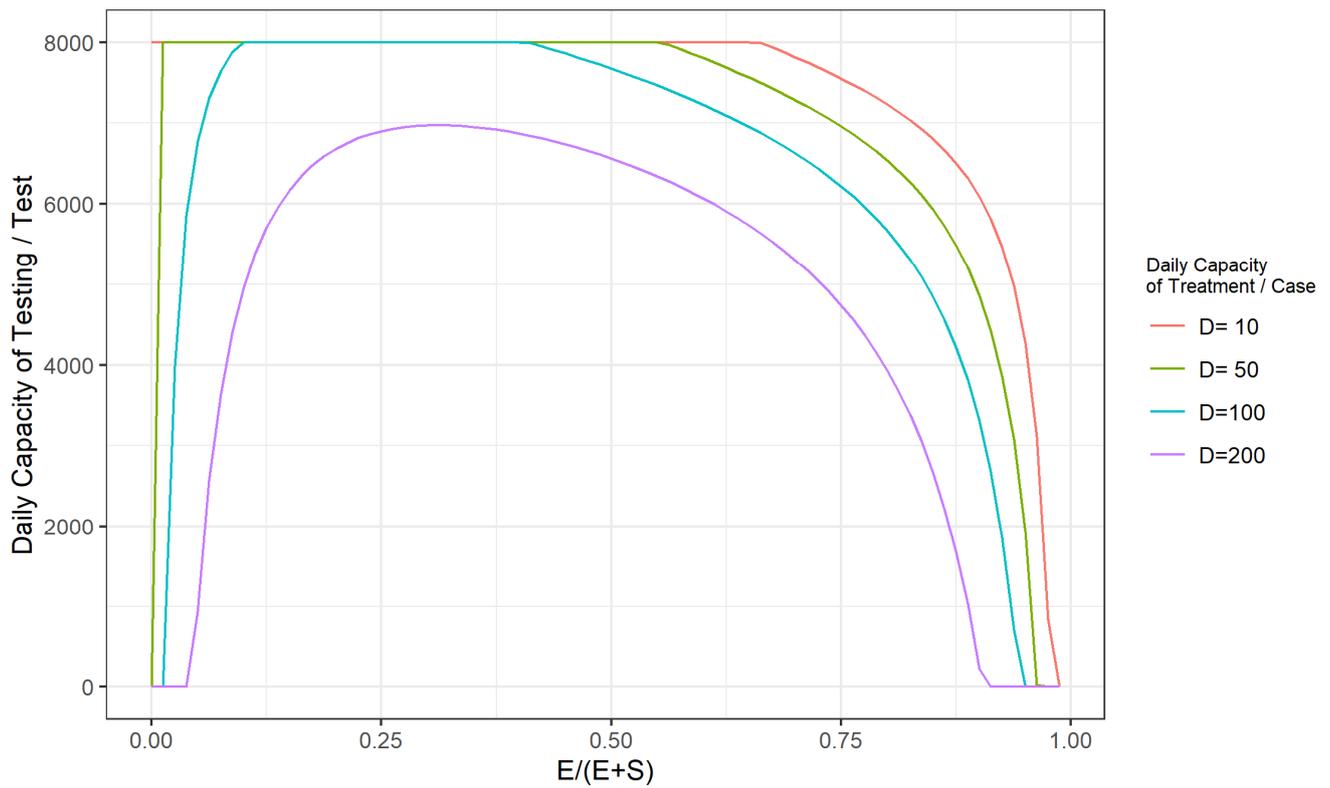
**Figure A6.** The influence of the daily testing capacity of 3000 person on the evolutionary process of the epidemic; (The unit of the ordinate is “person”).



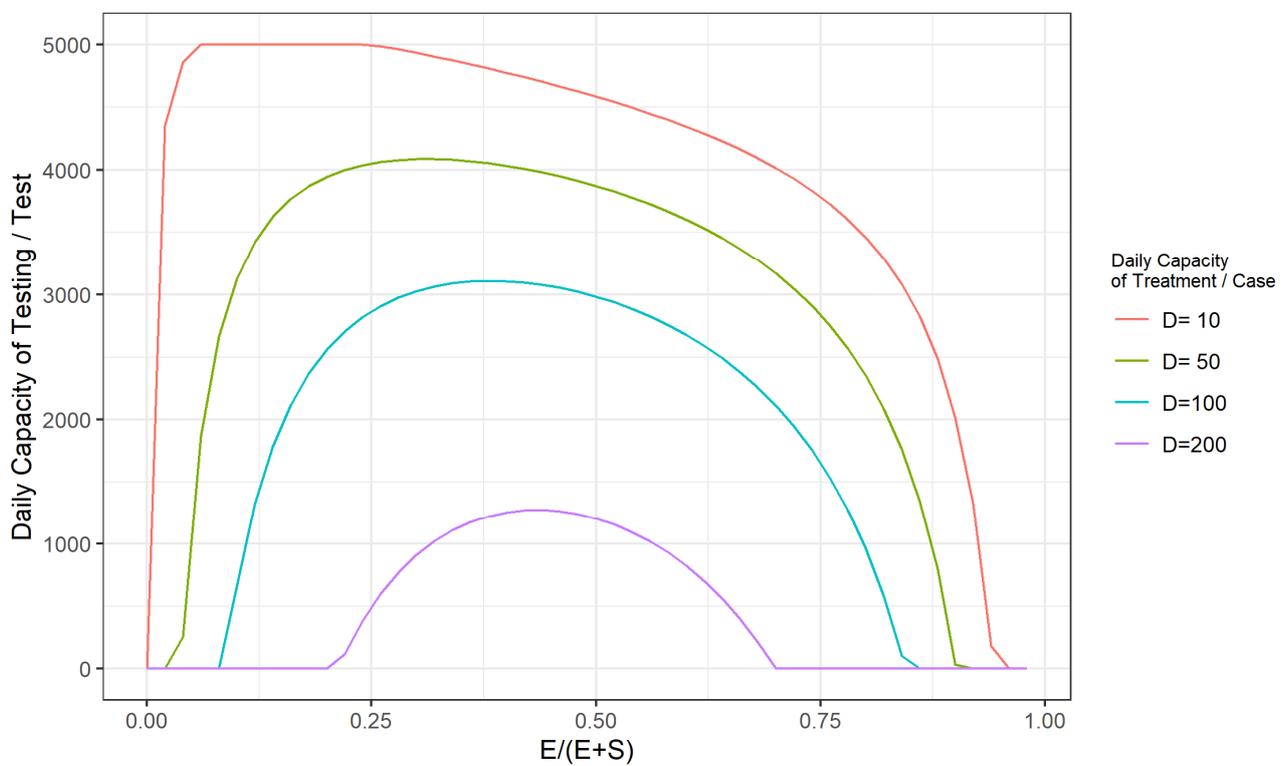
**Figure A7.** The effect of daily testing capacity on the ability to control the potential development level of the epidemic ( $S + E = 9999, I = 0$ ).



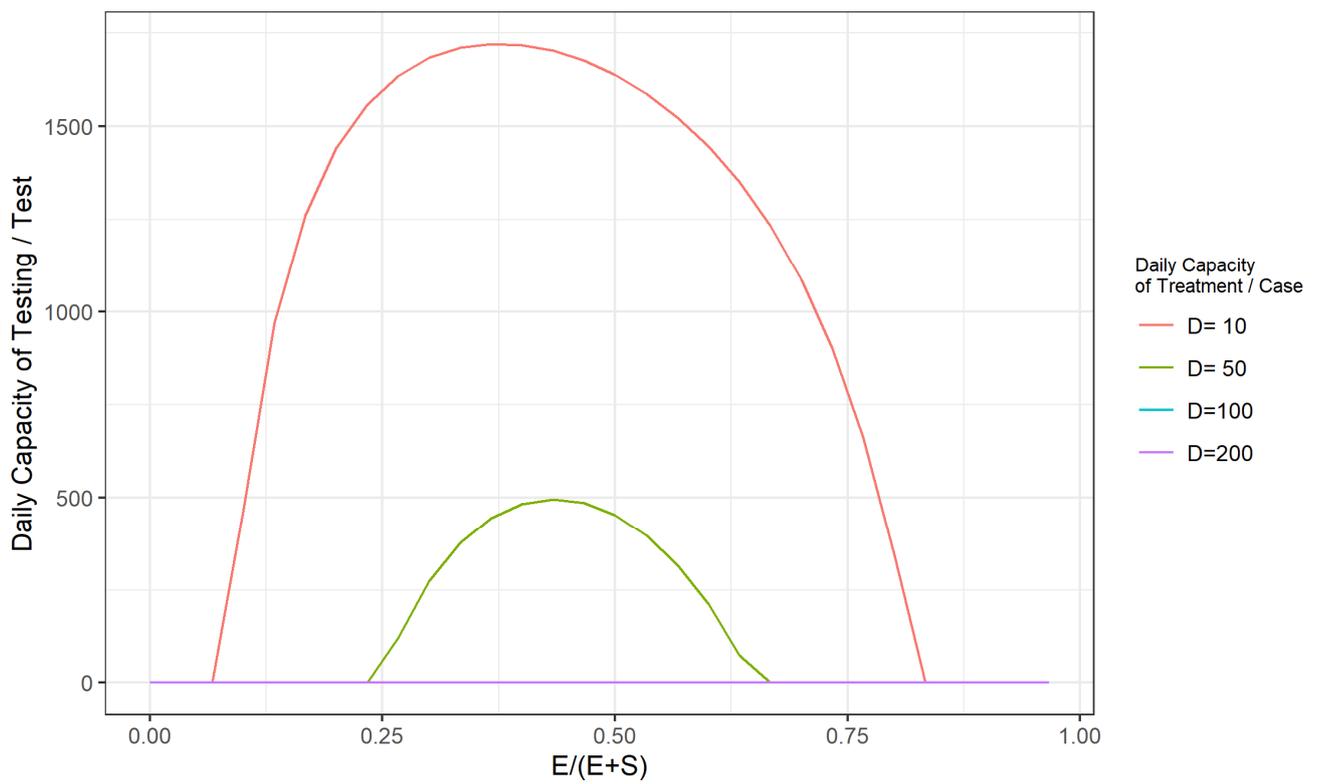
**Figure A8.** The effect of daily testing capacity on the ability to control the potential development level of the epidemic ( $S + E = 9000, I = 1000$ ).



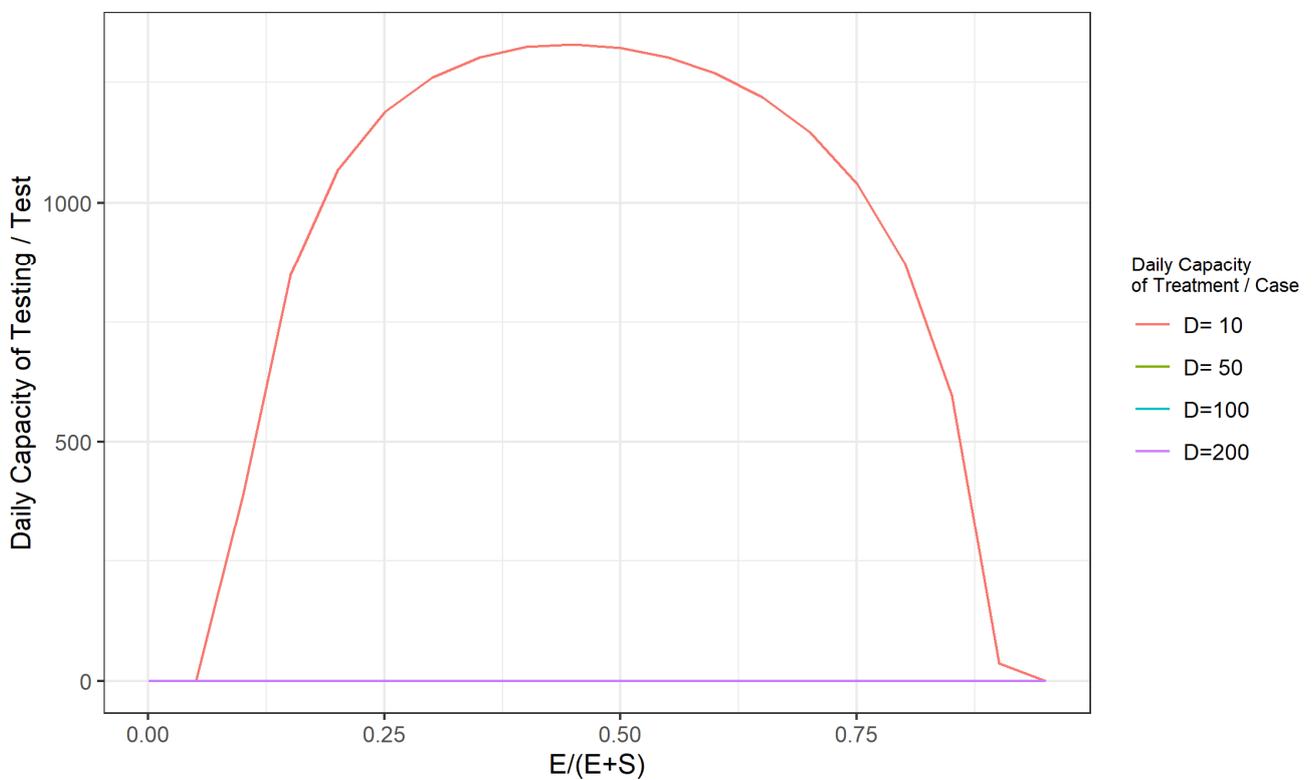
**Figure A9.** The effect of daily testing capacity on the ability to control the potential development level of the epidemic ( $S + E = 8000, I = 1000$ ).



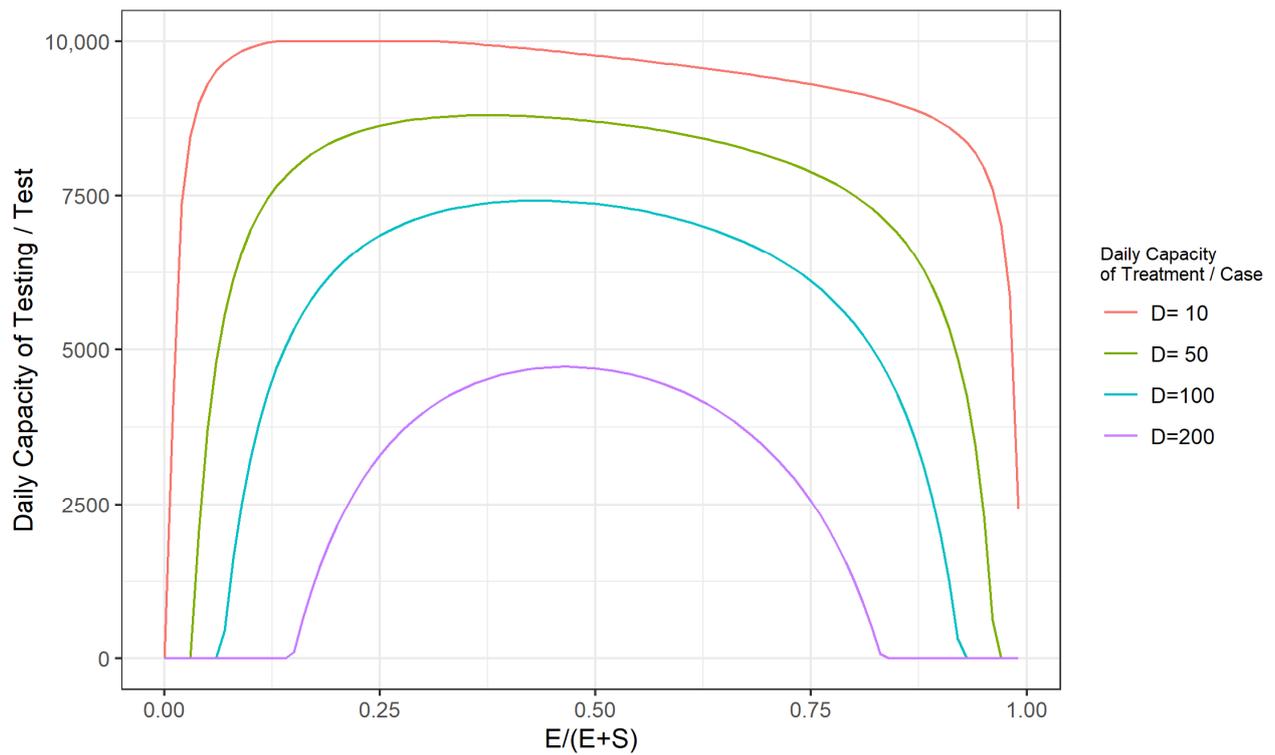
**Figure A10.** The effect of daily testing capacity on the ability to control the potential development level of the epidemic ( $S + E = 5000, I = 1000$ ).



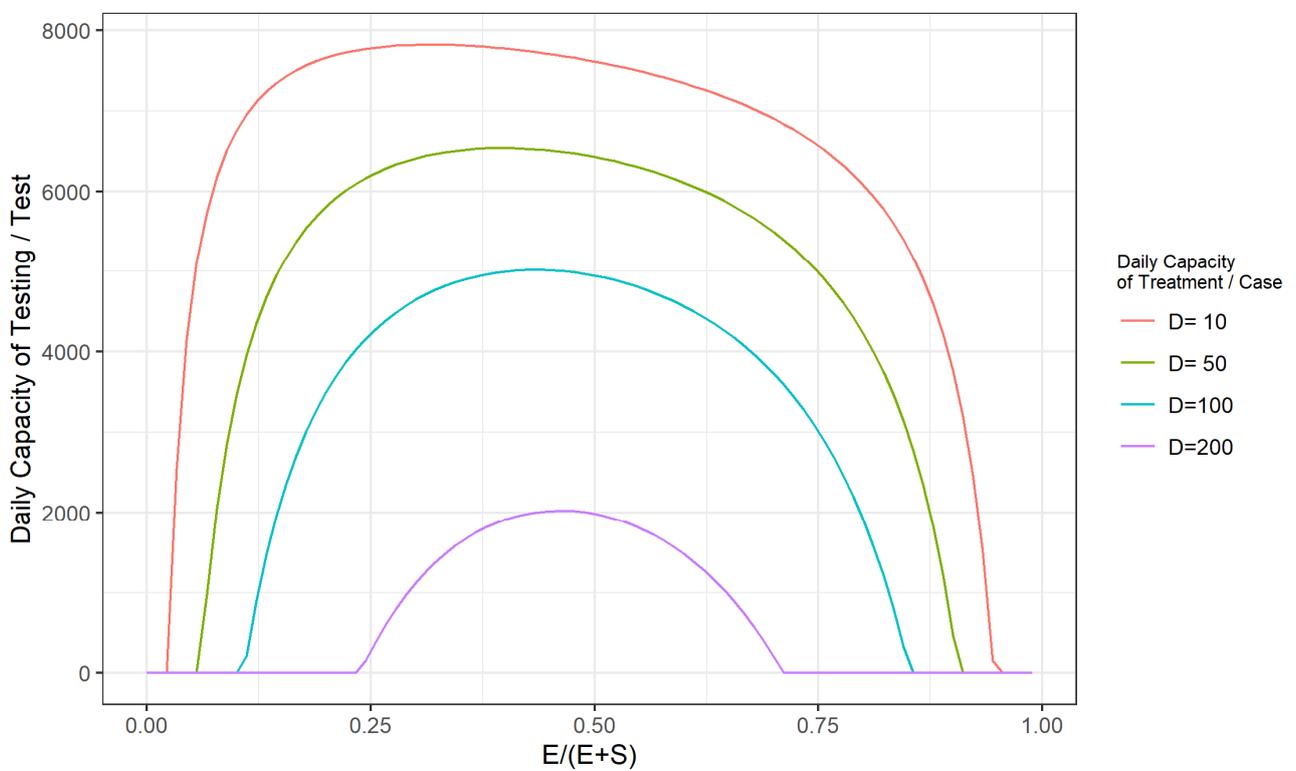
**Figure A11.** The effect of daily testing capacity on the ability to control the potential development level of the epidemic ( $S + E = 3000, I = 1000$ ).



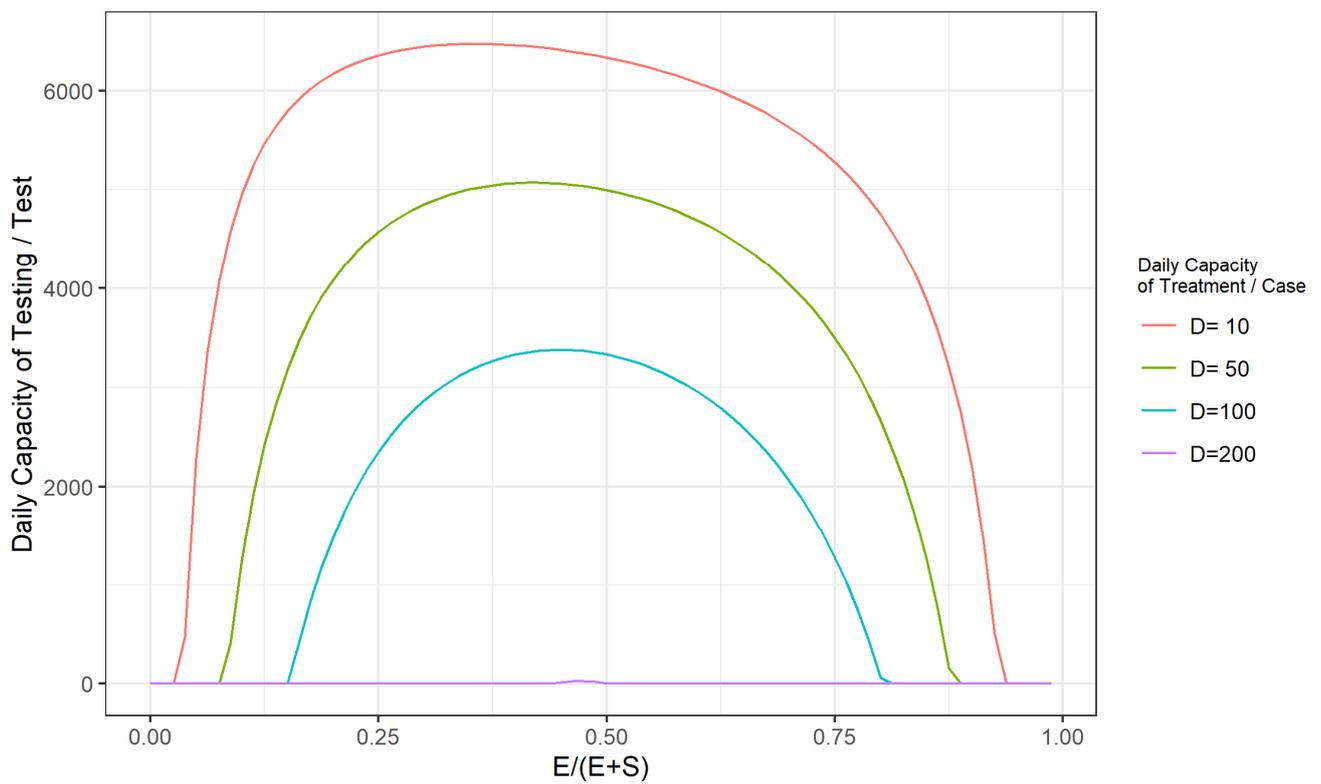
**Figure A12.** The effect of daily testing capacity on the ability to control the potential development level of the epidemic ( $S + E = 2000, I = 1000$ ).



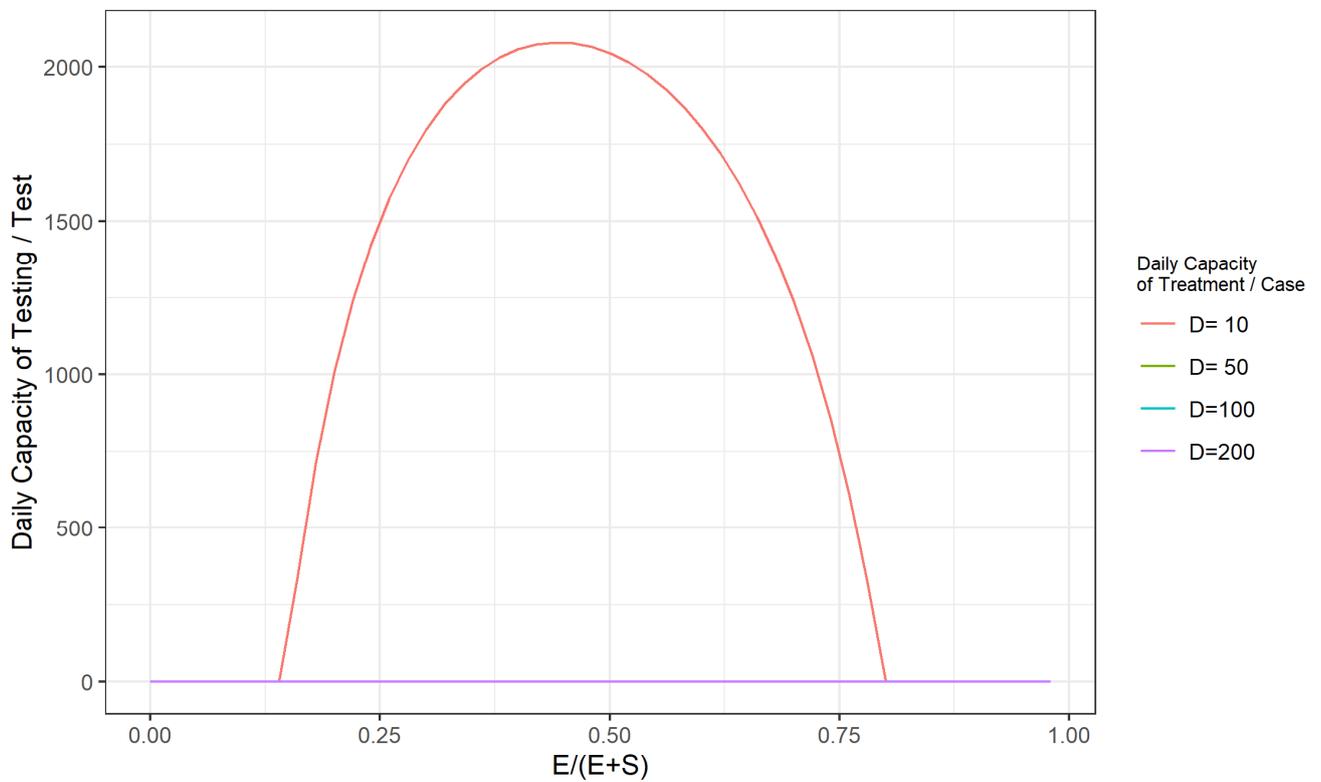
**Figure A13.** Relationship between the daily testing capacity of the epidemic and the potential level of the epidemic development ( $S + E = 9999, I = 0$ ).



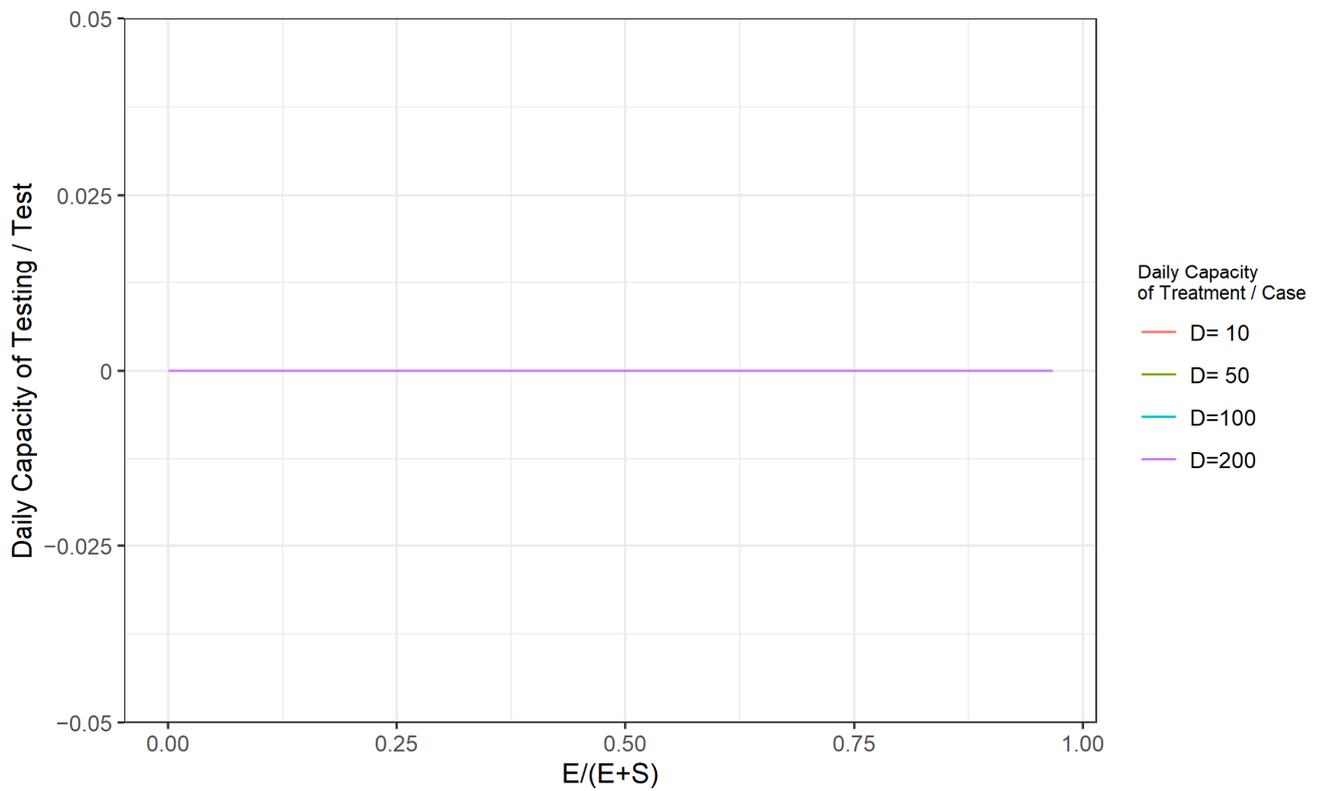
**Figure A14.** Relationship between the daily testing capacity of the epidemic and the potential level of the epidemic development ( $S + E = 9000, I = 1000$ ).



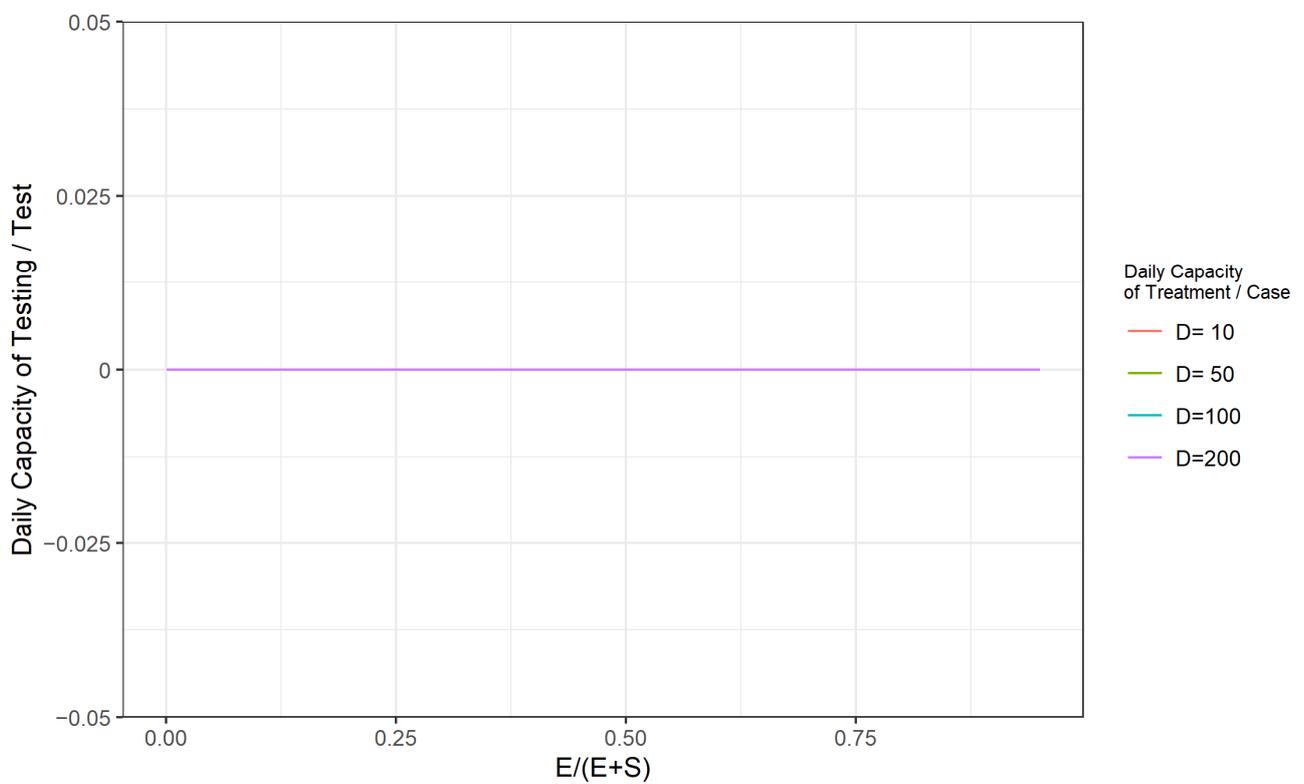
**Figure A15.** Relationship between the daily testing capacity of the epidemic and the potential level of the epidemic development ( $S + E = 8000, I = 1000$ ).



**Figure A16.** Relationship between the daily testing capacity of the epidemic and the potential level of the epidemic development ( $S + E = 5000, I = 1000$ ).



**Figure A17.** Relationship between the daily testing capacity of the epidemic and the potential level of the epidemic development ( $S + E = 3000, I = 1000$ ).



**Figure A18.** Relationship between the daily testing capacity of the epidemic and the potential level of the epidemic development ( $S + E = 2000, I = 1000$ ).

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