Supporting Decision-making for COVID-19 Outbreaks with the Modified SEIR Model

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Abstract—**The ongoing novel coronavirus disease (COVID-19) pandemic has ravaged human society and inflicted serious damage. The transmission history of COVID-19 demonstrates how infectious diseases can become global threats if they are not contained. Efficient response policies are required to contain these outbreaks. However, it is challenging to rapidly formulate and promulgate suitable response policies in various countries that experience outbreaks, given that the experience of controlling epidemics of highly contagious diseases is limited. This paper proposes a modified SEIR model that can simulate COVID-19 outbreaks by accounting for the capacity of the local healthcare system and possible intervention techniques to support decision-making during such outbreaks. Our paper provides answers to the following three questions: "What feasible intervention methods may serve to control outbreaks?", "To what extent can these methods reduce the damage caused by outbreaks?" and "What are the ideal intervention methods under various circumstances?".**

Index Terms—**Coronavirus, disease control, computer modelling, infections, epidemics, interventions.**

I. Introduction

AFTER Wuhan reported the outbreak of COVID-19, the disease rapidly spread to other cities and became a global health crisis [1], heavily impacting human society both medically and economically [2]. Previous epidemics, such as the outbreak of Ebola in West Africa [3], demonstrate the importance of the early detection of such outbreaks and the immediate implementation of remedial measures to mitigate their spread. The COVID-19 epidemic has once again raised concerns globally concerning appropriate preventative measures for avoiding such disasters.

To contain COVID-19 outbreaks in numerous countries, substantial effort has been spent on formulating effective emergency response policies [4][5] and forecasting future trends [6][7][8][9]. In the past, certain interventions were widely implemented to reduce the fatality and morbidity rates of infectious disease outbreaks [10]. Medical interventions, such as vaccination, have been shown to be highly effective [10]. However, facing outbreaks of novel infectious diseases without existing vaccines, such as COVID-19, other intervention techniques should be considered, such as the promotion of personal hygiene, the distribution of personal protective equipment, and extensive lockdowns.

Controlling and preventing outbreaks of an infectious disease require a better understanding of the unique characteristics of the disease. Mathematical models are effective methods for determining the characteristics of an infectious disease (e.g., transmission conditions, fatality rate, morbidity rate [11]). Mathematical models have also been widely used to predict the kinetics of infectious diseases since they allow researchers to predict the potential outcomes of outbreaks and determine the intervention measures that should be implemented by considering how a disease spreads and incorporating the correct parameters [12]. The ongoing construction, implementation, and improvement of mathematical modelling methods enable researchers to understand the characteristics of diseases and how to control outbreaks more effectively [12]. Although these models cannot provide precise predictions, they facilitate the decision-making process by providing best-estimated outcomes based on historical data from previous outbreaks [13]. Modelling and simulation allow researchers to quantify and analyse different scenarios concerning a disease's spread and control. Thus, mathematical simulations can facilitate data collection, disease prevention, and the control of future outbreaks [12,14].

In this paper, the SEIR epidemic model was modified to perform COVID-19 outbreak simulations that are close to real-life situations and to support decision making under various scenarios. We simulate outbreaks in Wuhan to illustrate the use of our model and provide insights into the COVID-19 outbreaks. Potential intervention measures were evaluated and contrasted based on their overall impacts on COVID-19 outbreak simulations. The model was thus able to prioritize various intervention techniques based on different outbreak scenarios, explore the potential shortcomings of individual local health systems, and provide decision-making support during actual outbreaks. The paper also provides insights into potential combinations of measures for preventing the occurrence of outbreaks in the future. However, the accurate simulation of outbreaks and prioritization of intervention methods remain enormous challenges due to a lack of the data required for the modelling and simulation of outbreaks [15][16], especially for newly discovered infectious diseases (COVID-19).

II. Related Work

There have already been many studies related to precisely simulating infectious disease outbreaks and exploring effective interventions before the COVID-19 pandemic arose. Previous studies [17][18][19] have focused on the global dynamic behaviour of epidemic models.

Recent studies have mainly focused on the trend prediction of COVID-19 [7][8][9][20][21] in specific areas. However,

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none of these models account for possible interventions. Our model allows simulations with various combinations of intervention techniques in different cities, which can support decision making for COVID-19 outbreaks under various scenarios.

Chowdhury [5] employed a prediction model that can perform simulations of COVID-19 outbreaks under various nonpharmacological interventions. They reduced the reproductive number R as a consequence of employing interventions instead of specifying the detailed effects. In contrast, our model accounts for the concrete effects of intervention techniques during the simulations. For example, applying the intervention 'Promotion of personal hygiene, personal protection, and the distribution of personal protective equipment' in our model reduces not only the subsequent rate of infection but also the number of close contacts for each individual. Moreover, we differentiated the general public and health care workers in our model to allow changes in the functionality of the local healthcare system during the outbreaks.

Moss [13] proposed a general modelling framework, a stochastic SEIR-type model, that can inform decision making during emerging infectious disease outbreaks in the Asia-Pacific region. Inspired by their work, we modified the SEIR model in light of the real COVID-19 outbreak and the interventions deployed. Two different stages, namely, suspected and confirmed infection, were included in our model to keep in line with the real-life situation occurring in Wuhan. By doing so, we proposed a more specialized model to simulate COVID-19 outbreaks and support decision making.

III. The Mathematical Model and Its Modification

This section describes the modified SEIR model and how the parameters were selected for constructing the city scenarios. The possible intervention measures included in the simulations are then outlined.

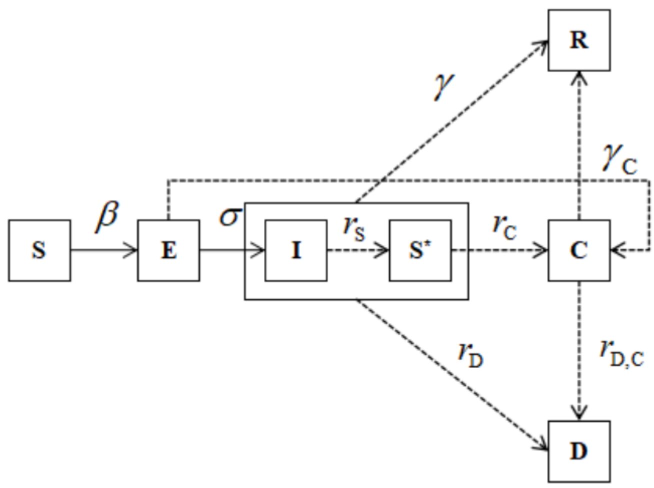

Fig. 1. Modified SEIR model. The entire population is initially susceptible (S). Individuals are exposed upon coming into close contact with other exposed or infected individuals (E). During this stage (E), hosts are infectious and asymptomatic. Exposed individuals (E) then either become symptomatic and infectious (I) or are identified through contact tracing (C). Once symptomatic individuals (I) are suspected of being infected, they become suspected cases (S*). Once suspected cases (S*) are confirmed to be infected, they become confirmed cases (C) and start to receive special treatment for COVID-19. Individuals subjected to contact tracing, suspected of being infected (S*), or confirmed of being infected (C) are placed in isolation until the city's isolation capacity reaches its limit. Suspected (S*) and confirmed (C) cases either recover (R) or succumb (D) to the disease, corresponding to the recovery rate and fatality rate of COVID-19.

A. *The Modified SEIR Epidemic Model*

The original SEIR epidemic model consists of four stages (susceptible, exposed, symptomatic-infectious, and recovered), and the modified model includes two additional stages (suspected and confirmed) to allow more precise simulation, as shown in Fig. 1. Individuals subjected to contact tracing, suspected cases, and confirmed cases are all placed in isolation. Two additional assumptions are made:

--First, recovered individuals acquire temporary immunity and cannot be infected again throughout the course of the simulation.

--Second, cadavers are handled carefully, thereby not resulting in any subsequent infections.

The general public and healthcare workers are differentiated in the model to simulate the changing functionality of the local healthcare system across various time intervals during the outbreak. Healthcare workers are initially subject to the same infection rate as the general public, while the outbreak goes undetected. Once the outbreak is detected, medical and personal protective equipment is used by healthcare workers and by the general public to reduce the risk of infection. Therefore, the infection rate after the disease is detected is relatively low in the model. Considering that healthcare workers are trained in the correct use of protective equipment and that medical equipment has strict production standards, the infection rate is lower for healthcare workers than for the general public. In addition, as a means of maintaining the functionality of the local healthcare system, the assumption is made that healthcare workers receive higher priority if they require treatment for COVID-19. Recovered healthcare workers gain temporary immunity and can return to the workforce.

B. *City-Related Parameters*

Five parameters (1-5) determined to be reasonable parameters for quantifying and assessing a country or city's local healthcare system capacity [13] are used in the model to enable the simulation of COVID-19 outbreaks in cities with varying healthcare system capacities. Instead of the case ascertainment rate used in previous research [13], a suspected case detection rate and case confirmation rate are used in this model. The population density is represented by the contact rate per case since social factors have been recognized as key determinants of the severity of infectious disease outbreaks in relevant past studies [13][22]. The supply of personal and medical protective equipment (9-10) are also important factors since the proper use of such equipment reduces exposure risk. It is worth noting that many pharmacies and hospitals in Wuhan reported being nearly out of stock of personal and medical protective equipment during the COVID-19 outbreak. In the simulations, the infection rates for the general public and healthcare workers return to their initial levels once the supply of personal and medical protective equipment runs out.

Parameters for city scenarios:

--(1) Population.

--(2) The total number of healthcare workers: Healthcare workers are essential for maintaining the functionality of the local healthcare system.

--(3) Contact tracing capacity: Contact tracing aims to identify and isolate those who have had close contact with infected individuals.

--(4) Isolation Capacity: The isolation of infected individuals reduces subsequent infections during the outbreak.

--(5) Detection date: Early detection of the first exposure is a key factor that affects the severity of outbreaks.

--(6) Suspected case detection rate: The rate at which symptomatic-infectious individuals (S) are suspected of being infected.

--(7) Confirmation rate: The rate at which suspected individuals (S*) are confirmed as being infected.

--(8) Contact number per case: The number of people who come into close contact with each infected case.

--(9) Stock of personal protective equipment, such as facemasks.

--(10) Stock of medical protective equipment, such as protective clothing.

C. Interventions

Interventions are powerful tools for infectious disease outbreaks [23]. The following are several of the interventions that were implemented during the COVID-19 outbreaks in China and are evaluated in our paper:

--(1) Additional isolation capacity through constructing emergency isolation hospitals: Emergency hospitals (e.g., Huoshenshan Hospital) constructed during the COVID-19 outbreak in China provided additional isolation capacity.

--(2) Additional healthcare workers: The healthcare workforce was bolstered to help maintain cities' healthcare systems.

--(3) Additional contact tracing capacity: Additional contact tracing specialists were recruited to identify and isolate infected individuals or individuals with a higher risk of infection.

--(4) COVID-19 testing papers: Testing papers serve as a preliminary diagnosis to help speed up the diagnosis process and increase diagnosis accuracy. However, testing papers are not immediately available for novel infectious diseases.

--(5) Additional supplies of medical protective equipment: Medical protective equipment reduces the infection rates suffered by healthcare workers.

--(6) Health propaganda (The promotion of personal hygiene and personal protection and the distribution of personal protective equipment): Teaching the public the correct ways of maintaining personal hygiene, using protective equipment, and minimizing social activity to avoid exposure.

--(7) Lockdowns: Placing cities on lockdown to minimize social activity is a highly effective intervention method[11] but also results in significant economic losses.

These interventions are further classified into two categories: enhancement-based interventions(1-5) which focus on enhancing the local health system; and policy-based interventions(6-7), which regulate the behaviour of the general public through policies.

Interventions and delays	Baseline	level 1	level 2	level 3	level 4	level 5
Additional isolation capacities	0%	50%	100%	150%	200%	250%
Additional healthcare workers	0%	40%	80%	120%	160%	200%
Additional contact tracing capacities	0%	1%	2%	3%	4%	5%
Additional testing papers	0%	1%	2%	3%	4%	5%
Additional personal protective equipment	0	3	6	9	12	15
Additional medical protective equipment	0	7	14	21	28	35
Controlling interventions	None/Promotion/Lockdown					
Delays(days)	[7, 21]					

Fig. 2. Experimental settings. Additional isolation capacities and healthcare workers are provided as proportions of the city's original isolation capacities and healthcare workers. Additional contact tracing capacities and testing papers are provided as a proportion of the city's population. The supplies of additional medical and personal protection equipment are measured in days.

IV. Experiments and Results

This section first outlines how the experimental simulations were designed and implemented. Then, we demonstrate our analyses of policy-based interventions. At the end of the section, the detailed effectiveness of the enhancement-based interventions is explored.

A. Experiment Setup

Wuhan was selected as the background city in all the simulations. Two months (60 days) were manually chosen as the duration in our simulations. The city-related parameters mentioned in section 2.2 were collected from reports released by institutions of the Chinese government [25][26][27]. The detection date used in our model was one week after the first exposed case occurred. Additionally, we assume that the simulation city possesses a stock of protective equipment that can last 14 days without receiving extra supply. The disease- and intervention-related parameters were taken from recent studies [14][24] calculated based on published data [25][26][27] and inferred from the opinions of experts working at the Chinese Center for Disease Control and Prevention. A detailed explanation for all the parameters used in the simulations can be found in Appendix A.

First, simulations with policy-based interventions were performed to reveal the efficacy of such interventions and serve as baselines for later study of enhance-based interventions. Then, we perform simulations with five different levels of combined enhancement-based interventions to determine the optimal intervention combination under various scenarios. Finally, we further evaluate each enhancement-based intervention by varying their value while maintaining the others unchanged. All sets of simulations are performed under three scenarios: with intervention health propaganda (6), under lockdown (7) or no

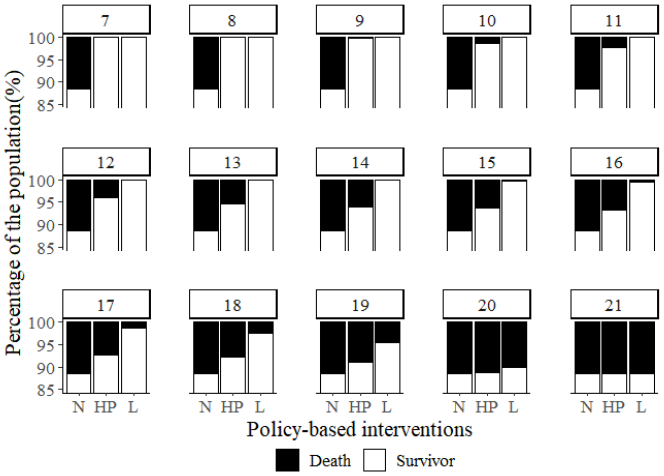

Fig. 3. Results of simulations of policy-based interventions across various delays (7-21 days). N, HP and L stand for no intervention, health propaganda and lockdown correspondingly.

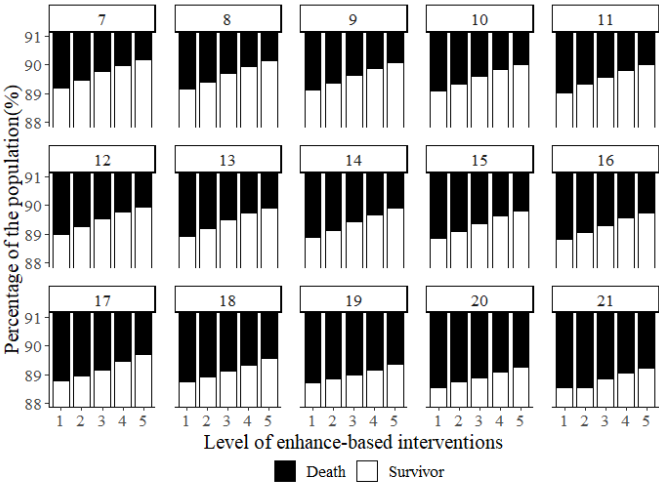

Fig. 4. Results of simulations of enhancement-based interventions with no policy-based interventions across various delays (7-21 days). 1-5 stand for level 1-5 combined enhancement-based intervention correspondingly.

policy-based interventions. Therefore, we can evaluate the effectiveness of different policy-based intervention methods. The detailed intervention settings used in our simulations can be found in Figure 2.

B. Policy-based Interventions

Distressingly, the simulation results presented in Figure 3. indicate that more than 11 percent of the population would die of the outbreaks because of the absence of interventions. However, the number of casualties can be significantly reduced with timely implementation of policy-based interventions.

Health propaganda with a delay within one week guarantees death rates less than 0.052 percent. The death rate rapidly rises to 5 percent when the delay of health propaganda reaches 13 days. Unfortunately, this intervention technique becomes completely inefficient once the outbreak has raged in the city without any other disease-curbing measures for more than 20 days.

Superior to health propaganda, lockdown unfailingly maintains lower casualties when implemented with the same delays. Less than 100 deaths would arise if lockdown was carried out within one week. The death rates do not exceed 0.1 percent even if the delay approaches 13 days. The effectiveness of lockdown only slightly diluted as the delay increased from 14 to 18 days, but immediately vanished after

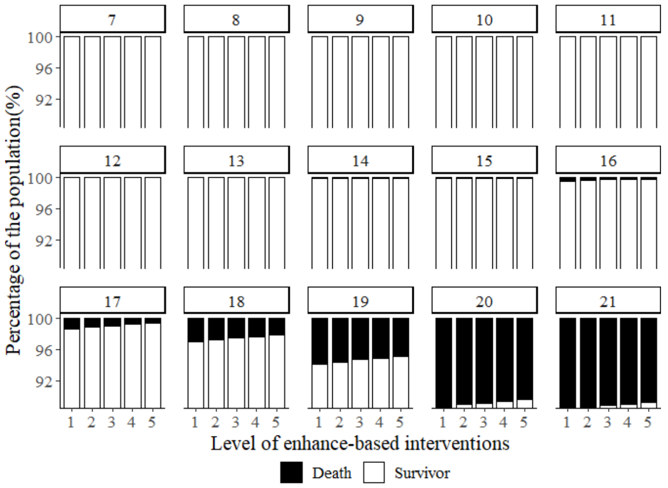

Fig. 5. Results of simulations of enhancement-based interventions with health propaganda across various delays (7-21 days). 1-5 stand for level 1-5 combined enhancement-based intervention correspondingly.

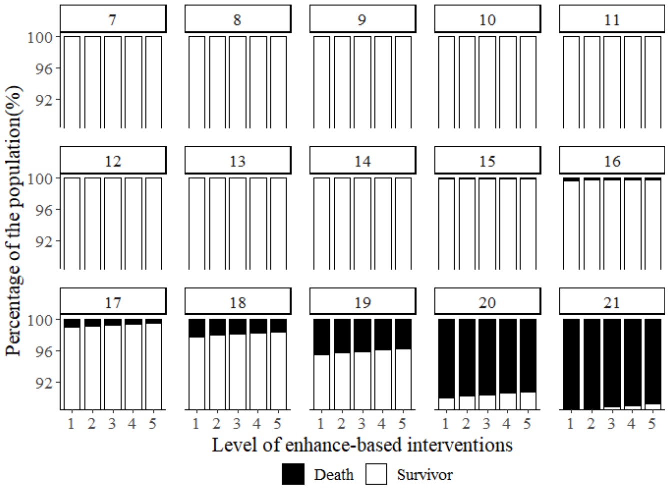

Fig. 6. Results of simulations of enhancement-based interventions with lockdown across various delays (7-21 days). 1-5 stand for level 1-5 combined enhancement-based intervention correspondingly.

this period.

C. Enhancement-based Interventions

First, the enhancement-based interventions were measured under the scenarios in which no policy-based interventions were involved. As shown in Figure 4, enhancement-based interventions are serviceable for mitigating the spread of the disease but are inadequate for containing the outbreak. Even with timely execution, the highest level of enhancement-based intervention could at most reduce the deaths of the population by 1.673 percent. Despite the relatively lesser utility, the enhancement-based interventions remain effective notwithstanding that the delay reaches above 20 days while the policy-based interventions are barely practical.

Afterwards, simulations involve both enhancement-based interventions and health propaganda, or lockdown generates uplift results. As presented in Figure 5. and Figure 6., the results suggest that such combinations are capable of containing the outbreak when exerted within two weeks. The casualties slightly increased when the delay reached 15 or 16 days, but burgeoned once the delay exceeded 17 days. Enhancement-based interventions combined with lockdown are more effective than with health propaganda, while the trends in changes in death rates are similar.

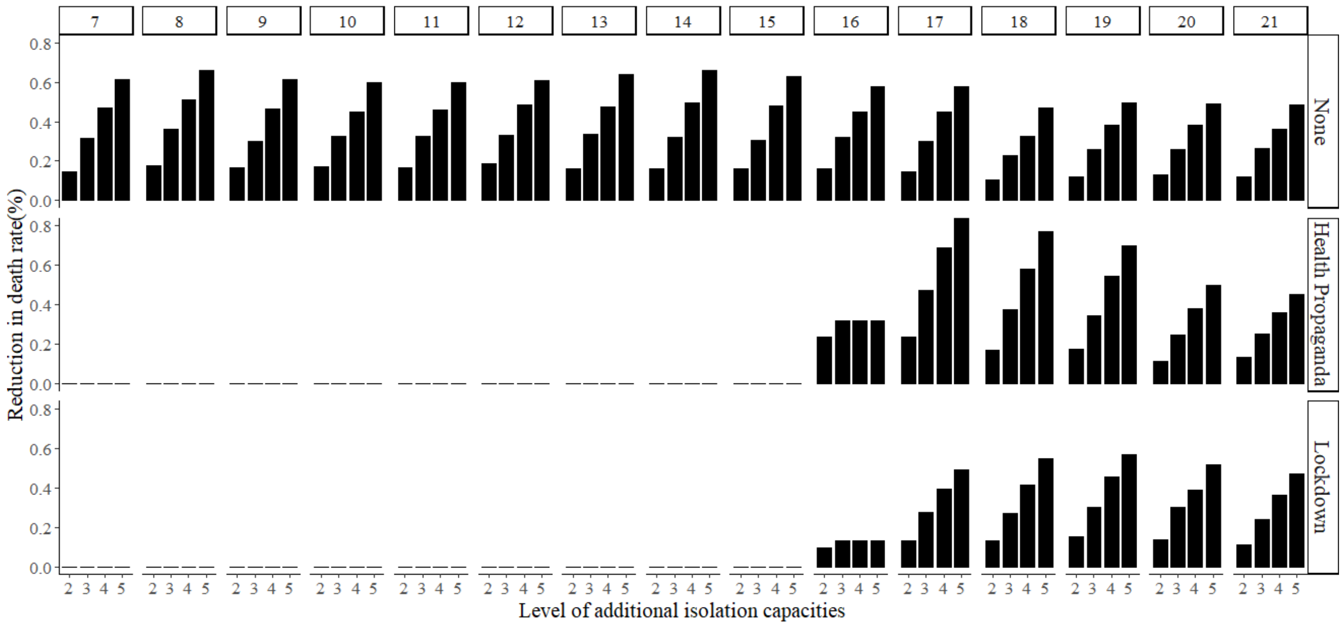

Fig. 7. Results of simulations of additional isolation capacities with health propaganda, lockdown, or no policy-based intervention across various delays (7-21 days). 2-5 stand for level 2-5 additional isolation capacities correspondingly. The y-axis represents the reduction in death rates comparing to simulations with level 1 additional isolation capacities.

Each of the enhancement-based interventions was then evaluated through more comprehensive simulations, and the results are presented in Figure 7-12. Starting with Figure 7, boosting isolation capacities can at most reduce the death rate by 0.662 percent with no policy-based intervention deployed. When health propaganda or lockdown is implemented, the reduction amount becomes 0.891 and 0.570 percent respectively. Nevertheless, it is pointless to enhance isolation capacities if any policy-based intervention is executed within 15 days.

As shown in Figure 8., recruiting more healthcare workers outstrips additional isolation capacities regardless of the policy-based interventions once the delay reaches 18 days. The maximum decrease in the death rate contributed by recruiting more healthcare workers was 1.322 percent. However, recruiting health care workers has a similar trend with boosting isolation capacities. With policy-based intervention implemented, the effectiveness of such intervention only appears when the delay reaches 17 days.

Unlike previous interventions, supplying additional contact tracing capacities and testing papers has diminutive effects when exerted with policy-based interventions. Even so, these interventions can still reduce the mortality rate by 0.1 to 0.2 percent if no policy-based interventions are performed.

Figure 11. and 12. present diverged outcomes. Providing additional personal protection equipment generates the utmost outcome among enhancement-based interventions, which reduced the death rate by 3.383 percent. However, it requires a parallel execution of health propaganda. Otherwise, such intervention can hardly contribute to curbing the outbreak. In contrast, serving more medical protection equipment, which lowers the mortality rate by 0.3 percent under most circumstances, is applicable in a much broader set

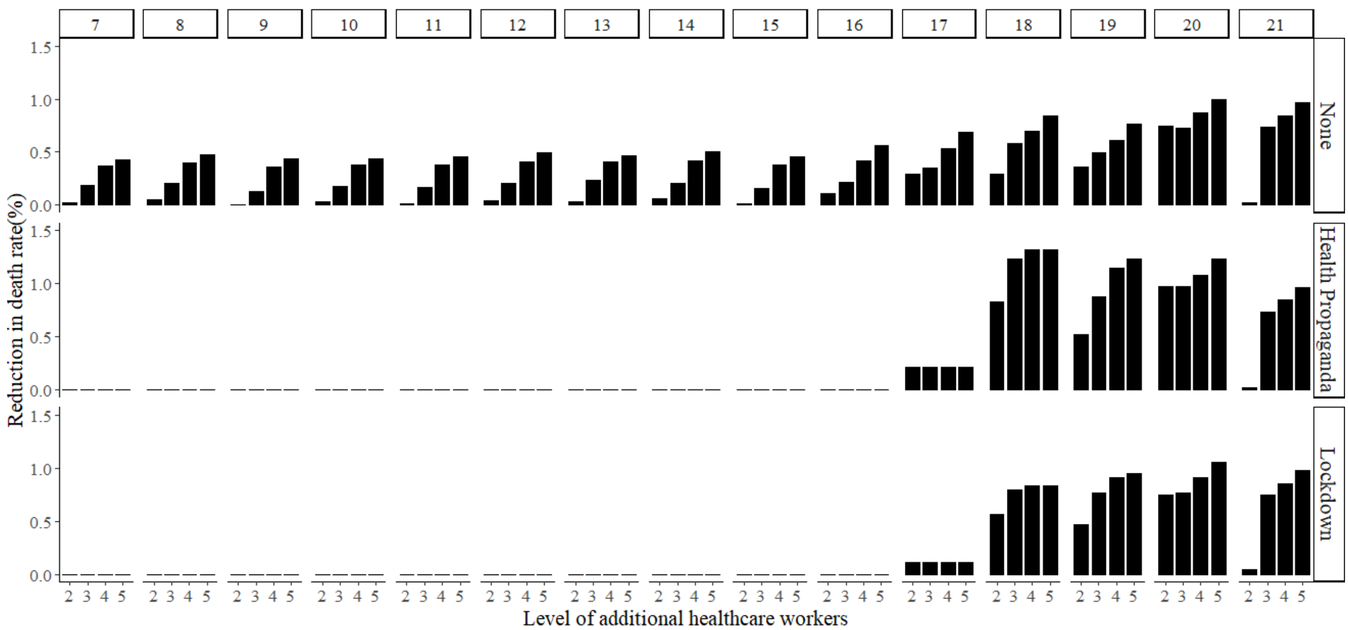

Fig. 8. Results of simulations of additional healthcare workers with health propaganda, lockdown, or no policy-based intervention across various delays (7-21 days). 2-5 stand for level 2-5 additional healthcare workers correspondingly. The y-axis represents the reduction in death rates comparing to simulations with level 1 additional healthcare workers.

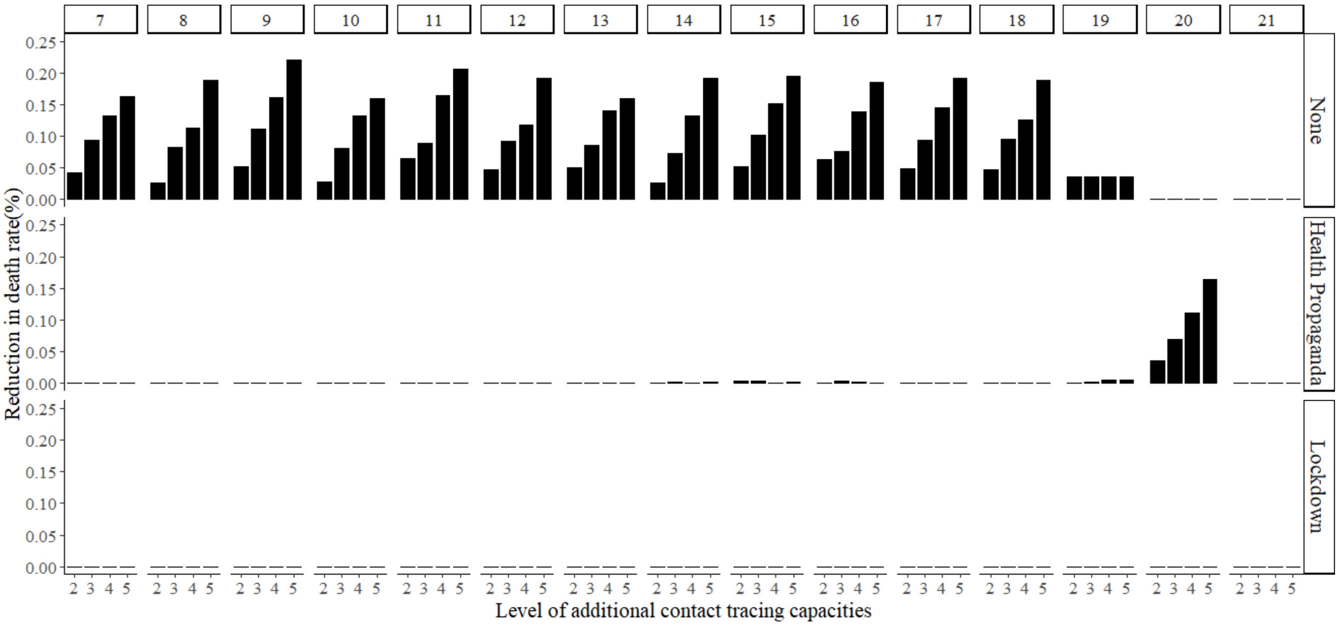

Fig. 9. Results of simulations of additional contact tracing capacities with health propaganda, lockdown, or no policy-based intervention across various delays (7-21 days). 2-5 stand for level 2-5 additional contact tracing capacities correspondingly. The y-axis represents the reduction in death rates comparing to simulations with level 1 additional contact tracing capacities.

of scenarios.

D. Discussion

The results have confirmed that the decision making during the first three weeks is critical for containing the outbreak. Therefore, the top priority is to determine or estimate when the first infected case occurred. The 7, 15 and 17 days after the first exposed case occurred are proven to be three vital turning points of the outbreak. Within the first week, the ideal intervention technique is health propaganda, which can contain the epidemic without ravaging the economy. Once the delay exceeds one week but less than 15 days, either the combination of health propaganda and enhancement-based interventions or lockdown are capable of eradicating the disease. During this period, formulating economic but efficient strategies to fight against the epidemic is still achievable. Unfortunately, the spread of the disease can barely be suppressed if the delay reaches beyond 15 days. Thus, if no interventions are applied within 15 days after the outbreak of the epidemic, a lockdown with the highest level of enhancement-based interventions is suggested to be applied as soon as possible before the outbreak reaches an uncontainable scale.

Experiments in this report indicate that the enhanced-based interventions are not sufficient for containing the outbreak. However, appropriate combinations of health propaganda and enhancement-based interventions, which were explored in our experiments, could surpass lockdown under certain scenarios. Additionally, enhancement-based interventions with lockdown can serve as emergency strategies to further reduce casualties in extreme scenarios.

Moreover, the experimental results also provide insight into the priorities of enhancement-based interventions.

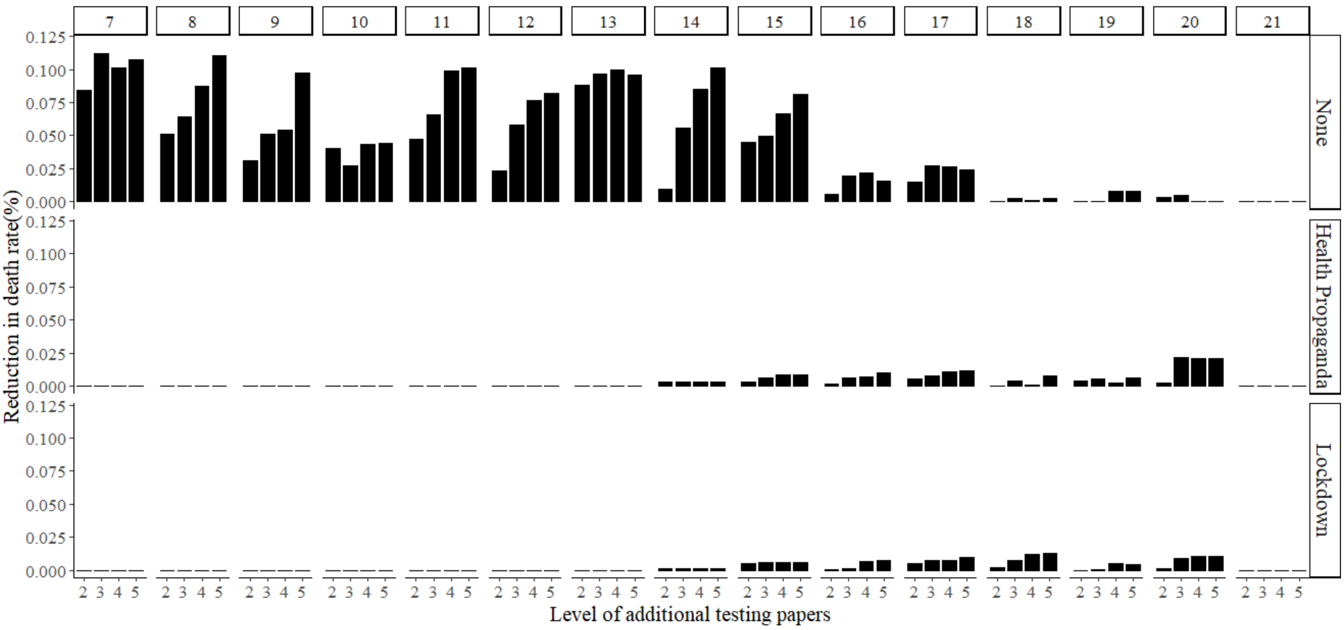

Fig. 10. Results of simulations of additional testing papers with health propaganda, lockdown, or no policy-based intervention across various delays (7-21 days). 2-5 stand for level 2-5 additional testing papers correspondingly. The y-axis represents the reduction in death rates comparing to simulations with level 1 additional testing papers.

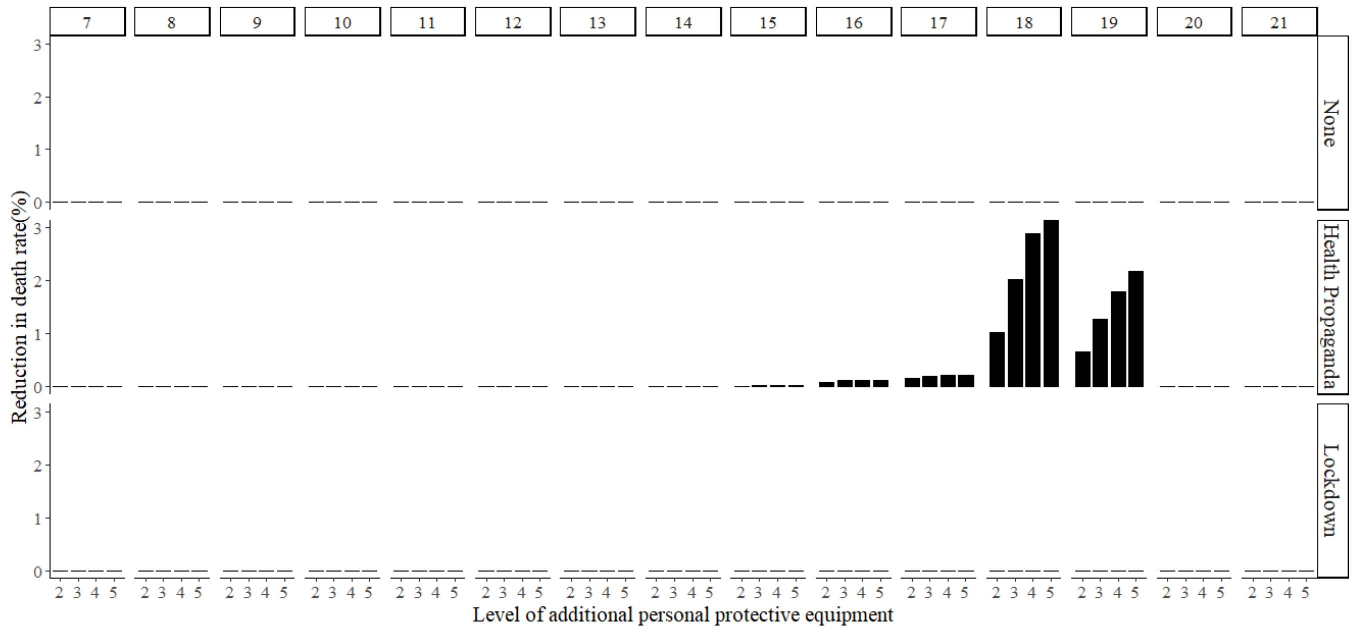

Fig. 11. Results of simulations of additional personal protective equipment with health propaganda, lockdown, or no policy-based intervention across various delays (7-21 days). 2-5 stand for level 2-5 additional personal protective equipment correspondingly. The y-axis represents the reduction in death rates comparing to simulations with level 1 additional personal protective equipment.

Recruiting more healthcare workers to help the local health system remain functional is the matter of primary importance under most circumstances. Distributing personal protection equipment only outstrips recruiting healthcare workers when the intervention delay is 18 or 19 days. Although the casualties reduced by boosting isolation capacities are less than recruiting healthcare workers in our simulations, the marginal benefit of the former surpasses the latter when the number of existing healthcare workers has reached a certain quantity, which is level 3 in our simulations. The decision maker should consider the marginal benefits of these two interventions with a limited budget. Supplying additional medical protective equipment is relatively less efficient than the enhancement-based interventions mentioned above, but it remains effective across a wider range of circumstances. Therefore, replenishing the local health system's stock of medical protective equipment can serve as a temporary strategy before patient zero is founded. Both contact tracing capacities and testing papers contribute slightly to containing the outbreak, especially when policy-based interventions are implemented at the same time. Thus, only when the budget is abundant or during the early stage of the outbreak in which no policy-based interventions were decided to be implemented should these two interventions be considered.

V. Conclusion and Future Work

This is the first study to propose a mathematical model that accounts for the detailed influence of interventions instead of simply changing the infection rate or reproductive number and separates healthcare workers from the general public for COVID-19 simulations. We have also determined the critical

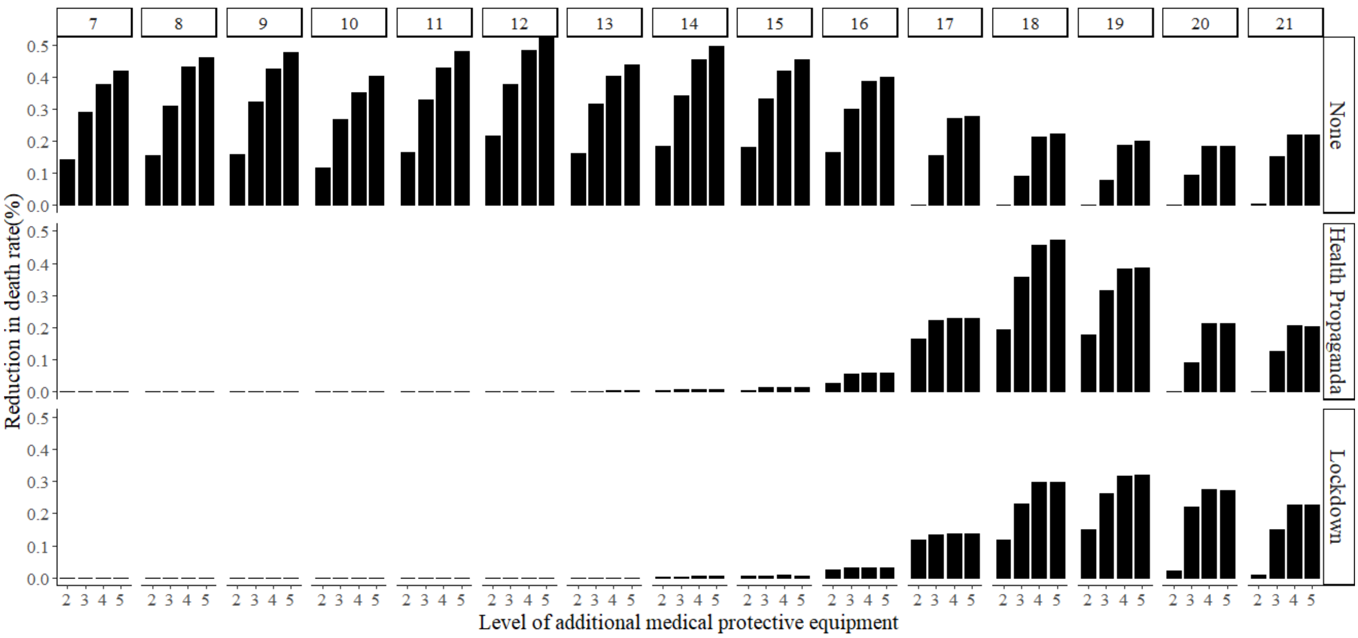

Fig. 12. Results of simulations of additional medical protective equipment with health propaganda, lockdown, or no policy-based intervention across various delays (7-21 days). 2-5 stand for level 2-5 additional medical protective equipment correspondingly. The y-axis represents the reduction in death rates comparing to simulations with level 1 additional medical protective equipment.

period of time and several crucial turning points in which action is essential after the first exposed case occurs for COVID-19 outbreaks. Moreover, the comprehensive analysis of policy-based interventions and enhancement-based interventions under various intervention delays are highly effective for prioritizing these intervention methods and formulating appropriate strategies under various scenarios of COVID-19 outbreaks.

The highly flexible model proposed in this report can be used for other infectious disease simulations with abundant data and proper adjustments. Therefore, our report can not only point out potential future data collection and research directions in infectious disease simulations and decision support, but also provide a flexible framework that simplifies the process of formulating new models. In the future, with more precise data related to the infection rate with the correct use of protective equipment and the infection rate among close contacts of asymptomatic exposed cases, the model can be used to precisely simulate different infectious disease outbreaks in various cities to explore valuable interventions under diverse scenarios. For instance, with proper adjustment the model can be used as a delay-involved HIV epidemic model which is considered valuable in recent research [28]. Additionally, with sufficient population mobility data, the model can be extended to simulate such outbreaks in various countries. Thus, data collection related to these topics is desired for future study. Although a COVID-19 vaccine is currently under development, the global number of infected people has reached 34,724,785, including 1,030,160 deaths, according to the 'WHO Coronavirus Disease (COVID-19) Dashboard' [29]. The world will likely face a shortage of vaccines once a vaccine becomes available. Therefore, devising suitable COVID-19 vaccination strategies across countries is necessary to achieve optimal outcomes with limited resources, which is a potential research topic.

APPENDIX

A. Parameters and States in the Model

Tables 1 and 2 contain detailed explanations of the corresponding parameters and states. Unavoidably, we need to make assumptions and inferences about some parameters because of the absence of sufficient data. Although we conducted interviews with experts and doctors, the inferred parameters inevitably affect the precision of our model. Thus, to accurately simulate outbreaks and more comprehensively support decision making, the precise value of inferred parameters is still urgently required.

According to the data published by the National Bureau of Statistics [27], the population of Wuhan is 8,364,000, with approximately 100,000 health care workers. Based on the WHO's Q&A [30], the common incubation period is five to six days. Therefore, the incubation period used in our simulations is 6 days. Additionally, the WHO states that 80% of infected individuals can recover without hospital treatment, while 20% (one-fifth) of patients become seriously sick. Moreover, we assumed that all patients would either recover or die within a 30-day postdetection period t_P. Hence, the daily natural recovery rate used in our model is 80%/t_P. In the same way, the daily natural fatality rate is calculated as 20%/t_P since severe patients can hardly survive without hospital treatment. Similarly, the daily recovery and fatality rates with special treatment were calculated based on the data (0.034 fatality rate) published by the WHO [31]. The parameters $n_{contact}$, n_H, n_C and n_{S*} were inferred based on specialists' opinions. Following the instructions of the WHO [31], we used a 14-day contact tracing (isolation) period. The value of maximum contact tracing capacity was estimated by the data published by the health commission of Hubei Province [26].

Moreover, the beta of China estimated in recent research10 was used as the force of infection from infected individuals. Exposed individuals are less infectious in our model. Since individuals with suspected or confirmed infection are put under strict isolation to reduce subsequent infections and we lack data to identify the precise values of β_S and β_C, we assume that such individuals are not infectious in our simulations. Additionally, facing the absence of sufficient data required for quantifying the values of r_{S*} and r_C, we have to infer these values based on the data published by the National Health Commission of the PRC [25], the health commission of Hubei Province [26] and the opinions from experts and doctors.

TABLE 1
PARAMETERS IN THE MODEL

Symbol	Value	Meaning
N	8,364,000	The population size of the simulation city.
N_H	100,000	The number of health care workers.
σ	6	The incubation period of the disease.
t_P	30	The post-detection period.
γ	0.04 (0.8/t_P)	The natural recover rate per day.
r_D	0.00667 ((1-γ)/t_P)	The mortality rate (with special treatment) of the disease per day.
$n_{contact}$	15	Number of close contacts for each individual in general public and healthcare system per day.
n_H	30	Number of patients diagnosed or treated for each health care worker per day.
n_C	5	Number of health care workers required per day by each confirmed case.
n_{S*}	3	Number of health care workers required per day by each suspected case.
t_{CT}	14	The contact tracing (isolation) period.
N_{CT}^{MAX}	2,000	The maximum contact tracing capacity.
B_I	0.38	Force of infection from infected (symptomatic) individuals.
B_E	0.038 (B_I/10)	Force of infection from exposed (non-symptomatic) individuals.
$B_{I,H}$	[0, B_I]	Force of infection from symptomatic cases among health care workers.
B_{S*}	0	Force of infection from suspected cases.
B_C	0	Force of infection from confirmed cases.
r_{S*}	0.62	The rate at which an infected case becomes a suspected case.
r_C	0.78	The rate at which a suspected case becomes a confirmed case.

TABLE 2
STATES IN THE MODEL

Symbol	Meaning
$S_G(t)$	The number of individuals in the general public who are susceptible to infection.
$S_H(t)$	The number of healthcare workers who are susceptible to infection.
$N_{CT,G}(t)$	The number of healthcare workers who are subjected to contact tracing.
$N_{CT,H}(t)$	The number of healthcare workers who are subjected to contact tracing.
$E_G(t)$	The number of individuals in the general public who are exposed.
$E_H(t)$	The number of healthcare workers who are exposed.
$I_G(t)$	The number of individuals in the general public who are infected and symptomatic.
$I_H(t)$	The number of healthcare workers who are infected and symptomatic.
$S_G^*(t)$	The number of individuals in the general public who are suspected of infection.
$S_H^*(t)$	The number of healthcare workers who are suspected of infection.
$C_G(t)$	The number of individuals in the general public who are confirmed of infection.
$C_H(t)$	The number of healthcare workers who are confirmed of infection.
$R_G(t)$	The number of individuals in the general public who recover and move into the resistant phase.
$R_H(t)$	The number of healthcare workers who recover and move into the resistant phase.
$D_G(t)$	The number of individuals in the general public who die.
$D_H(t)$	The number of healthcare workers who die.
$n_{CT,G}(t)$	The number of individuals in the general public who are newly subjected to contact tracing.
$n_{CT,H}(t)$	The number of healthcare workers who are newly subjected to contact tracing.
$N_{receive}(t)$	The maximum number of patients the local health system can receive or treat per day.

B. *Equations*

(1) $$S_G(0) = N - S_H(0) - E_G(0)$$

(2) $$S_H(0) = N_H$$

(3) $$E_G(0) = 1$$

(4) $$\frac{\mathrm{d}S_G}{\mathrm{d}t} = -E_G \cdot n_{contact} \cdot \beta_E - I_G \cdot n_{contact} \cdot \beta_I + N_{CT,G} / t_{CT}$$

(5) $$\frac{\mathrm{d}N_{CT,G}}{\mathrm{d}t} = n_{CT,G}(1-\beta_I) - N_{CT,G} / t_{CT}$$

(6) $$\frac{\mathrm{d}S_H}{\mathrm{d}t} = -E_H \cdot n_{contact} \cdot \beta_E - I_H \cdot n_{contact} \cdot \beta_{I,H} + N_{CT,H} / t_{CT}$$

(7) $$\frac{\mathrm{d}N_{CT,H}}{\mathrm{d}t} = n_{CT,H}(1-\beta_I) - N_{CT,H} / t_{CT}$$

(8) $$\frac{\mathrm{d}E_G}{\mathrm{d}t} = E_G \cdot n_{contact} \cdot \beta_E + I_G \cdot n_{contact} \cdot \beta_I - E_G / \sigma$$

(9) $$\frac{\mathrm{d}E_H}{\mathrm{d}t} = E_H \cdot n_{contact} \cdot \beta_E + I_H \cdot n_{contact} \cdot \beta_I - E_H / \sigma + (S_G^* + S_H^*) \cdot n_{S^*} \cdot \beta_{S^*} + (C_G + C_H) \cdot n_C \cdot \beta_C$$

(10) $$\frac{\mathrm{d}I_G}{\mathrm{d}t} = E_G / \sigma - I_G \cdot (r_{S^*} + \gamma + r_D)$$

(11) $$\frac{\mathrm{d}I_H}{\mathrm{d}t} = E_H / \sigma - I_H \cdot (r_{S^*} + \gamma + r_D)$$

(12) $$\frac{\mathrm{d}S_G^*}{\mathrm{d}t} = \min(I_G, N_{receive}\text{-}\max(N_{receive}, I_H)) \cdot r_{S^*} - S_G^* \cdot (r_C + \gamma + r_D)$$

(13) $$\frac{\mathrm{d}S_H^*}{\mathrm{d}t} = \min(I_H, N_{receive}) \cdot r_{S^*} - S_H^* \cdot (r_C + \gamma + r_D)$$

(14) $$\frac{\mathrm{d}C_G}{\mathrm{d}t} = S_G^* \cdot r_C - C_G \cdot (\gamma_C + r_{D,C}) + n_{CT,G} \cdot \beta_I$$

(15) $$\frac{\mathrm{d}C_H}{\mathrm{d}t} = S_H^* \cdot r_C - C_H \cdot (\gamma_C + r_{D,C}) + n_{CT,H} \cdot \beta_{I,H}$$

(16) $$\frac{\mathrm{d}R_G}{\mathrm{d}t} = (I_G + S_G^*) \cdot \gamma + C_G \cdot \gamma_C$$

(17) $$\frac{\mathrm{d}R_H}{\mathrm{d}t} = (I_H + S_H^*) \cdot \gamma + C_H \cdot \gamma_C$$

(18) $$\frac{\mathrm{d}D_G}{\mathrm{d}t} = (I_G + S_G^*) \cdot r_D + C_G \cdot r_{D,C}$$

(19) $$\frac{\mathrm{d}D_H}{\mathrm{d}t} = (I_H + S_H^*) \cdot r_D + C_H \cdot r_{D,C}$$

(20) $$\frac{\mathrm{d}n_{CT,G}}{\mathrm{d}t} = \min((S_G^* \cdot r_C + n_{CT,G} \cdot \beta_I) \cdot n_{contact}, N_{CT}^{MAX} - N_{CT,G} - N_{CT,H})$$

(21) $$\frac{\mathrm{d}n_{CT,H}}{\mathrm{d}t} = \min((S_H^* \cdot r_C + n_{CT,H} \cdot \beta_{I,H}) \cdot n_{contact}, N_{CT}^{MAX} - N_{CT,G} - N_{CT,H})$$

(22) $$N_{receive} = \min((S_H + R_H) \cdot n_H - (S_G^* + S_H^*) \cdot n_S^* - (C_G + C_H) \cdot n_C, 0)$$

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