Modeling of suppression and mitigation interventions in the COVID-19 epidemics

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Modeling of suppression and mitigation interventions in the COVID-19 epidemics

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Abstract **Background:** The global spread of the COVID-19 pandemic has become the most fundamental threat to human health. In the absence of vaccines and effective therapeutical solutions, non-pharmaceutic interventions have become a major way for controlling the epidemics. Soft mitigation interventions are able to slow down the epidemic but not to halt it well. While strict suppression interventions are efficient for controlling the epidemics, long-term measures are likely to have negative impacts on economics and people's daily lives. Hence, dynamically balancing the interventions of suppression and mitigation plays a fundamental role in manipulating the epidemic curves.

Methods: We collected data of the number of infections for several countries during the COVID-19 pandemics and found a clear phenomenon of periodic waves of infections. Based on the observation, by connecting the infection level with the medical resources and a tolerance parameter, we propose a mathematical model by combining intervention measures to understand the epidemic dynamics.

Results: Depending on the parameters of the medical resources, tolerance level, and the starting time of interventions, the combined intervention measure dynamically changes with the infection level, resulting in a periodic wave of infections controlled within an accepted level. The study reveals that, (a) with an immediate, strict

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suppression, the number of infections and deaths is well controlled with a significant reduction in very short time period; (b) an appropriate, dynamical combination of suppression and mitigation may find a feasible way in reducing the impacts of epidemics on people's lives and economics.

Conclusions: While the assumption of interventions deployed with a cycle of period in the model is limited and unrealistic, the phenomenon of periodic waves of infections in reality is captured by our model. These results provide helpful insights for policy-makers to dynamically deploy an appropriate intervention strategy to effectively battle against the COVID-19.

Keywords COVID-19 · Basic reproduction number · Interventions · Suppression · Mitigation

Background

The COVID-19 pandemic has become a major global threat for human lives. In the absence of vaccines, effective medicines, and with limited knowledge of the virus [1, 2], non-pharmaceutic interventions have been adopted to slow down the disease propagation. Nations around the world implemented a number of containment policies aimed at mitigating the epidemics. With the progression of the epidemics, individuals have improved their awareness of infection and changed their behavior to reduce their risk of infection by wearing face-masks and washing hands frequently [3]. Policies such as lockdown of the city [4], travel restrictions [5–7], school closure [8], quarantine [9, 10] or stay-at-home [11], social distancing [12, 13], bans on gatherings of more than a number of people, tracking individuals who are potentially infected [14, 15] have been implemented to reduce the contact rate to halt the epidemics. Some countries like Singapore used contact tracing to efficiently slow down the epidemics, while other countries such as the UK, opted to herd immunity and then changed to a strict lockdown soon.

Policy-makers are confronted with difficult choices for controlling the epidemics. On one hand, strict measures on suppressing the epidemics can save people's lives from death, while likely increasing the risk of economical loss; on the other hand, gentle mitigation interventions can reduce negative effects on economics but sacrificing people's lives for deaths. Hence, it is necessary to estimate the epidemic dynamics in order to implement efficient, economical interventions accordingly [16, 17]. Many studies have developed mathematical models to evaluate the role of restriction measures on the dynamics of the COVID-19 pandemic [10, 17–21]. Most of previous studies focused on the dynamical functions of transmission rate β to reflect the role of interventions [15, 22]. For instance, a two-step control strategy relating suppression and mitigation was proposed [10, 17], which is consistent with the real data. Optimal control of the COVID-19 from the point of view of economics was also studied in [19]. It has found that a combination of home isolation, such as home quarantine, and social distancing might reduce deaths by half but still result in hundreds of thousands of deaths, while suppression measure requires a combination of social

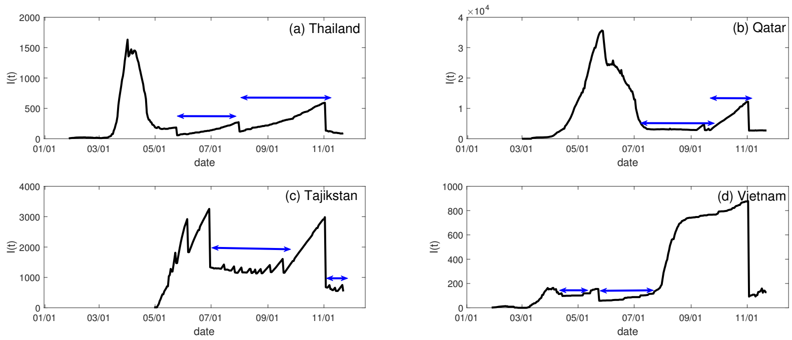

Fig. 1 The number of existing confirmed cases in some typical countries. (a) Thailand; (b) Qatar; (c) Tajkstan; (d) Vietnam. The arrow in each panel indicates the plateau period due to the interventions being introduced.

distancing of the entire population, such as home isolation, supplemented by school closure, etc. In a recent study [23], an adaptive intervention strategy was proposed for the control of the COVID-19 epidemics by considering individuals' mobility between cities. The authors assumed that intervention measures change the transmission rate with a controlled parameter and the floating population. Although intensive interventions can effectively reduce the transmission rate, the epidemics may rebound if interventions are relaxed [20].

So far, there is a lack of common evidence of what to do next for controlling the epidemic. Since the epidemic is highly dynamic, rapidly changing with the increase of infection cases, appropriate interventions should be responsive to the outbreak and change with the epidemic dynamics accordingly. To capture this aspect, in this work, we explore a standard epidemiological model modified by considering two types of interventions, i.e., suppression and mitigation, which are dynamically implemented by considering factors, such as the city's medical resources and its tolerance for infection. We propose a combined strategy of suppression and mitigation to control the disease propagation. Instead of setting the cycle of the strategies at a fixed period, the system is allowed to dynamically adjust the control strategy depending on the infection level. By doing so, the epidemics is under control within an acceptable level and a strict suppression intervention is not necessarily deployed during the control period.

Methods

In order to understand the impact of different interventions on controlling the epidemics, we firstly collect the data from data source DXY [24] and observe the curves of existing infections in different countries, as shown in Fig. 1. We clearly see that in some countries, the number of existing infections shows a typical, nonuniform periodic wave with different peaks and periods. For instance, in Thainland (Fig. 1 (a)), the number of existing infections achieves the peak around 1500 cases on April, 1st, 2020, and decreases to 100 cases soon before May, 25th, 2020. Then, it follows a period wave of infections less than 200 cases. Recently, it increases to 500 cases again. Also in Qatar (Fig. 1 (b)), during the period from July 12th, 2020 to Sep. 11th, 2020, the number of infections was controlled less than 4000 cases and then it decreases again on Nov. 1st, 2020. Similar phenomena can also be found in Tajikstan and Vietnam (Fig. 1 (c) and (d)). Although the periods of the waves and the peak values of infections may be different, such a phenomenon of period waves indeed reflects various interventions deployed by nations to battle against the COVID-19 pandemic.

In the following, we perform a modeling study to understand interventions for the appearance of periodic waves of infections. Since the COVID-19 can cause infections with no symptoms [25], we model it in a population based on the classical susceptible-exposed-infected-recovered (SEIR) epidemiological model, where individuals belong to six states: susceptible (S), exposed (E), asymptomatic (A), symptomatic (I), dead (D), and recovered (R). See Fig. 2. The total population size is denoted as $N = S+E+A+I+D+R$. At time t, susceptible individuals get infected by having contacts (asymptomatic or symptomatic) infectious individuals and move to exposed state (E) at a rate $\beta(t)$, where $\beta(t)$ varies with time due to the involvment of interventions.The infectiousness of asymptomatic infected individuals compared with symptomatic infected individuals is adjusted by a factor θ_a. A fraction p of exposed individuals move to symptomatic infections (I) at rate δ, while the remainder of $1-p$ exposed individuals move to asymptomatic infection class (A) at the same rate δ. Asymptomatic and symptomatic infected individuals move to recoverd state (R) with rate γ_A and γ_I, respectively. Symptomatic infected Windividuals move to dead state (D) at rate μ. Thus, the dynamics of the model is given by,

$$
\begin{aligned}
\frac{dS}{dt} &= -\beta(t)S\frac{\theta_a A + I}{N}, \\
\frac{dE}{dt} &= \beta(t)S\frac{\theta_a A + I}{N} - \delta E, \\
\frac{dA}{dt} &= \delta(1-p)E - \gamma_A A, \\
\frac{dI}{dt} &= \delta pE - \gamma_I I - \mu I, \\
\frac{dD}{dt} &= \mu I, \\
\frac{dR}{dt} &= \gamma_A A + \gamma_I I, \qquad (1)
\end{aligned}
$$

where N is the total population size.

The basic reproduction number $\mathbf{R}_0$ is usually estimated in the early stage of the outbreak as a constant value. With the introduction of interventions, the transmission rate β is time-dependent. Consequently, the basic reproduction number changes with time, often named as effective reproduciton number and expressed as $\mathbf{R}_t$. By linearing the system (Eq. (1)) at the disease free state $(S,E,A,I,D,R) = (S_0,0,0,0,0,0)$ and setting the vector $v = (E,A,I)^T$, we obtain $\dot{v} = (\mathscr{F} - \mathscr{V})v$, where $\mathscr{F}$ is the new

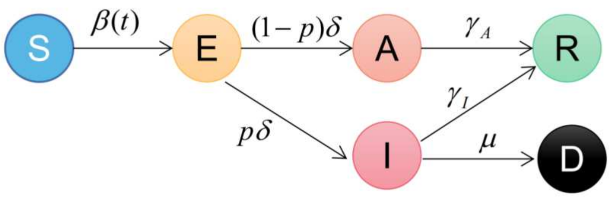

Fig. 2 The flow diagram of the compartmental model. Host states are idicated by circles and transitions by arrows.

infection rate in each class and $\mathscr{V}$ is the transition rate for each class by transferring in or out of each class, given by

$$\mathscr{F} = \begin{pmatrix} 0 & \theta_a\beta(t) & \beta(t) \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}, \mathscr{V} = \begin{pmatrix} \delta & 0 & 0 \\ -\delta(1-p) & \gamma_A & 0 \\ -\delta p & 0 & \gamma_I+\mu \end{pmatrix},$$

from which we can obtain the effective reproduction number of the model (Eq. (1)) as the spectral radius $\rho(\mathscr{F}\mathscr{V}^{-1})$ of the next generation matrix $\mathscr{F}\mathscr{V}^{-1}$. The effective basic reproduction number $\mathbf{R}_t$ is given by

$$\mathbf{R}_t = \beta(t)(\frac{\theta_a(1-p)}{\gamma_A} + \frac{p}{\gamma_I+\mu}). \tag{2}$$

Specifically, the basic reproduction number is recovered as $\mathbf{R}_0 = \beta_0(\frac{\theta_a(1-p)}{\gamma_A} + \frac{p}{\gamma_I+\mu})$, where β_0 is the transmission rate in the early stage. The difference between interventions of suppression and mitigation is the aim for affecting the epidemics. Suppression aims at halting the epidemics with extremely strict strategies to satisfy the condition $\mathbf{R}_t < 1$, while mitigation aims at slowing down the epidemics with relaxed control strategies, resulting in a reduced $\mathbf{R}_t$ larger than 1. A strict suppression is more likely to bring negative effects on economics and social lives, while a gentle mitigation may not be able to efficiently control the epidemics. Thus, how to implement an effective intervention strategy to balance the aims is an important and difficult issue to answer.

In order to devise efficient intervention strategies to control epidemics, one has to consider medical resources a city possesses, since infected individuals take use of medical resources for treatment. Also, the time of interventions being deployed plays a key role in containing epidemics. A delayed, relaxed intervention strategy might be invalid for controlling the epidemics, since the accumulated existing infections may overload the medical resources and further promote the spread of epidemics. Thus, at this stage, a strict suppression strategy is preferentially deployed. On the other hand, if the infection is not at risk for medical resources, a gentle, relaxed mitigation strategy is sufficient enough to control the epidemics.

In the following, we assume that intervention strategies deployed by a city is closely related with its medical resources and a tolerance level for epidemics. Let us denote the medical resources as I_s and the tolerance parameter for epidemics as I_m.

At time t_0, if the total infection during a recent period τ is higher than the medical resources I_s with factor c, a strict suppression strategy is implemented; otherwise, a mitigation invervention is implemented. Then, the effective reproduction number $\mathbf{R}_t$ is given by

$$\mathbf{R}_t = \begin{cases} \alpha_s R_0, & \text{if } \sum_{t-(\tau-1)}^{t} I(t) > cI_s, t \geq t_0 \text{ (suppression)} \\ \alpha_m R_0, & \text{if } \sum_{t-(\tau-1)}^{t} I(t) > I_m, t \geq t_0 \text{ (mitigation)} \end{cases}$$

where α_s and α_m are the mean intensity values for suppression and mitigation, followed by a given distribution [22]. Here, for simplicity, we assume that both α_s and α_m are constants satisfying $\alpha_s < \alpha_m < 1$. I_s represents the medical resources, which may depend on the economical level. For instance, in the US, $I_s = 1.2$ beds per thousand people. I_m represents the tolerance parameter for epidemics, e.g., $I_m = 1\%$, meaning that the tolerance of 1% of infections in the population. The relationship between I_s and I_m is tuned by the factor c. A value of c satisfying $cI_s > I_m$ can capture the condition of suppression and mitigation, i.e., $\alpha_s < \alpha_m$. Given parameters α_s, α_m, and the starting time t_0, the role of interventions is captured by the evolving curve of $\mathbf{R}_t$ or $\beta(t)$.

It is to note that the deployment of interventions depends on the recently confirmed cases $\sum_{t-(\tau-1)}^{t} I(t)$, which is fundamental but difficult to determine in reality. For a real case such as COVID-19, since the real number of infections is generally unknown and only the number of confirmed cases is available, it is necessary to use some approaches to evaluate it [26,22]. Here, in the following for the real data analysis, we borrow a deconvolution method proposed in [22] to evaluate the real number of infection cases from the reported infection cases as the initial values for the model to study the impact of interventions of suppression and mitigation on epidemics.

Results

Modeling results

We first perform simulations on the proposed model in a host population with no interventions. Then, we compare the effects of interventions such as suppression, mitigation, and the combined of them with the proposed model. The total population is set as $N = 10^6$ and the fraction of symptomatic infected individuals is $I(0) = 10^{-3}$. The basic reproduction number is set as $\mathbf{R}_0 = 3.54$ for the COVID-19 as Ref. [27]. The incubation period is $\frac{1}{\delta} = 5.1$ days [28] and $\frac{1}{\gamma_A} = \frac{1}{\gamma_I} = 7$ days [29]. The fraction of symptomatic infection is $p = 0.82$ as calculated in Ref. [30]. Since it has been found that there is no difference in the transmission rates between symptomatic and asymptomatic patients [31], we set $\theta_a = 1$. Without specification, the factor constant c is set as $c = 5$. The choice of c does not change the main results of the present study. The fatality rate is $\mu = 0.016$ [32]. Most of the parameters are chosen according to the recently published results and some of them are assumed, as summarized

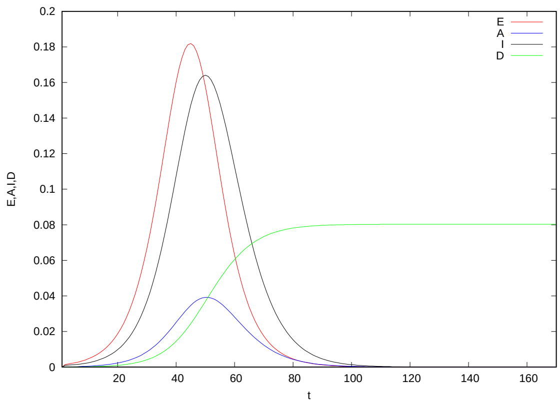

Fig. 3 The epidemics dynamics of the model (Eq. (1)) with no interventions. The exposed (E, red line), asymptomatic infectious (A, blue line), symptomatic infectious (I, black line), and dead (D, green line) are shown in time.

in Table. 1. Figure 3 illustrates the results for the baseline model, where no interventions are involved. We observe that the infected number grows exponentially and reaches the peak at around 50 days. The death ratio reaches to 8% of the population, approximately 80000 people.

Table 1 Parameters used in the main text.

Parameter	Description	Value (range)
$\beta(t)$	Transmission rate with time	$\beta(t) = \frac{\mathbf{R}_t}{(\frac{\theta_a(1-p)}{\gamma_A} + \frac{p}{\gamma_I+\mu})}$
$\mathbf{R}_0$	Basic reproduction number	3.54 [27]
$\frac{1}{\delta}$	Incubation period	5.1 days [28]
$\frac{1}{\gamma_A}$	Recovery period for asymptomatic infectious individuals	7 days [assumed]
$\frac{1}{\gamma_I}$	Recovery period for symptomatic infectious individuals	7 days [29]
p	Proportion of symptomatic infections	0.82 [30]
μ	Fatality rate (day^{-1})	0.016 day^{-1} [32]
θ_a	Infectious factor for asymptomatic infections	1.0 [31]
I_s	Medical resources	0.0023 [caculated] [33]
I_m	Tolerence parameter for infection	$\frac{100}{N}$ [assumed]
α_s	Suppression coefficient	$[0.1, 0.3]$ [assumed]
α_m	Mitigation coefficient	$[0.4, 0.8]$ [assumed]

Effects of suppression intensity α_s and the starting time t_0

In this scenario, we assume that if the accumulated ratio of infections during the past $\tau = 7$ days, $\sum_{t-7}^{t} I(t)$, is larger than the medical resources by a factor, cI_s, a suppression intervention will be implemented. We take it as a constant control intensity with the average value $\alpha_s = 0.3, 0.1$ starting at time $t_0 = 20, 30, 40$. These parameters are

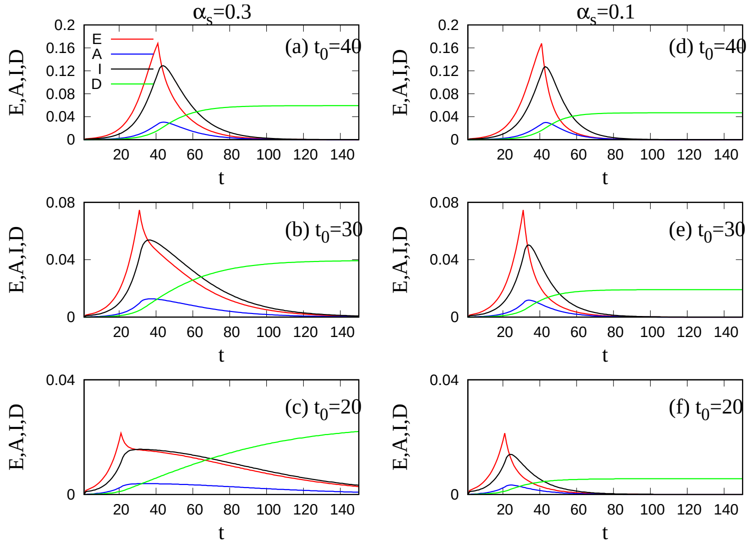

Fig. 4 Comparison of the epidemic dynamics under suppression interventions with $\alpha_s = 0.3$ (left column) and $\alpha_s = 0.1$ (right column) starting at different time. (a) and (d) $t_0 = 40$; (b) and (e) $t_0 = 30$; (c) and (f) $t_0 = 20$. Other parameters are the same as Table 1.

chosen such that the effective reproduction number $\mathbf{R}_t$ is approximatively less than 1. In Fig. 4, we see that with the introduction of suppression measures with $\alpha_s = 0.3$, the peak of infections dramatically reduces to a lower level. For instance, the epidemic peak is reduced from 0.16 to 0.12 at $t_0 = 40$. The earlier the intervention is deployed, the lower the peak will be. If the intervention is deployed 20 days earlier, the infection could be further reduced less than 0.02, see Fig.4 (c). Earlier deployment of suppression strategies flattens the curve of dynamics with a significally reduced peak value and keeps the epidemic under control for long time.

With a more intensive suppression ($\alpha_s = 0.1$), the sharp reduction in infections narrows the curve of the dynamics and the peak of infections arrives earlier. In addition, a timely intensive suppression can reduce the number of deaths to $\frac{1}{20}$ of that with no interventions. Even with a delayed intervention at $t_0 = 40$, the deaths can be reduced to half. Therefore, to save lives from epidemics, an efficient, strict suppression should be deployed as early as possible. The decreasing slopes of the epidemic curves also provide insightful information for evaluating the effect of different control measures.

Effect of mitigation intensity α_m and the starting time t_0

Since a suppression intervention is likely to bring negative effects on economics and social activities, a gentle mitigation intervention is feasible to gradually reduce the basic reproduction number $\mathbf{R}_0$. If the ratio of the accumulated existing infections during the past week is larger than some tolerance parameter I_m, the mitigation intervention is implemented. To compare different mitigation measures, we consider

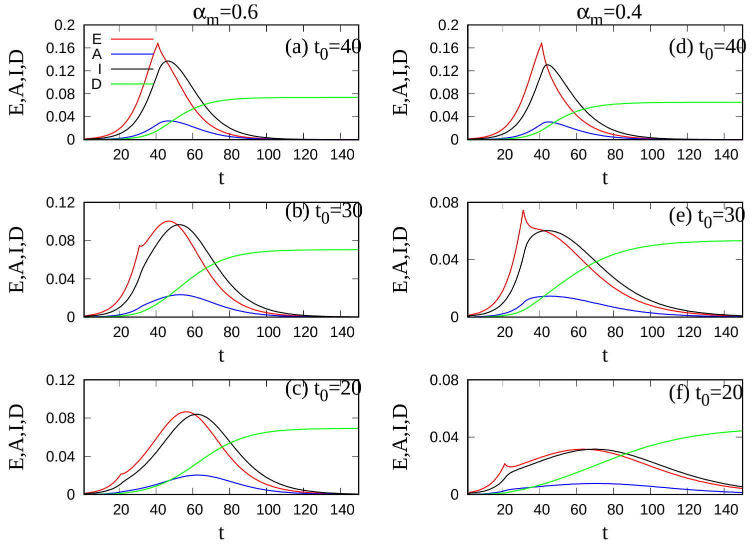

Fig. 5 Comparison of the epidemic dynamics under the intervention of mitigation with $\alpha_m = 0.6$ (left column) and $\alpha_m = 0.4$ (right column) starting at different time. (a) and (d) $t_0 = 40$; (b) and (e) $t_0 = 30$; (c) and (f) $t_0 = 20$. Other parameters are the same as Table 1.

$\alpha_m = 0.6, 0.4$, evaluating $\mathbf{R}_t = 2.1, 1.4 \in [1, \mathbf{R}_0]$, respectively. In Fig. 5, we see that with a very gentle mitigation $\alpha_m = 0.6$, the peak of infections can be reduced to half if the measure is deployed at early time with $t_0 = 20$. A delayed mitigation strategy almost does not affect the peak of infections, e.g., $t_0 = 40$, due to the limited effect of the measure on epidemics. Compared with the sharp reduction in the curve for suppression intervention, the curve for mitigation further flattens and lasts for longer time.

A more intensive mitigation intervention with $\alpha_m = 0.4$ further flatterns the curve of epidemic dynamics with a reduced peak value. The ratio of deaths is also dramatically reduced to half of that with no interventions. With a more intensive mitigation, the starting time of the mitigation measure plays a key role in changing the curve of the epidemic dynamics. Earlier interventions can efficiently suppress the epidemic spread and reduce the deaths.

A combined intervention of suppression and mitigation

From the above analysis, we find that with an appropriate suppression intervention, the epidemic can be efficiently controlled in short time, while with a gentle mitigation intervention, the epidemics can be slowed down to some degree. To further understand the effects of the two types of interventions on the epidemics, we investigate a combined intervention of suppression and mitigation. Instead of a manual adjustment of the cycle of the intervention period, we propose a dynamical intervention measure composed of suppression and mitigation depending on the infection level. If the accumulated number of existing infections during last week is larger than

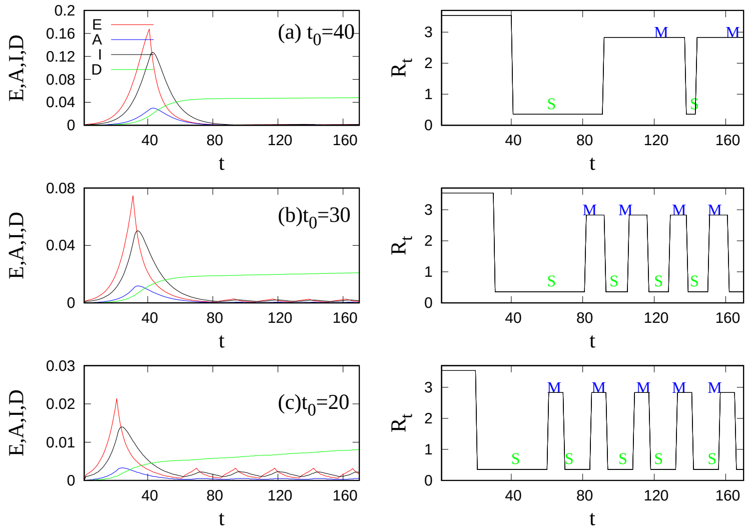

Fig. 6 The epidemic dynamics with a combined intervention of suppression and mitigation for different intervention time t_0. (a) $t_0 = 40$; (b) $t_0 = 30$; (c) $t_0 = 20$. The right column corresponds to the effective reproduction number $\mathbf{R}_t$ calculated by the intervention strategies."S" denotes suppression and "M" denotes mitigation. Parameters are set as $\alpha_s = 0.1$ and $\alpha_m = 0.8$. Other parameters are the same as Table 1.

the medical resources by a factor, then a strict suppression is deployed to suppress the epidemic spread in order to avoid the medical resources overloaded. If it is larger than some accepted value, determined by policy-makers, such as 100 infected cases, then a gentle, relaxed mitigation intervention is implemented. By doing so, the system can dynamically adjust the interventions depending on the real infections. Based on this assumption, we propose a combined intervention by setting parameters as $\alpha_s = 0.1$ ($\mathbf{R}_t = 0.354 < 1$) and $\alpha_m = 0.8$ ($\mathbf{R}_t = 2.832 > 1$) starting at different time t_0.

From Fig. 6, we see that when the intervention is deployed at delayed time $t_0 = 40$, due to the increased accumulated number of infections, a suppression measure lasting for more than two months is necessary in order to keep the epidemic under control, after which a relaxed mitigation measure follows. Since the deployment of a relaxed mitigation measure may cause the increase of infections again, then a strict suppression follows. Such a periodic wave of suppression and mitigation iteratively proceeds with the infections being controlled within a lower level. The period wave for the curve of epidemic dynamics is determined by the intervention time t_0, the medical resources I_s and the tolerance parameter I_m. A timely intervention switching between suppression and mitigation will lead to a significant reduction in both infections and deaths.

Our analysis is different from previous study [10], where a period of lockdown or quarantine is fixed manually [10]. By dynamically alternating the intervention with the epidemic dynamics, it is possible to keep the infection under control while allowing a sustainable economy as well as normally social activities.

Real world data analysis

In the following, we explore the impact of intervention measures on epidemics by analyzing the data of Wuhan for the COVID-19 epidemic. We are aware that the actual infection number is unknown and can only be inferred from other epidemiological observations (e.g., the daily confirmed cases). Such observations are lagging behind the infection events due to inevitable time delays between an individual being infected and reported (e.g., days for symptom onset). In Ref. [22], the authors proposed a deconvolution method to estimate the infection cases from the dairly reported confirmed cases with the renewal process. Detailed descriptions of the method refer to Ref. [22]. In this work, we borrow this method to infer the daily infection cases on Jan. 11th, 2020. The daily number of onset patients in Wuhan (i.e. daily confirmed cases) is obtained from the study by Pan *et al* [34]. Then, we evaluate the infection cases on Jan. 11th as $I(0) = 284$. Combined with the information of the ratio of symptomatic infection over asymptomatic infection $\frac{p}{1-p}$, the number of asymptomatic infected cases is evaluated as $A(0) = 62$. By assuming that the incubation period is 5.1 days, we can get the number of exposed cases on Jan. 11th from the number of onset patients on Jan. 16th as $E(0) = 294$. The numbers of recovered cases and death cases on Jan. 11th, 2020 are obtained from [24]. The total population of Wuhan is $N = 11081643$. The basic reproduction number is estimated as $\mathbf{R}_0 = 3.54$ [27] and accordingly, the transmission rate is calculated as $\beta_0 = 0.5512$. With the available data of beds number in Wuhan, the medical resource of Wuhan is calculated as $I_s = 0.0023$ [33]. Other parameters are the same as in Table 1.

Figure 7 (a) shows the epidemic dynamics with no intervention. We see that with no interventions being introduced, it will cause more than 1 million deaths in Wuhan. While in reality, as a part of the national emergency response, the public transport by bus and subway rail were suspended, public gathering was banned in Wuhan [5, 35]. The measures taken in Wuhan dramatically reduced the death number less than four thousand, as shown in Fig. 7 (b). It is to note that measures such as lockdown of Wuhan and the construction of mobile cabin hospitals play a key role in suppressing the epidemics, which reduce the reproduction number $\mathbf{R}_t < 1$ in very short time. To compare the model prediction with the real case, we also perform simulations on the proposed model with the real data. By setting $t_0 = 12$ on the lockdown day of Wuhan and $\alpha_s = 0.1$ in Fig. 7 (c), we see that the extremely strict intervention will immediately reduce the basic reproduction number $\mathbf{R}_t$ less than 1 and the peak value of infections will reduce to several thousands and the arrival of the peak value will be one month earlier than expected. In reality, the intervention intensity α_s depends on several factors, such as medical resources and the construction of mobile cabin hospitals. The difficulty of obtaining these resources may hinder the control of the epidemics.

Next, we investigate what would happen if dynamical interventions were deployed in Wuhan, as shown in Fig. 8. Depending on the intervention time t_0, alternative interventions are dynamically deployed. For instance, with a delayed time $t_0 = 50$ (Fig. 8 (a)), the number of infections will inrease more than two hundred thousands, consequently, a strict suppression has to be deployed for more than 70 days in order to efficiently control the epidemics, after which a gentle mitigation and a strict suppres-

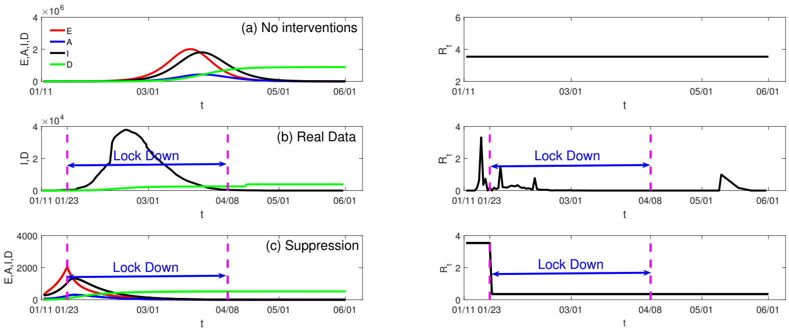

Fig. 7 The epidemic dynamics in Wuhan, China from Jan. 11th, 2020 to July 1st, 2020 under different situations. (a) No interventions; (b) real data; (c) suppression intervention with $t_0 = 12$ and $\alpha_s = 0.1$. The medical resources factor is $c = 1$. The lockdown period is indicated by the blue arrow within the dashed lines.

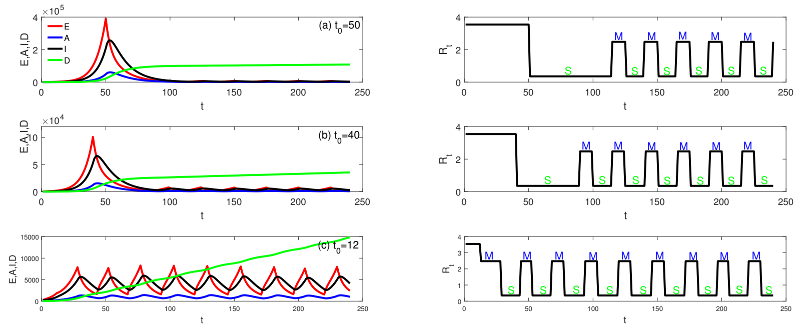

Fig. 8 The epidemic dynamics in Wuhan with the combined interventions. (a) t_0=50; (b) t_0=40; (c) t_0=12. The right column shows the effective reproduction number $\mathbf{R}_t$ under the combined intervention with $\alpha_m = 0.7$ and $\alpha_s = 0.1$. The medical resources factor is $c = 1$. Other parameters are the same as Table 1.

sion alternatively follow. If the interventions start by 10 days earlier (Fig. 8 (b)), the peak value of infections can be reduced to sixty thousand. Then, a shorter suppression followed by a shorter mitigation alternatively controls the epidemics. Finally, if the interventions are deployed at early time with $t_0 = 12$, the peak value of infections further reduces to six thousand and the epidemics is completely controlled periodically.
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Discussion

So far, although several vaccines for the COVID-19 are nearing approval, non-pharmaceutical interventions are still effective actions to control the COVID-19 pandemic. Therefore, how to implement appropriate interventions for the next stage is fundamentally important for the control of epidemics while sustaining normally social lives. It is interesting to point out that extremely strict interventions, such as lockdown and quarantine measures, have substantial effects on changing the epidemic dynamics. With a strict suppression strategy, the number of deaths and the number of infection cases can be reduced to a lower level while long-term measures may bring negative effects on economics and social lives.

To solve such a dilemma, we propose a combined intervention of suppression and mitigation, which dynamically alternate with the epidemic dynamics. The suppression intervention is assumed to be relevant with the medical resources, that is, if the accumulated number of infections during a given period is close to the medical resources with a factor, then a strict suppression will be implemented to avoid the medical resources overloaded. If the number of infections is controlled less than some tolerance level, a relaxed mitigation, such as social distancing and hygiene measures, may be efficient to control the epidemics. Depending on the tolerance level, the mitigation strategy can be dynamically switched on or off. The deployment of a strict suppression intervention is able to dramatically reduce the number of infections and the number of deaths to keep the epidemics under control. A early suppression intervention will shift the peak value to an earlier date, calling for an instant preparation for the arrival of the peaks. While a early mitigation intervention will flatten the epidemic curve with a prolonged period. With a combined intervention of suppression and mitigation, the epidemic is contained with an acceptable level, where the two measures alternatively interchange with different periods. Such a dynamical strategy is able to keep the trade-off between economics and epidemics and take less negative effects on social lives. The waves of epidemics may exist for long time until the availability of vaccines.

Our study has certain limitations as well. In reality, the periodic waves of infections in different nations show diverse features, e.g. peaks and periods, depending on how the prevention measures are deployed. Using a simplified Heaviside function alternating between two interventions is not sufficient enough to reflect such a complicated situation in reality. Instead, a non-linear function is expected to help solve it. Consequently, the present analysis and interpretation of the results are limited to a modeling study of such a phenomenon of periodic waves of infections.

Conclusions

By analysing the data for countries in battling against the COVID-19 pandemic, we found a periodic-like wave in the number of infections in several countries, which indicates a clear relationship between the infection and the deployed interventions when facing the COVID-19 epidemic. The present study explores the combined effect of suppression and mitigation measures on the epidemics. The findings are as follows: (a) depending on the medical resources that a city contains and its tolerance parameter, a combined intervention of suppression and mitigation can efficiently reduce the peak of infections and negative effects on social lives and economics; (b) an immediate, strict suppression measure is highly efficient in reducing the number of infections and brings less losses on people's lives, as occured in Wuhan, China; (c) a delayed intervention has to be accompanied by a longer suppression followed by a shorter mitigation alternatively, which is expected to balance the loss of people's lives and that of economics for a long-term control of the COVID-19.

List of abbreviations

COVID-19: Corona Virus Disease 2019; R_0: Basic reproduction number; SEIR model: Susceptible-Exposed-Infected-Recovered model;

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

Not applicable.

Conflict of interest

The authors declare that they have no conflict of interest.

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Authors' contributions

YH: Conceptualization, Writing; ZX: Acquisition, Analysis; YG: Review and editing; BW: Methodology, Writing. All authors have read and approved the final manuscript.

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Figures

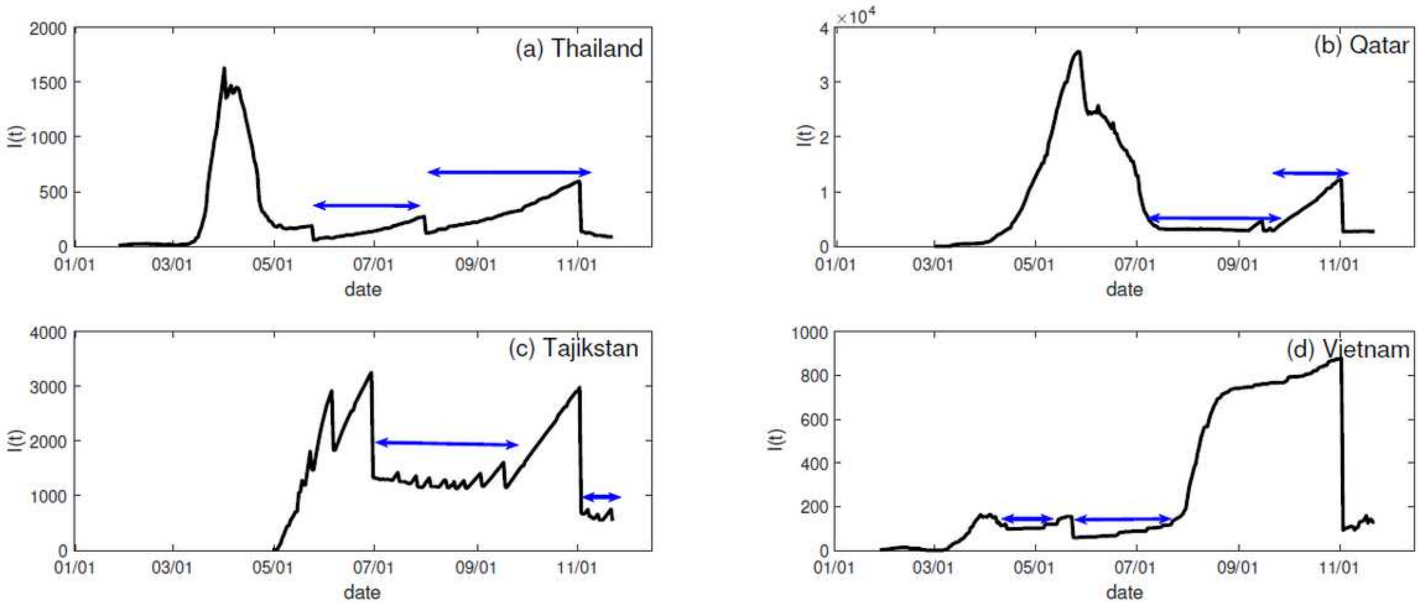

Figure 1

The number of existing confirmed cases in some typical countries. (a) Thailand; (b) Qatar; (c) Tajkstan; (d) Vietnam. The arrow in each panel indicates the plateau period due to the interventions being introduced.

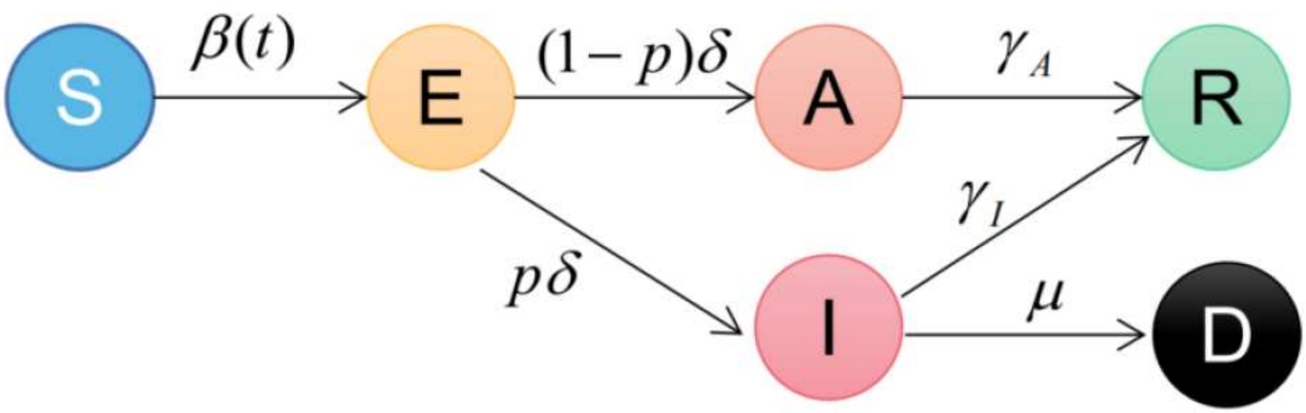

Figure 2

The flow diagram of the compartmental model. Host states are idicated by circles and transitions by arrows.

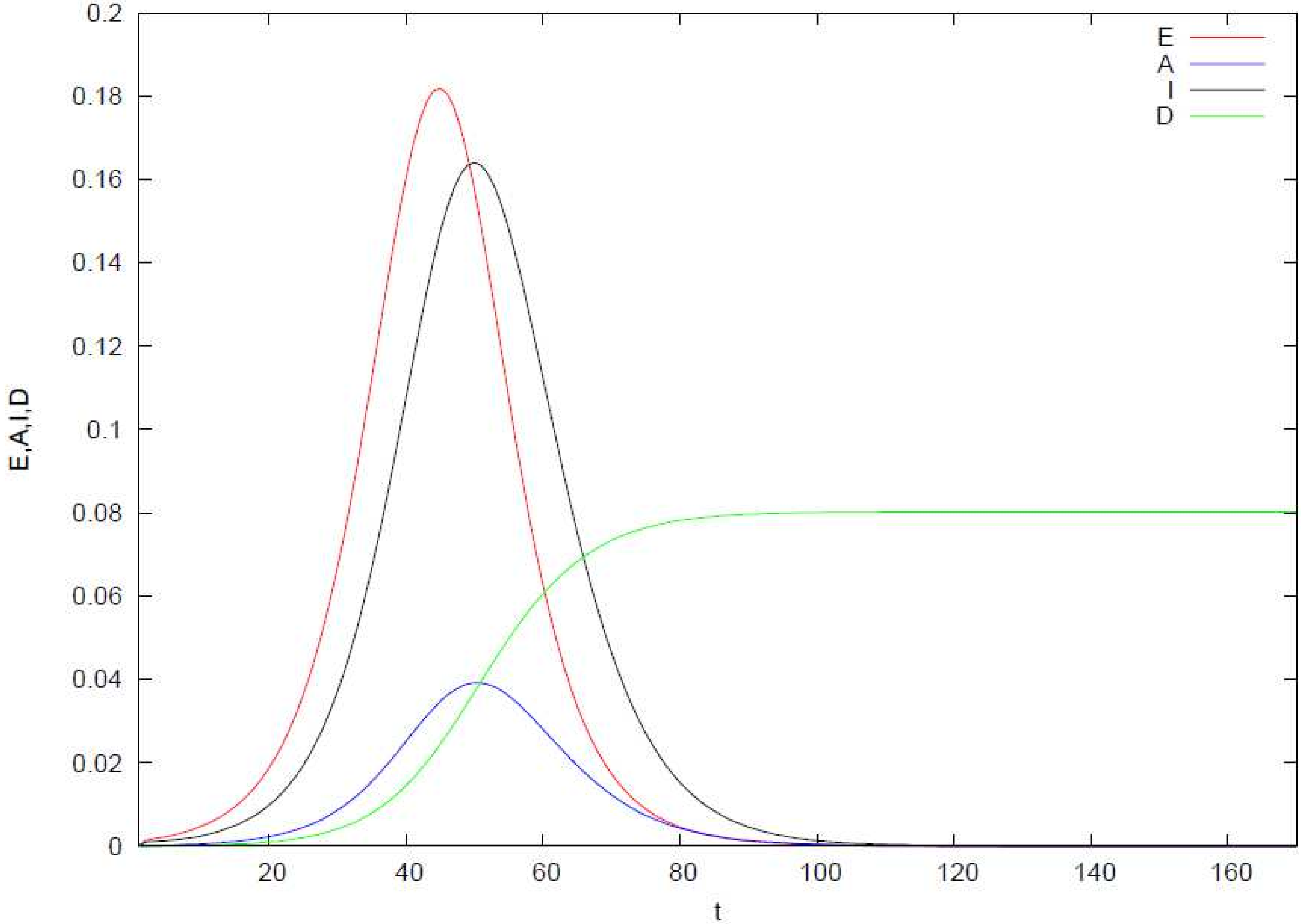

Figure 3

The epidemics dynamics of the model (Eq. (1)) with no interventions. The exposed (E, red line), asymptomatic infectious (A, blue line), symptomatic infectious (I, black line), and dead (D, green line) are shown in time.

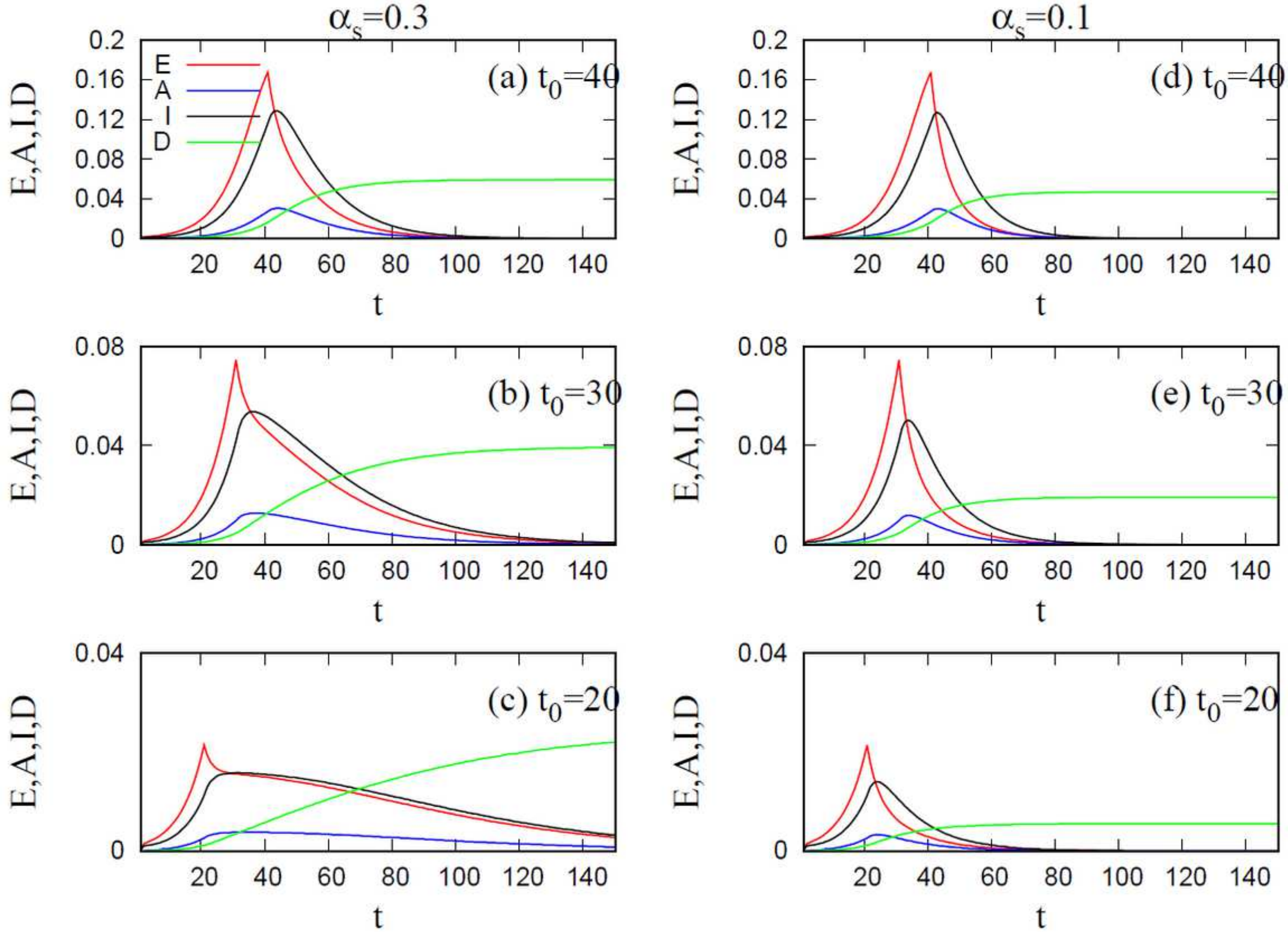

Figure 4

Comparison of the epidemic dynamics under suppression interventions with αs = 0.3 (left column) and αs = 0.1 (right column) starting at different time. (a) and (d) t0 = 40; (b) and (e) t0 = 30; (c) and (f) t0 = 20. Other parameters are the same as Table 1.

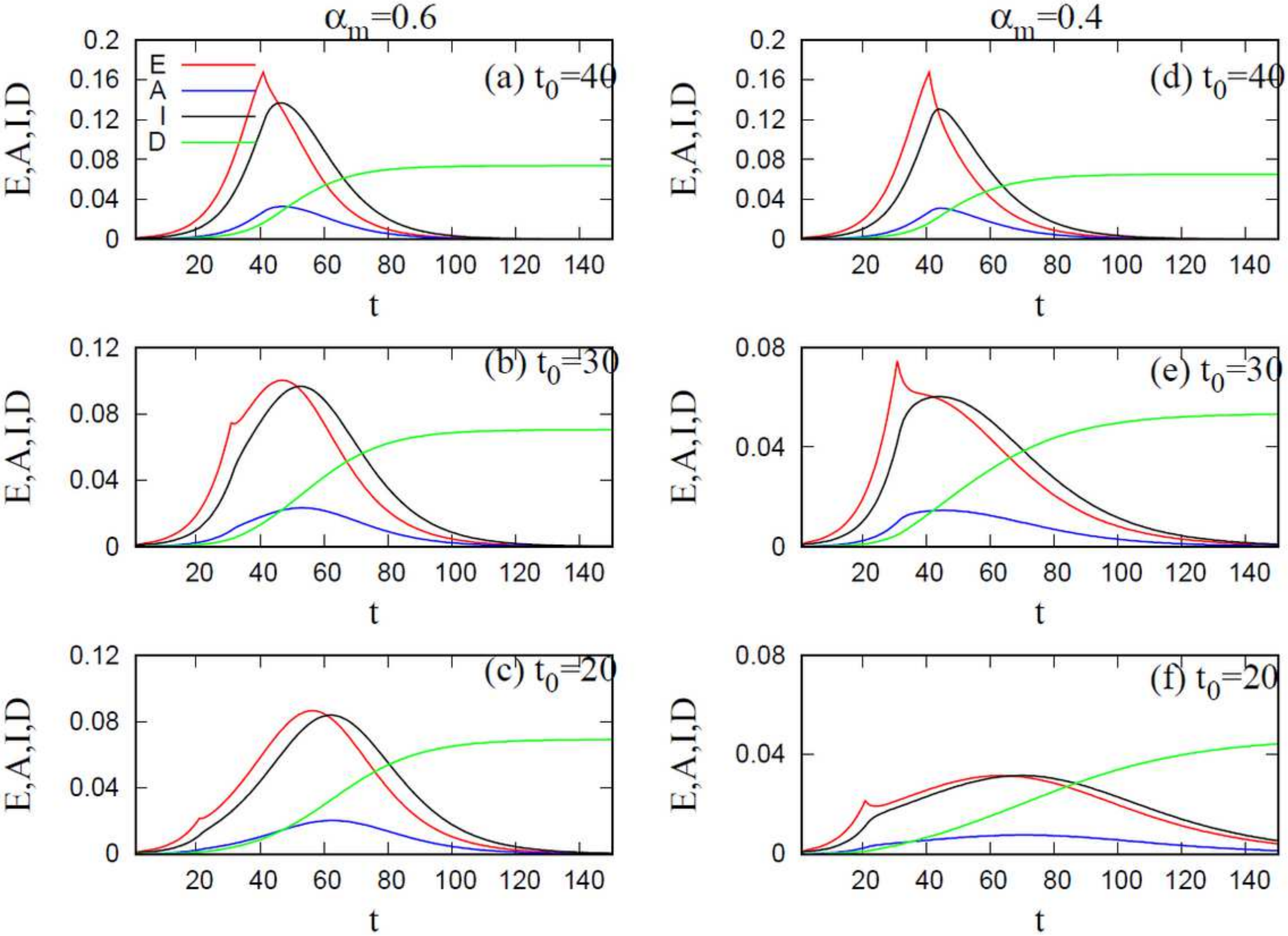

Figure 5

Comparison of the epidemic dynamics under the intervention of mitigation with αm = 0.6 (left column) and αm = 0.4 (right column) starting at different time. (a) and (d) t0 = 40; (b) and (e) t0 = 30; (c) and (f) t0 = 20. Other parameters are the same as Table 1.

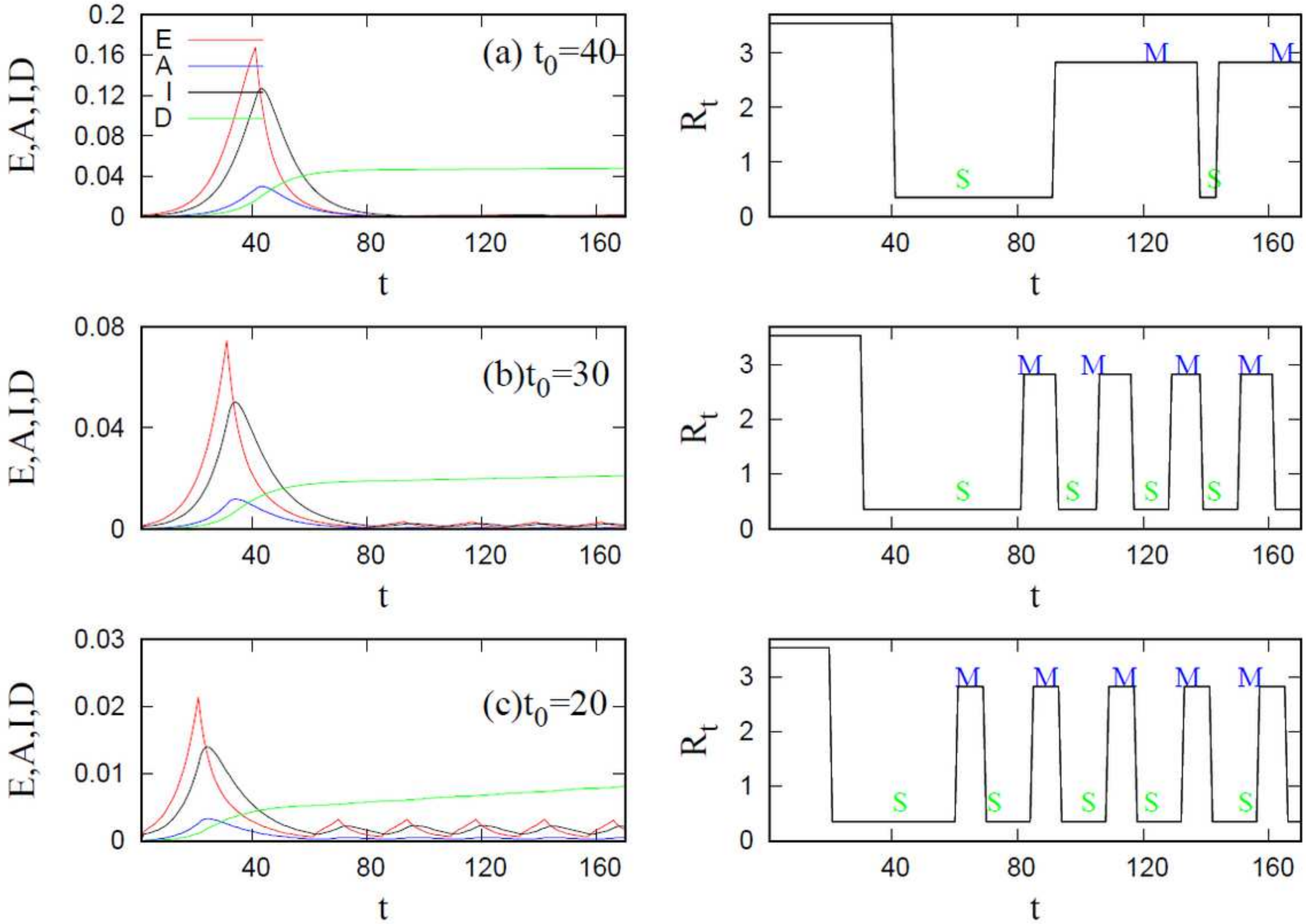

Figure 6

The epidemic dynamics with a combined intervention of suppression and mitigation for different intervention time t0. (a) t0 = 40; (b) t0 = 30; (c) t0 = 20. The right column corresponds to the effective reproduction number Rt calculated by the intervention strategies."S" denotes suppression and "M" denotes mitigation. Parameters are set as αs = 0.1 and αm = 0.8. Other parameters are the same as Table 1.

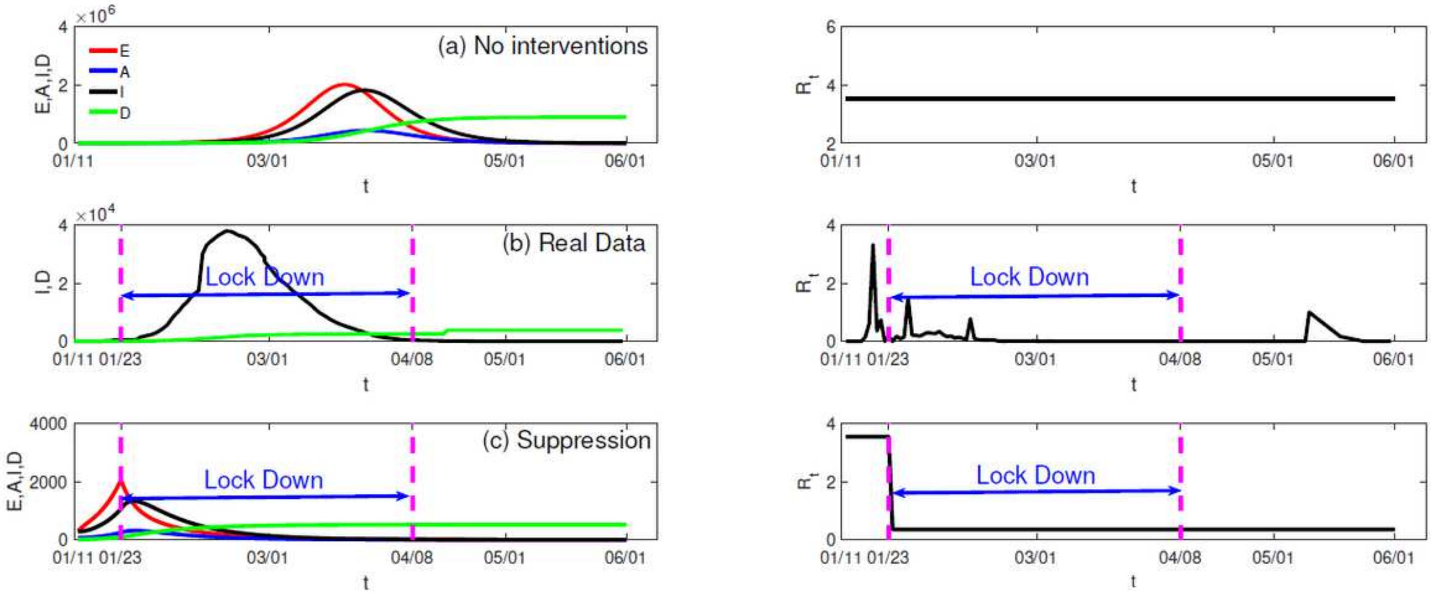

Figure 7

The epidemic dynamics in Wuhan, China from Jan. 11th, 2020 to July 1st, 2020 under different situations. (a) No interventions; (b) real data; (c) suppression intervention with t0 = 12 and αs = 0.1. The medical resources factor is c = 1. The lockdown period is indicated by the blue arrow within the dashed lines.

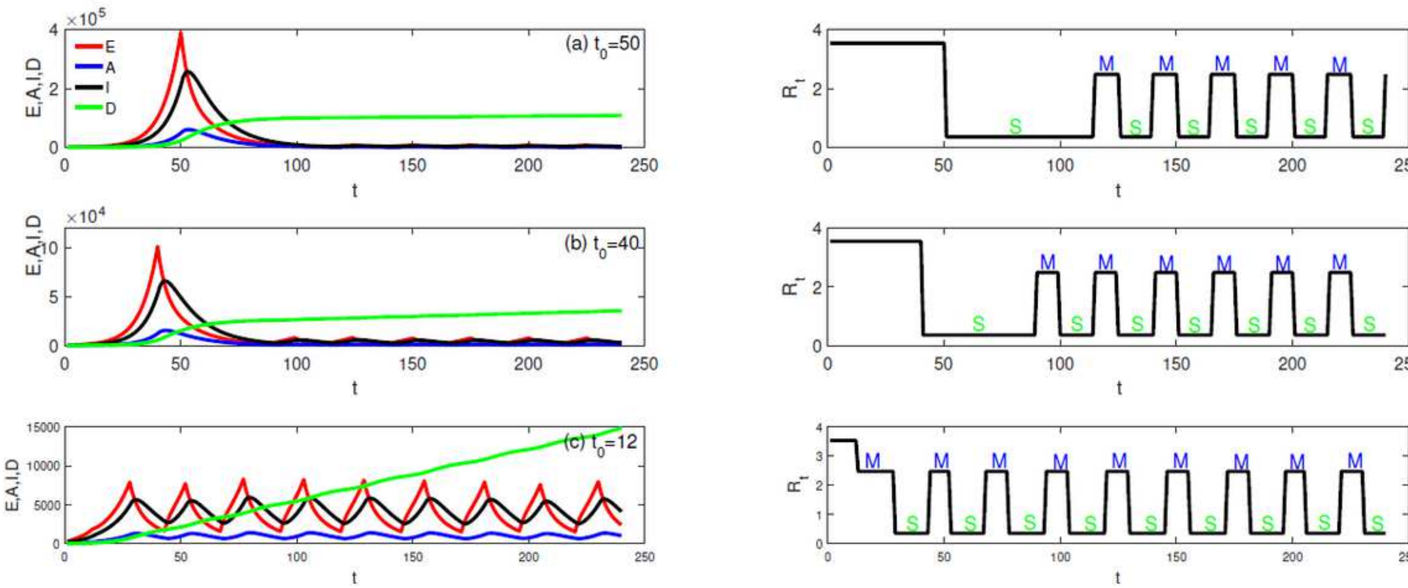

Figure 8

The epidemic dynamics in Wuhan with the combined interventions. (a) t0=50; (b) t0=40; (c) t0=12. The right column shows the effective reproduction number Rt under the combined intervention with αm = 0.7 and αs = 0.1. The medical resources factor is c = 1. Other parameters are the same as Table 1.