Role of suppression and mitigation interventions in controlling 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 lives. In the absence of vaccines and effective therapeutic solutions, non-pharmaceutic interventions have been a major way to control the epidemics. Relaxed mitigation interventions can slow down the epidemics but cannot control it well, while strict suppression interventions can efficiently halt the spread of epidemics, bringing negative effects on economics and people’s daily lives. Hence, suppression strategy and mitigation strategy play different roles in manipulating the epidemic curves.

Methods: Here, we propose a mathematical model to understand the roles of suppression and mitigation in changing the epidemic dynamics. By connecting the infection level with the consideration of the medical resources and a tolerance parameter, a combined intervention strategy of suppression and mitigation is proposed.

Results: The combined intervention strategy is able to adaptively change with the infection level, resulting in a periodic wave of controlled infections. Depending on the tolerance level, the mitigation strategy can be adaptively switched on or off. The combined intervention can efficiently reduce the numbers of deaths and confirmed cases.

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cases, and keep the infection within a low level, while such a wave of infection may
exist for a long time before the availability of vaccines.

**Conclusion:** In order to control the epidemics, policy-makers have to consider the is-
sues of human lives and economics. To solve such a dilemma, we propose a combined
intervention strategy of suppression and mitigation, which can adaptively alternate
with the epidemic dynamics. The combined strategy of suppression and mitigation
is able to effectively control the epidemics within a low level, it can also reduce the
negative effect on economics and human’s normal lives.

**Keywords** COVID-19 · Basic reproduction number · Interventions

1 Introduction

The COVID-19 pandemic has become a major global threat. It brings more than 260
thousands deaths and 3 million confirmed infected cases around the world (May,7th,
2020). So far, China has deployed very strict measures, e.g., lockdown, and efficiently
halted the epidemic spread. The COVID-19 has rapidly spread first throughout Eu-
rope and then in US, and Africa. In the absence of vaccines, effective medicines,
and with limited knowledge of the virus [1,2], non-pharmaceutic interventions were
adopted as a strategy to slow down the disease propagation. Different nations are fac-
ing the COVID-19 pandemic by imposing different restrictions on social activities
for entire populations. With the progression of epidemics, individuals have improved
their awareness of infection and changed their behavior to reduce their risk of infec-
tion by wearing face-masks, washing hands frequently [3]. In addition, governments
take different control measures to suppress the epidemics, such as lockdown [4],
school closure, quarantine [5,6], social distancing [7,8], bans on gatherings of more
than a number of people, tracking individuals who are potentially infected [9], to
reduce contact rate to halt the epidemics. Some countries like Singapore takes the
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. On one hand, strict measures
on suppressing the epidemics could save people’s lives from death, while increasing
the risk of economical loss; on the other hand, gentle mitigation interventions would
reduce the economical loss but sacrificing people’s lives. Hence, it is necessary to
estimate epidemic dynamics and implement efficient, economical interventions ac-
ccordingly [10,11]. Many researches have developed mathematical models to describe
the role of restriction measures on the dynamics of COVID-19 epidemic [11–13,6,
14,15]. Most of previous works focus on the dynamical functions of the transmission
rate $\beta$ to reflect the role of interventions [16]. For instance, a two-step control strategy relating suppression and mitigation is proposed [11,6], which is consistent with
the real data. An optimal control of COVID-19 from the point of view of economics
is also explored in Ref. [13]. It has found that a combination of home isolation, home
quarantine, and social distancing, might reduce deaths by half but still result in hun-
dreds of thousands of deaths, while suppression requires a combination of social dis-
tancing of the entire population, home isolation, supplemented by school closure, etc.
Although intensive interventions can effectively reduce transmission, it may rebound if interventions are relaxed [14].

So far, there is a lack of common evidence of what to do next for the intervention measure while keeping the epidemic under control. Since the epidemic is highly dynamic, rapidly changing with the increase of case numbers, 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 implemented by taking factors, such as the medical resources and the tolerance level for infection, into account. 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, we allow the system adaptively to adjust the control strategy depending on the social tolerance of infection level. By doing so, the epidemic level is controlled within an, accepted level, and the strict suppression intervention is not necessarily implemented during the entirely dynamical period.

2 Methods

Since COVID-19 can cause infections with no symptoms [17], we model the epidemics of COVID-19 in a population based on the SEIR model, where individuals belong to five states: susceptible (S), exposed (E), asymptomatic (A), symptomatic (I), dead (D), and recovered (R). See Fig. 1. At time $t$, the total population size is denoted as $N = S + E + A + I + D + R$. Susceptible individuals get infected by contacting (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 involvement of interventions. Asymptomatic infectious individuals are assumed to possess weaker infectiousness compared with symptomatic infectious individuals by a factor $\theta_a$. A fraction $p$ of exposed individuals move to symptomatic infections (I) at rate $\delta$, while the remainder of $1 - p$ exposed individuals move to asymptomatic infection class (A) at the same rate $\delta$. Asymptomatic and symptomatic individuals move to recover state (R) with rate $\gamma_A$ and $\gamma_I$, respectively. Symptomatic individuals move to dead state (D) at rate $\mu$. Thus, the dynamics of the model is given by,
\[
\begin{align*}
\frac{dS}{dt} &= -\beta(t)S \frac{aA+I}{N}, \\
\frac{dE}{dt} &= \beta(t)S \frac{aA+I}{N} - \delta E, \\
\frac{dA}{dt} &= \delta(1-p)E - \gamma A, \\
\frac{dI}{dt} &= \delta pE - \gamma I - \mu I, \\
\frac{dD}{dt} &= \mu I, \\
\frac{dR}{dt} &= \gamma A + \gamma I,
\end{align*}
\]

where \(N\) is the total population size.

At the early stage of the epidemics without the interventions being imposed, the basic reproduction number \(R_0\) is a constant. With the introduction of interventions, the transmission rate \(\beta\) is time-dependent. Consequently, \(R_0\) changes with time and it is often named as effective reproduction number \(R(t)\). By linearizing the system (1) at the disease free state \((S,E,A,I,D,R) = (S_0,0,0,0,0,0)\) and setting the infectious \(v = (E,A,I)\), we obtain \(\dot{v} = (F-V)v\), where \(F\) is the rate of new infections in each class and \(V\) is the rate into each class by transferring in or out of each class, given by \[
F = \begin{pmatrix}
0 \theta_a \beta(t) \\
0 & 0 & 0
\end{pmatrix}, \quad V = \begin{pmatrix}
\delta & 0 & 0 \\
-\delta(1-p) \gamma & 0 & 0 \\
-\delta p & 0 & \gamma + \mu
\end{pmatrix},
\]
from which we can obtain the effective reproduction number of the model (1) as the spectral radius \(\rho(FV^{-1})\) of the next generation matrix \(FV^{-1}\). The effective basic reproduction number, denoted by \(\mathcal{R}(t)\), is given by \[
\mathcal{R}(t) = \beta(t)\left(\frac{\theta_a(1-p)}{\gamma} + \frac{p}{\gamma + \mu}\right).\] (2)

Specifically, the basic reproduction number \(R_0 = \beta_0\left(\frac{\theta_a(1-p)}{\gamma} + \frac{p}{\gamma + \mu}\right)\). After the interventions are involved, \(\mathcal{R}(t)\) usually decreases with time. The difference between suppression and mitigation is the aim for affecting the epidemics. Suppression aims at halting the epidemics with extremely strict strategies to achieve the result of \(\mathcal{R}(t) \ll 1\), while mitigation aims at slowing down the epidemics with relaxed control strategies with a lower value of \(\mathcal{R}(t)\). However, a strict suppression would bring negative effect on economics, social lives, etc., while a gentle mitigation may not be able to control the epidemics. Thus, how to implement the strategies for the next step would be a difficult issue to answer.

To make intervention strategies for controlling epidemics, we have to consider the medical resources and the starting time of it, since the infected individuals take use of medical resources for treatment. A delayed, relaxed mitigation strategy might be
ineffective for controlling the epidemics and the accumulated existing infection cases may overwhelm the medical resources. Thus, a strict suppression strategy should be deployed to control the epidemics. On the other hand, when the infection is not at risk for medical resources, a mild level of infection could be controlled with a gentle, relaxed mitigation strategy.

Let us denote the medical resources as \( I_m \) and the tolerance parameter for epidemics as \( I_m \). At time \( t_0 \), if the total infection during a recent period \( \tau \) is higher than the medical resources \( I_m \) with factor \( c \), a strict suppression strategy with some intensity is implemented; otherwise, a mitigation intervention is implemented. Then, the effective reproduction number \( R(t) \) is given by

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

Intervention parameters \( \alpha_s \) and \( \alpha_m \) are the mean values of suppression and mitigation coefficients describing the intensity of interventions, followed by a given distribution and satisfied the condition: \( \alpha_s < \alpha_m < 1 \). \( I_m \) represents the medical resources, which may depend on the economical level of a nation. For instance, in the US, 1.2 beds per thousand people. \( c \) is a constant factor. \( I_m \) represents the tolerance parameter for epidemics, e.g., \( I_m = 1\% \), means that the tolerance of 1% of infections in the population.

The relationship between \( I_m \) and \( I_m \) is tuned by the factor \( c \). A value of \( c \) that satisfies \( c I_m \) larger than \( I_m \) can capture the condition of suppression and mitigation, i.e., \( \alpha_s < \alpha_m \). This equation determines the intervention strategy by deciding the intervention parameters \( \alpha_s \) and \( \alpha_m \). Given \( \alpha_s \), \( \alpha_m \), and the starting time \( t_0 \), we can capture \( \beta(t) \), which provides the effect of interventions.

We assume that only symptomatic infectious individuals are immediately hospitalized and occupy medical resources for treatment. Thus, we can denote the medical resources as \( I_s \), which may depend on the economical level of a nation. For instance, in the US, 1.2 beds per thousand people. \( c \) is a constant factor. We further denote \( I_m \) as the tolerance parameter for epidemics, e.g., \( I_m = 1\% \), means that the tolerance of 1% of infections in the population. Intervention parameters \( \alpha_s \) and \( \alpha_m \) are the mean values of suppression and mitigation coefficients describing the intensity of interventions, followed by a given distribution and satisfied the condition: \( \alpha_s < \alpha_m < 1 \). This equation determines the intervention strategy by deciding the intervention parameters \( \alpha_s \) and \( \alpha_m \). Given \( \alpha_s \), \( \alpha_m \), and the starting time \( t_0 \), we can capture \( \beta(t) \), which provides the effect of interventions.

We have to note that the deployment of interventions depends on the recent 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, because the real number of infections is generally not known and only confirmed cases are available, it is necessary to develop data-driven approaches to evaluate it [18], which is not the main concern of the present work. Here, to model the combined impact of the two interventions, i.e., suppression and mitigation, we simply assume that \( \sum_{t-(\tau-1)}^{t} I(t) \) is evaluated from simulations in Eq. (1).
3 Results

We start the simulation of the epidemic dynamics during several weeks in a host population without pharmaceutic intervention. The total population is set as \( N = 10^6 \). The basic reproduction number is set as \( R_0 = 2.5 \) for the COVID-19 as Ref. [1]. The ratio of symptomatic over asymptomatic infected individuals is set as \( p = 0.9 \), \( \gamma_A = 10 \) days, \( \gamma_I = 2.9 \) days, \( \theta_a = 0.5 \), and the fatality rate is \( \mu = 0.006 \). Most of the parameters are chosen according to the recent results in related works and some of them are assumed, as summarized in Table 1. Fig. 2 illustrates the baseline model, where no interventions are involved. We observe that the infected number grows exponentially and reaches the peak at around 90 days. The death ratio reaches to 4% of the population, approximately 40,000 people.

3.1 Effects of suppression intensity \( \alpha_s \) and the starting time \( t_0 \)

In this scenario, if the infected ratio during the past \( \tau = 7 \) days, \( \sum_{t-\tau}^t I(t) \), is larger than the medical resources by a factor, \( cI_s \), a suppression intervention is implemented. We simulate it as a constant control intensity with the average value \( \alpha_s = 0.2, 0.4 \), starting at different starting time \( t_0 = 20, 30, 40 \). These parameters are chosen such that the effective reproduction number \( \mathcal{R}(t) \) can be forced to be less than 1. In Fig. 3, we see that with the introduction of suppression measures at a medium level \( \alpha_s = 0.4 \) with \( \mathcal{R}(t) = 1 \), the ratio of infected individuals dramatically reduces to a lower level. For instance, the epidemic peak is reduced from 0.13 to 0.02 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 can be further reduced by three fourth, see Fig. 3 (c). Furthermore, although the epidemic peak is reduced, the time period for epidemics
is prolonged for several weeks. The death ratio depends on both the intensity of suppression $\alpha_s$ and the starting time $t_0$. The earlier the intervention measure is involved, the more efficient it is to reduce the deaths.

If the suppression intensity is further strengthened with $\alpha_s = 0.2$ at earlier starting time $t_0 = 20$ days, the epidemics is almost halted and controlled by less than 100 confirmed cases within 100 days and the total number of deaths is dramatically reduced to $\frac{1}{10}$ of the deaths with no interventions. Even with delayed intervention at $t_0 = 40$, the deaths can be reduced by 90%. Therefore, to save lives from epidemics, an efficient, strict suppression should be deployed as early as possible. In addition, the decreasing slopes of infectious ratios shown in Fig. 3 also provide insightful information for evaluating the efficiency of different control measures.
3.2 Effect of mitigation intensity $\alpha_m$ and the starting time $t_0$

Since suppression intervention often brings substantial effects on economics and social activities, a gentle control measure or containment that caused by people’s behavior to reduce the basic reproduction number $R(t)$ is necessary. If the existing infected ratio during the past week is larger than some tolerance parameter $I_m$, the mitigation intervention is implemented. To compare different intensity of mitigation, we consider the mitigation coefficient as $\alpha_m = 0.7, 0.5$, which evaluate $R(t) = 1.75, 1.25 \in [1, R_0]$, respectively. In Fig. 4, we see that with a very gentle mitigation $\alpha_m = 0.7$, the infectious ratio can be reduced to half. With such a mitigation measure, the starting time does not seem to obviously influence the infected ratio, while the time for the epidemic peak is obviously prolonged.

With a more intensive control $\alpha_m = 0.5$, earlier mitigation can dramatically reduce the infection ratio and flatten the epidemic curve with a prolonged period. The ratio of deaths is also dramatically reduced to half of that in the baseline model. It means that with the enforced intensity for mitigation, the role of starting time becomes important. Earlier interventions can efficiently suppress the epidemic spread and reduce the deaths.

3.3 Combined intervention of suppression and mitigation

From the above analysis, we find that with appropriate suppression intervention, the epidemic can be efficiently controlled, however, a strict suppression intervention would possibly cause economic losses and constrain social activities. While with gentle mitigation intervention, the epidemics can be slowed down to some degree but still causing a high level of infection. To further understand the effects of the two types of interventions on the epidemics, we investigate a combined intervention of
suppression and mitigation, adaptively implemented by the system instead of manual adjustment of the cycle of the intervention period. We propose alternative intervention measures for suppression and mitigation depending on the infection level. If the number of existing infected cases during the last week is larger than the medical resources by a factor, then a strict suppression is deployed to suppress the epidemic spread and to avoid the medical resources overwhelmed, while 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 adaptively adjust the intervention depending on the infections. Based on this observation, we propose a combined intervention measure with parameters as \( \alpha_s = 0.2 (\mathcal{R}(t) = 0.5 < 1) \) and \( \alpha_m = 0.7 (\mathcal{R}(t) = 1.75 > 1) \) starting at different time \( t_0 \) in Fig. 5.

If the starting time is delayed at \( t_0 = 40 \), a suppression intervention has to be involved to reduce the epidemic to a lower level and then a gentle mitigation intervention is sufficient to control the epidemics. The interventions of suppression and mitigation are alternatively deployed, thus, the epidemic dynamics shows a wave of increasing and decreasing trend. With a strict suppression intervention, the infected ratio decreases to a lower level, then increases slowly to a higher level, and a gentle mitigation intervention is involved. This process iteratively proceeds with the infected ratio being controlled within a lower level. For instance, after the epidemics being reduced to a lower level by suppression for a longer period (40 days), a relaxed mitigation and a strict suppression are alternatively implemented. The period for intervention alternation is about 12 days for mitigation and 14 days (\( t_0 = 20 \)) for suppression, respectively.

Our analysis is different from previous works on setting fixed period of lockdown or quarantine manually [6]. By adapting the intervention to the epidemic dynamics, it is possible to keep the infection load lower while allowing a sustainable economy as well as normally social activities.

**Conclusions**

So far, non-pharmaceutical interventions are the only actions performed to control the COVID-19 pandemic before the available of vaccines. Therefore, how to implement appropriate intervention strategies for the next stage is fundamental for the control of epidemics while sustaining normally social lives. It is interesting to point out that very strict interventions, such as lockdown and quarantine control measures, would have substantial effects on changing the epidemic dynamics. With a strict suppression strategy, the number of deaths and cases can be reduced to a lower level, while sustaining strict suppression strategy would bring substantial economical loss and social lives, and ceasing it may rebound the epidemics to a higher level again.

To solve such a dilemma, we propose a combined intervention strategy of suppression and mitigation, which can adaptively alternate with the epidemic dynamics. The suppression intervention is related with the medical resources, that is, if a recent accumulative number of infected individuals is close to the medical resources with a factor, then a strict suppression should be implemented to avoid the medical resources overwhelmed. If the infection number is under control less than some toler-
ence level, a relaxed mitigation, such as home quarantine, wearing face-masks, may efficiently reduce the transmission rate to control the epidemics. Depending on the tolerance level, the mitigation strategy can be adaptively switched on or off. Such a trade-off strategy between economics and epidemics, i.e., a strict suppression, alternatively combined with a relaxed mitigation would keep the epidemics within a lower level and take less negative effects on social lives. We have to note that such a wave of epidemics would exist for a long time before the availability of vaccines.

**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 and BW designed the study, analysed and interpreted the results. YG reviewed, and gave appropriate direction for the methodology, suggestions, and comments. All the authors read and approved the final manuscript.

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