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Rolling Interventions for Controlling COVID-19 Outbreaks in the UK to Reduce Healthcare Demand

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ABSTRACT

For curbing recent outbreaks of coronavirus disease 2019 (COVID-19), suppression or mitigation are two typical intervention strategies. But both strategies have their merits and limitations, and hardly achieve an optimal balance between healthcare demand and economic protection. In this paper, we designed a model to attempt to infer the impact of mitigation, suppression and multiple rolling interventions for controlling COVID-19 outbreaks in London and the UK. Our model assumed that each intervention has equivalent effect on the reproduction number R across countries and over time; where its intensity was presented by average-number contacts with susceptible individuals as infectious individuals. We considered two important features: direct link between Exposed and Recovered population, and practical healthcare demand by separation of infections into mild and critical cases. We combined the calibrated model with data on the cases of COVID-19 in London and non-London regions in the UK during February 2020 and March 2020 to estimate the number and distribution of infections, growth of deaths, and healthcare demand by using multiple interventions. Our results show given that multiple interventions with an intensity range, one optimal strategy was to take suppression with very high intensity in London from 23rd March for 100 days, and 3 weeks rolling intervention between very high intensity and high intensity in non-London regions. In this scenario, the total infections and deaths in the UK were limited to 2.43 million and 33.8 thousand; the peak time of healthcare demand was due to the 65th day (April 11th), where it needs hospital beds for 25.3 thousand severe and critical cases. This strategy would potentially reduce the overall infections and deaths, and delay and reduce peak healthcare demand.

CCS CONCEPTS

• Information systems → Data mining; • Computing methodologies→ *Machine Learning*;

KEYWORDS

Epidemic propagation, COVID-19, Mitigation, Suppression, SEIR.

INTRODUCTION

Throughout human history, Infectious diseases (ID), also known as transmissible diseases or communicable diseases, are considered as serious threats to global public health and economics [1]. From the 1918 influenza pandemic in Spain resulting in nearly 50 million deaths in 1920s, to recent ongoing global outbreaks of coronavirus disease 2019 (COVID-19) killing over 11 thousands people in all over the world [2], infectious disease is a leading contributor to significant mortality and causes huge losses to society as well as personal family burden. Among a variety of factors leading to emergence and outbreaks of ID, the key issues are population density and human mobility where in these cities with developed transportation systems, pathogens can be spread to large geographic space within a short period of time. For instance, the ongoing global epidemic outbreak of COVID-19 has spread to at least 146 countries and territories on 6 continents in 2 months. In order to give an accurate prediction of outbreaks, many researchers have been working in traditional ID propagation models [3-7] like SIR, SEIR,.et.al, for understanding COVID-19 transmission with human mobility and predicting outbreak process of epidemics. Meanwhile, as realizing a long period of this battle against COVID-19, many of them recently focus on intervention strategies [8-10] that can balance a trade-off between limited human mobility and potential economic loss in COVID-19 control. It poses an important research area that explores how and when to take what level of interventions in light of multiple natures and capabilities of countries.

In traditional compartmental models paradigm in epidemiology, SIR (Susceptible-Infectious-Recovered) [3] and SEIR (Susceptible –Exposure-Infectious-Recovered) [4] are two popular approaches to simulate and predict how infectious disease is transmitted from human to human. These two models have defined several variables that represent the number of people in each compartment at a particular time. As implied by the variable function of time, these models are dynamic to reflect the changes and fluctuations of these numbers in each compartment over time. For COVID-19 control in Wuhan, Zhong, et.al [11] introduced a modified SEIR model in prediction of the epidemics trend of COVID-19 in China, where the results showed that under strong suppression of "lockdown Hubei", the epidemic of COVID-19 in China would achieve peak by late February and gradually decline by the end of April 2020. Some other extended models [8] [12] are also proposed for predicting the epidemics of COVID-19 in Wuhan and give some similar forecasts. While above methods demonstrate good performance in prediction of COVID-19 outbreak by taking strong public intervention, also named as suppression strategy [13] that aims to reverse epidemic growth, one important challenge is that taking suppression strategy only is to treat disease controls as single-objective optimisation of reducing the overall infectious populations as soon as possible, and require strategic consistency in a long term. In real-world, taking public health intervention strategies is actually a multiple-objective optimisation problem including economic loss and society impacts. Thus, most countries have taken different intervention strategies, like enhanced surveillance and isolation to affected individuals in Singapore [14], four-stage response plan of the UK [15], mitigation approaches [13] and even multiple interventions taken in many EU countries. Due to the fact that standalone intervention strategy has apparent merits and limitations, it becomes highly necessary to study the feasibility of intervention strategies to certain country in light of its multiple natures and capabilities.

Targeting at this problem, this paper conducts a feasibility study that analyses and compares mitigation and suppression intervention strategies for controlling COVID-19 outbreaks in Wuhan and London. Taking Wuhan as a simulated case using data from [11], we demonstrated performance of taking different intervention strategies: a) No interventions: the peak of daily infections would be up to 2.1 million, but will be completed in 150 days. The epidemics lasts a relatively shorter period of 140 - 150 days, but lead to more death. b) Contain phase: taking 90% effectiveness of surveillance and isolation from the 2nd day of confirmed case potentially enables controlling a new outbreak of COVID-19, but it needs to be maintained over 300 days. c). Suppression intervention from the 32nd day: the peak of daily infections greatly reduced to 16 thousand, but it had to be followed at least 200 days. Nearly 3 months suppression may potentially lead to economic loss even crisis. d). Mitigation intervention from the 32nd day: the peak of daily infectious populations increased to 27.7 thousand, but the period of maintenance extended to 150 days. It implied there would be growing death but less economic loss compared to suppression. e). Hybrid intervention of taking both suppression and intervention every 2 weeks: the epidemics of COVID-19 appeared a long-term multimodal trend where the peaks of daily infectious populations were within a range of 40-60 thousand. This might lead to less daily critical cases and offer more time to hospital for releasing their resources.

Above analysis demonstrates the complexity of controlling COVID-19 outbreaks that how and when to take what level of interventions. In this paper, we proposed a mathematical model: SEMCR to study this problem. The model extended traditional SEIR (Susceptible-Exposed-Infectious-Recovered) model [3] [4] by adding one important fact: there has been a direct link between Exposed and Recovered population. Then, it defined parameters to classify two stages of COVID control: active contain by isolation of cases and contacts, passive contain by suppression or mitigation. The model was fitted and evaluated with public dataset containing daily number of confirmed active cases including Wuhan, London, Hubei province and the UK during January, 2020 and March 2020. For each point, we design and set up experimental protocols for comparison and exploration, highlighting following contributions:

- Immediate suppression taken in Wuhan significantly reduced the total exposed and infectious populations, but it has to be consistently maintained at least 90 days (by the middle of April 2020). Its success heavily relied on sufficiently external support from other places of China. This mode were not suitable to other countries that have no sufficient resources.
- In the UK, we estimated given that one optimal strategy was to take suppression with very high intensity in London from 23rd March for 100 days, and 3 weeks rolling intervention between very high intensity and high intensity in non-London regions. In this scenario, the total infections and deaths in the UK were limited to 2.43 million and 33.8 thousand; the peak time of healthcare demand was due to the 65th day (April 11th), where it needs hospital beds for 25.3 thousand severe and critical cases.
- To release rolling intervention intensity to moderate level and simultaneously implement them in all regions of the UK, the COVID-19 outbreak would not end in 1 year and distribute a multi-modal mode, where the total infections and deaths in the UK possibly reached to 16.2 million and 257 thousand.
- Our results show that taking rolling intervention is probably an optimal strategy to effectively and efficiently control COVID-19 outbreaks in the UK. As large difference of population density and social distancing between London and non-London regions in the UK, it is more appropriate to implement consistent suppression in London for 100 days and rolling intervention in other regions. This strategy would potentially reduce the overall infections and deaths, and delay and reduce peak healthcare demand.

The remainder of this paper is arranged as follows. Section 2 introduces the model. In the Section 3, the materials and implementation of experiment are reported. Section 4 provides detailed experimental evaluation and discussion. The conclusion and future directions are given in Section 5.

1. METHODOLOGY

2.1 Problem formulation of COVID-19 outbreak

We implemented a modified SEIR model to account for a dynamic Susceptible [S], Exposed [E] (infected but asymptomatic), Infectious [I] (infected and symptomatic) and Recovered [R] or Dead [D] population's state. For estimating healthcare needs, we categorised infectious group into two sub-cases: Mild [M] and Critical [C]; where Mild cases did not require hospital beds; Critical cases need hospital beds but possibly cannot get it due to shortage of health sources. Conceptually, the modified modal is shown in Fig.1. The model accounted for delays in symptom onset and reporting by including compartments to reflect transitions between reporting states and disease states.

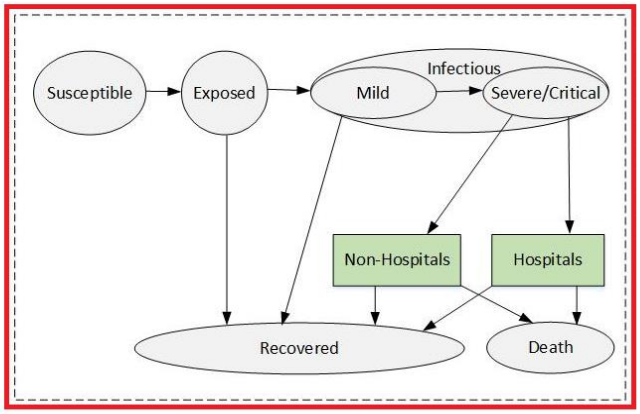

Figure 1: Extended SEMCR model structure: The population is divided into the following six classes: susceptible, exposed (and not yet symptomatic), infectious (symptomatic), mild (mild or moderate symptom), critical (severe symptom), death and recovered (i.e, isolated, recovered, or otherwise non-infectious).

Here, this modal assumed that S is initial susceptible population of certain region; and incorporated an initial intervention of surveillance and isolation of cases in contain phase by a parameter β [14] [15]. If effectiveness of intervention in contain phase was not sufficiently strong, susceptible individuals may contract disease with a given rate when in contact with a portion of exposed population E. After an incubation period α_1, the exposed individuals became the infectious population I at a ratio $1/\alpha_1$.The incubation period was assumed to be 5.8 days.[8] Once exposed to infection, infectious population started from Mild cases M to Critical cases C at a ratio *a*, Critical cases led to deaths at a ratio *d*; other infectious population finally recovered.

Notably, two important features in our model differ with other SIR or SEIR models.[12,13] The first one was that we built two direct relationships between Exposed and Recovered population, Infections with mild symptoms and Recovered population. It was based on an observation of COVID-19 breakouts in Wuhan that a large portion (like 42.5% in Wuhan) of self-recovered population were asymptomatic or mild symptomatic.[14] They did not go to hospital for official COVID-19 tests but actually were infected. Without considering this issue, the estimation of total infections were greatly underestimated.[13] In order to measure portion of self-recovery population, we assumed that exposed individuals at home recovered in 3.5 days; mild case at home recovered in 7 days.[19] The second feature was to consider shortage of health sources (hospital beds) in the early breakouts of COVID-19 might lead to more deaths, because some severe or critical cases cannot be accommodated in time and led to death at home (non-hospital). For instance, in Wuhan, taking an immediate suppression intervention on 23rd Jan 2020 increased serious society anxiety and led to a higher mortality rate. In order to accurately quantify deaths, our modal considered percentage of elder people in the UK at a ratio *O*, occupancy of available NHS hospital beds over time at a ratios H_t and their availability for COVID-19 critical cases at a ratio J_t. We assumed that critical cases at non-hospital places led to death in 4 days; elderly people in critical condition at hospital led to death in 14 days, and non-elderly people in critical condition at hospital led to death in 21 days [20].

One parameter was defined to measure intervention intensity over time as M_t. which was presented by average number of contacts per person per day. We assumed that transmission ratio β equals to the product of intervention intensity M_t and the probability of transmission (b) when exposed (i.e., β= mb). In Wuhan, intervention intensity was assumed within [3-15], and gave with a relatively accurate estimation of COVID-19 breakouts [11]. We calibrated its value with respect to the population density and human mobility in London and the UK, and estimated outcomes of COVID-2019 outbreaks by implementing different interventions. Using Wuhan's data, our estimation was close to the practical trend of outbreaks in Wuhan, and gave similar results to other works.[13.22] We tested that transmission rate from I to S is about 0.157; transmission rate from E to S is about 0.787.[13] The incubation period was assumed to be 6 days.[8] As for other parameters, we followed the COVID-19 official report from WHO[19], and gave a medium estimation on average durations related from infectious, to mild or critical case, and death or recovery were shown in Table.1.

Table 1: Parameters estimation in SEMCR model

Name	Representation	Value [20]
N	UK population by Aug 2019	6.6 million
i	Efficiency of isolation contacts	0.88-1.00
β_1	Transmission rate from I to S	0.157
β_2	Transmission rate from E to S	0.787
α_1	Incubation period	6 days
α_2	Average period from M to C	7 days
γ_1	Average period from E to R	3.5 days
γ_2	Average period from M to R	7 days
γ_3	Average period from Non-H to R	42 days
γ_4	Average period of older people from H to R	18 days
γ_5	Average period from non-older people from H to R	13 days
d_1	Average period from Non-H to D	4 days
d_2	Average period of older people from H to D	14 days
d_3	Average period of non-older people from H to D	21 days
m	Proportion of Mild case	0.80
s	Proportion of Severe case	0.138
c	Proportion of Critical case	0.061
B_t	Number of hospital beds in the UK	167589
O	Percentage of people over 65 in the UK	0.18

H_t	Percentage of unoccupied hospital beds	0.20-0.60
J_t	Percentage of available hospital beds for COVID-19 critical cases	0.8-1
M_t	The intensity of intervention	3-15

Regard as the percentage of elderly people in the UK, it was assumed as 18%.[21] The total number of NHS hospital beds was given as 167589 with an initial occupied ratio up to 85%.[22] Considering that UK government began to release NHS hospital beds after COVID-19 breakouts, we assumed the occupied ratio reduced to 80% and would further fall to 40% by April 04, 2020. Accounting for other serious disease cases requiring NHS hospital beds in the early breakout of COVID-19, we assumed that a ratio of available hospital beds for COVID-19 critical cases was initially at 80%, and gradually raised to 100%.

The intervention intensity was related to the population density and human mobility. We gave an initialization to London and non-London regions: London (M=15, population: 9.3 million), non-London regions (M=15, population: 57.2 million). After taking any kind of interventions, we assumed the change of M would follow a reasonable decline or increase in 3-5 days.

If we assumed the overall population of a certain region is *N*, the number of days is *t*, the dynamic transmissions of each components of our model are defined as follow:

$$\frac{dS(t)}{dt} = -\frac{\beta_1 S(t)I(t)}{N} - \frac{\beta_2 S(t)E(t)}{N} \quad (1)$$

$$\frac{dE(t)}{dt} = \frac{\beta_1 S(t)I(t)}{N} + \frac{\beta_2 S(t)E(t)}{N} - \alpha_1 E(t) - \gamma_1 E(t) \quad (2)$$

$$\frac{dI(t)}{dt} = M(t) + C(t) \quad (3)$$

$$\frac{dR(t)}{dt} = \gamma_1 E(t) + \gamma_2 M(t) + \gamma_3 C(t) \quad (4)$$

Regarding Mild cases, Critical cases and Death, the dynamic transmission is as below:

$$\frac{dM(t)}{dt} = \alpha_1 E(t) - \alpha_2 \frac{c+s}{m} M(t) - \gamma_2 M(t) \quad (5)$$

$$\frac{dC(t)}{dt} = \alpha_2 \frac{c+s}{m} M(t) - \gamma_3 C(t) - d\frac{c}{c+s} C(t) \quad (6)$$

$$\frac{dD(t)}{dt} = d\frac{c}{c+s} C(t) \quad (7)$$

2.2 Implementation of dynamic transmission

In practical cases, it needs to estimate the defined parameters including $\boldsymbol{\alpha_1}$, $\boldsymbol{\alpha_2}$, β, and $\boldsymbol{\gamma_1}$, $\boldsymbol{\gamma_2}$, $\boldsymbol{\gamma_3}$, b, where β is the product of the people exposed to each day by confirmed infected people (k) and the probability of transmission (b) when exposed (i.e., β= kb) and σ is the incubation rate which is the rate of latent individuals becoming symptomatic (average duration of incubation is $1/\boldsymbol{\alpha_1}$). According to recent report [8], the incubation period of COVID-19 was reported to be between 2 to 14 days, we chose the midpoint of 7 days. γ is the average rate of recovery or death in infected populations. Using epidemic data from [6], we used SEMCR model to determine the probability of transmission (b) which was used to derive β and the probability of recovery or death (γ). The number of people who stay susceptible in each region was similar to that of its total resident population. Other transmission parameters were estimated with early prediction of Hubei cases in [6] on January 23 2020 using Monte Carlo simulation, as shown in the Table.1

Parameter i is the efficiency of isolation contacts. Parameter m is the proportion of mild case, parameter s is the proportion of severe case, and parameter c is the proportion of critical case. Parameter O is the percentage of people over 65 in the UK.

Parameter β_1 is the transmission rate from I to S, Parameter β_2 is the transmission rate from E to S. Parameter φ_1 is the transmission rate from E to M ($1/\ \alpha_1$ (incubation period)), Parameter φ_2 is the transmission rate from M to C ($1/\ \alpha_2$(average period from M to C)).

Parameter γ_1 is the transmission rate from E to R ($1/\ \Upsilon_1$ (average period from E to R)), parameter γ_2 is the transmission rate from M to R ($1/\Upsilon_2$(average period from M to R)), parameter γ_3 is the transmission rate from NH to R ($1/\Upsilon_3$(average period from NH to R)), parameter γ_4 is the transmission rate of older people from IH to R ($1/\Upsilon_4$(average period of older people from IH to R)), parameter γ_5 is the transmission rate of non-older people from IH to R ($1/\Upsilon_5$(average period of non-older people from IH to R)).

Parameter δ_1 is the transmission rate from NH to R ($1/\ d_1$ (average period from NH to D)), parameter δ_2 is the transmission rate of older people from IH to R ($1/\ d_2$(average period of older people from IH to D)), parameter δ_3 is the transmission rate of non-older people from IH to R ($1/\ d_3$(average period of non-older people from IH to D)).

Parameter B_t is the number of hospital beds in the UK, parameter J_t is the percentage of available hospital beds for COVID-19 critical cases, H_t is the percentage of unoccupied hospital beds， M_t is the intensity of intervention.

Notably, as for the strength of intervention M, it was related to the population density in a region. We used a benchmark reported in [11] that assumes Hubei province with no intervention as M = 15, and after suppression intervention, M reduced to 3. When applying SEMCR model into other simulated cases, M was initialized according to the population density and human mobility in these places. Also, after taking any kind of interventions, the change of M would follow a reasonable decline or increase over few days, not immediately occur at the second day.

Following previous assumptions, the implementation of dynamic transmission of SEMCR model follows steps as below:

$$S_{t+1} = S_t - \frac{\beta_1 M_t I_t S_t}{N_t} - \frac{i\beta_2 M_t I_t S_t}{N_t} \quad (8)$$

$$E_{t+1} = E_t + \frac{\beta_1 M_t I_t S_t}{N_t} + \frac{i\beta_2 M_t I_t S_t}{N_t} - \varphi_1 E_t - \gamma_1 E_t \quad (9)$$

$$M_{t+1} = M_t + \varphi_1 E_t - \varphi_2 (\frac{s+c}{m}) M_t - \gamma_2 M_t \quad (10)$$

If $C_t > B_t J_t H_t$:

$$NH_t = C_t - B_t J_t H_t \quad (11)$$

$$IH_t = B_t J_t H_t \quad (12)$$

else

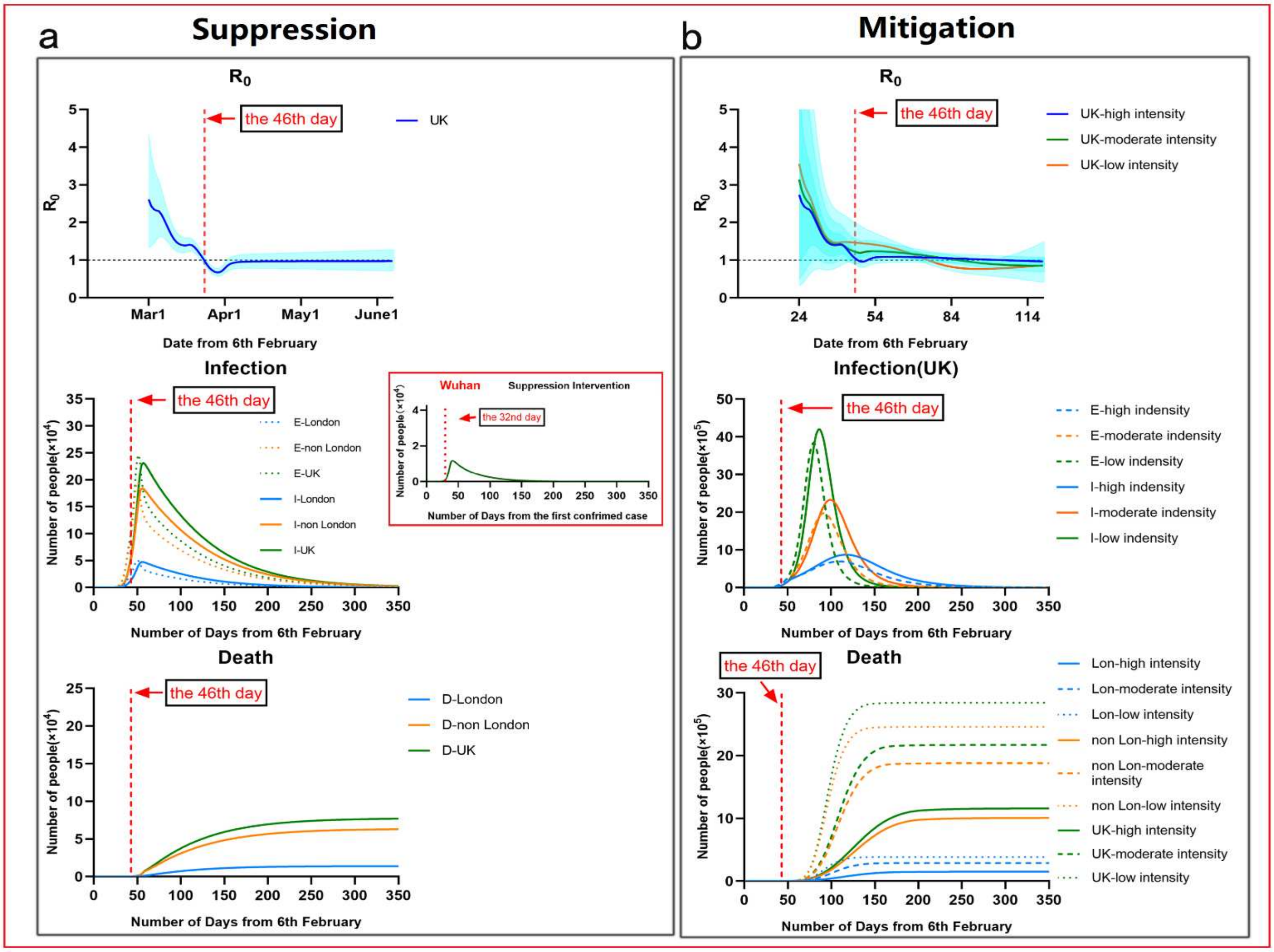

Figure 2: Illustration of controlling COVID-19 outbreaks in London and non-London regions by taking suppression and mitigation with parameters (a) London population: 9.30 million; non-London population: 57.2 million. (b) Suppression Intervention (M = 3), Mitigation Intervention: Low (M = 10). Moderate (M = 8). High (M =6). (c) Effectiveness of isolation in contact phase (before 12th March 2020): London. 94%, non-London: 88%.

$$NH_t = 0 \tag{13}$$

$$IH_t = C_t \tag{14}$$

$$\mathrm{C_{t+1}} = \mathrm{C_t} + \varphi_2\left(\frac{\mathrm{s+c}}{\mathrm{m}}\right)\mathrm{M_t} - \gamma_3\mathrm{NH_t} - \gamma_4 O\mathrm{IH_t} - \gamma_5(1-O)\mathrm{IH_t} - \delta_1\left(\frac{c}{s+c}\right)\mathrm{NH_t} - \delta_2\left(\frac{c}{s+c}\right)O\mathrm{IH_t} - \delta_3\left(\frac{c}{s+c}\right)(1-O)\mathrm{IH_t} \tag{15}$$

$$\mathrm{I_{t+1}} = \mathrm{M_t} + \mathrm{C_t} \tag{16}$$

$$\mathrm{D_{t+1}} = \mathrm{D_t} + \delta_1\left(\frac{c}{s+c}\right)\mathrm{NH_t} + \delta_2\left(\frac{c}{s+c}\right)O\mathrm{IH_t} + \delta_3\left(\frac{c}{s+c}\right)(1-O)\mathrm{IH_t} \tag{17}$$

$$\mathrm{R_{t+1}} = \mathrm{R_t} + \gamma_1\mathrm{E_t} + \gamma_2\mathrm{M_t} + \gamma_3\mathrm{NH_t} + \gamma_4\mathrm{OIH_t} + \gamma_5(1-O)\mathrm{IH_t} \tag{18}$$

2. EXPERIMENTS

3.1 Effectiveness of suppression

We estimated that suppression with intensity M = 3 was taken in both London and non-London regions in the UK on the 46th day (March 23rd, 2020). The model reproduced the observed temporal trend of cases within London, non-London and the UK. As shown in Fig.3, it captured the exponential growth in infections between the 35th day (March 12th, 2020) and the 55th day (April 1st, 2020). We estimated that at the day (on March 23th, 2020) to take intervention, daily infectious population (Exposed) in the UK actually reached 78579. Our results suggested there were nearly 11 times more infections in the UK than were reported as confirmed cases (6650 on March 23rd, 2020). The infections in London nearly occupied about 51% of the overall UK infections. After implementing suppression, the results in the UK appeared a similar trend as Wuhan in Fig.1, where daily exposed and infectious

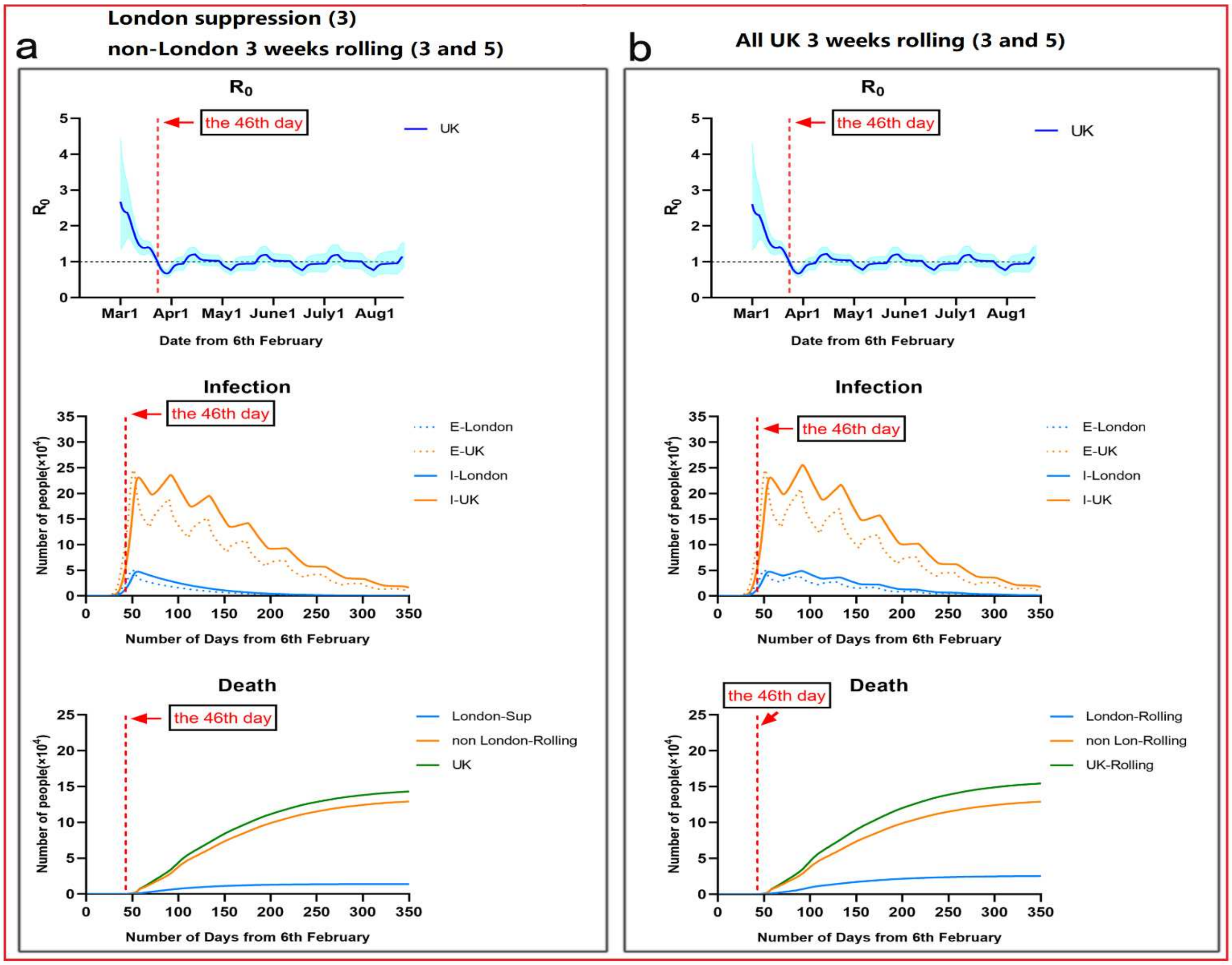

Figure 3: Illustration of controlling COVID-19 outbreaks in London and non-London regions by taking suppression and 3 weeks rolling intervention with parameters (a) London population: 9.30 million; non-London population: 57.2 million. (b) Suppression Intervention (M = 3), 3 weeks rolling intervention: M = 3-5-3-5, M = 3-4-3-4-3-4. (c) Effectiveness of isolation in contact phase (before 12th March 2020): London. 94%, non-London: 88%.

population were greatly reduced. The total deaths by the 200th day (August 24th, 2020) in the UK was about 23805, where London had about 9388 deaths and non-London regions had about 14117 deaths. The outbreak of COVID-19 could be possibly controlled by the 100th day (May 16th 2020), and can be nearly ended by the 150th day (July 5th 2020). The difference was that the peak of daily infectious population (E = 54760) of London was nearly 3.4 times greater than the one in Wuhan (E = 15870); the peak time (the 50th day) of daily infections in London was 14 days later than the one (the 36th day) in Wuhan. It was probably because suppression applied in Wuhan (the 32nd day) was 3 days earlier than London (the 35th day). It implied that earlier suppression could reduce infections significantly, but may lead to an earlier peak time of healthcare demand.

We estimated that the predicted R_t of London, non-London and the UK dramatically raised in the first 7 days to 2.5 above, and varied from the 2nd days (February 8th 2020) to from the 46th day (March 23th 2020), with values ranging from 2.5 to 3.2. Notably, non-London regions had slightly higher value of R than London during these days. That was because the total population in non-London regions was about 5 times more than the Figure 3 in London, as a result of more susceptible and exposed population in non-London regions. After taking suppression in the UK, we estimated a rapid decline in R in later March, from 3 at the 46th day (March 23th 2020) to 1.4 at the 230th day (September 23rd 2020).

3.2 Effectiveness of mitigation

We simulated that mitigation with low, moderate and high intensity (M = 6, 8, 10) were taken in both London and non-London regions in the UK at the 46th day (March 23rd, 2020), as show in Fig.3. Considering that the UK went to delay phase on the 35th day (March 12th, 2020), M in the UK was adjusted to 12 from March 12th 2020 to March 23th 2020.

The results showed that mitigation strategies were able to delay the peak of COVID-19 breakouts but ineffective to reduce daily infectious populations. We estimated that the peak of daily infectious population was reduced to 3.10 million (M = 10) to 1.33 million (M = 8) or 0.28 million (M = 6); the peak date of daily infections was about on the 82^{th}, 100^{th} and 135^{th} day. Compared to suppression, the total deaths in the UK increased to 2.17 million (M = 10) to 1.47 million (M = 8) or 37 thousand (M = 6), where London had about 0.27 million (M = 10) to 165 thousand (M = 8) or 41 thousand (M = 6) and non-London regions had about 1.90 million (M = 10) to 1.30 million (M = 8) or 330 thousand (M = 6). The periods of breakouts with varied mitigations were extended to 180, 200 or 300 days.

Compared to suppression, mitigation taken in the UK gave a slower decline in R in late March, from 3 on the 46^{th} day (March 23^{rd} 2020) to 1.4 on the 280^{th} day (November 12^{nd} 2020). It implied that during this period, there were more infections in the UK. But London had lower R than non-London regions; it implied that London probably would reach a certain level of "herd immunity" earlier. Above simulations appeared similar trends as findings,[4] taking mitigation intervention in the UK enabled reducing impacts of an epidemic by flattening the curve, reducing peak incidence and overall death. While total infectious population may increase over a longer period, the final mortality ratio may be minimised at the end. But as similar as taking suppression, mitigation need to remain in place for as much of the epidemic period as possible.

3.3 Effectiveness of multiple interventions

We simulated two possible situations in London and the UK by implementing rolling interventions as shown in Fig. 4. We assumed that all regions in the UK implemented an initial 3 weeks suppression intervention (M=3) from the 46^{th} day (March 23^{rd} 2020) to the 67^{th} day (April 13^{rd} 2020). Then, two possible rolling interventions were given: 1) to keep suppression in London, and take a 3 weeks rolling intervention between suppression and high intensity mitigation (M = 5) in non-London regions; (2) to take a 3 weeks rolling intervention between suppression and high intensity mitigation (M = 5) in all UK.

The simulated results showed the epidemic appeared a unimodal distribution trend over 350 days, longer than the period of suppression. Similar to suppression in Fig.3, the peak date of infectious population in London or non-London regions remain same at the 50^{th} day. After three weeks, rolling intervention with released intensity in non-London regions led to a fluctuation with 4 or 5 peaks of infections until the end of epidemic. The total deaths and infectious population in the UK were greatly reduced to a range from 33 thousand to 37 thousand. It was about 37% - 54% more than the outcome of taking suppression in all the UK.

Above two rolling interventions taken in the UK gave a similar trend of R as suppression, where there was a fast decline in R in late March, from 3 on the 46^{th} day (March 23^{rd} 2020) to 1.4 on the 230^{th} day (September 23^{rd} 2020). It implied that 3 weeks rolling intervention (M = 3 or 5) had equivalent effects on controlling transmissions as suppression, but need to be maintained in a longer period of 350 days.

3.4 Optimal rolling intervention

We simulated other possible rolling interventions with varied period (2, 3 and 4 weeks) and intensity (M = 4, 5 and 6), as shown in Table.2. The results first revealed that rolling intervention with middle intensity (M = 6) cannot control the outbreaks in one year, where the distribution of epidemic was a multimodal trend as similar to mitigation outcomes in Fig.3. The overall infections and deaths significantly increased to over 450 thousand and 60 thousand. While the peak time of healthcare demand for severe critical cases delayed to the 80^{th} – 110^{th} day, the total deaths of the UK would be double than other rolling interventions with low intensity.

Another finding was that given equivalent intensity (M= 3 or 5) of rolling interventions, the longer period (4 weeks) led to slight reduction of the total deaths to 36288, compared to 37432of 3 weeks rolling and 38537 of 2 weeks rolling in the UK. The peak time of healthcare demand nearly occurred at same: the 64^{th}-65^{th} day; with an equivalent peak value. Thus, in balance of total deaths and human mobility restriction, 3 weeks of period might be a feasible choice.

We considered the length of intervention in the UK impacting on social and economic. Maintaining a period of suppression in London, it was possible to control the outbreaks at the 100^{th}-150^{th} day that minimized economic loss to the greatest extent. Due to lower population density and less human mobility of non-London regions, 3 weeks rolling intervention was appropriated to non-London regions for balancing the total infections and economic loss, but the length of this strategy was extended to 300 days.

DISCUSSION

Notably, the total infections estimated in our model was measured by Exposed population (asymptomatic), which might be largely greater than other works only estimating Infectious population (symptomatic). We found that a large portion of self-recovered population were asymptomatic or mild symptomatic in the COVID-19 breakouts in Wuhan (occupied about 42%-60% of the total infectious population). These people might think they had been healthy at home because they did not go to hospital for COVID-19 tests. It was one important issue that some SEIR model predicted infectious population in Wuhan that 10 times over than confirmed cases.[12.13] Early release of intensity might increase a risk of the second breakout. There are some limitations to our model and analysis. First, our model's prediction depends on an estimation of intervention intensity that is presented by average-number contacts with susceptible individuals as infectious individuals in a certain region. We assumed that each intervention had equivalent or similar effect on the reproduction number in different regions over time. The practical effectiveness of implementing intervention intensity might be varied with respect to cultures or other issues of certain county. In the UK or similar countries, how to quantify intervention intensity needs an accurate measure of combination of social distancing of the entire population, home isolation of cases and household quarantine of their family members. As for implementing rolling interventions in the UK, the policy needs to be very specific and well-estimated at each day according to the number of confirmed cases, deaths, morality ratio, health resources, etc. Secondly, our model used a variety of plausible biological parameters for COVID-19 based on current evidence as shown in Table.1, but these assumed values might be varied by populations or countries. For instance, we assumed that average period of mild cases to critical cases is 7 days, and average period of elderly people in hospital from severe cases to deaths was 14 days, etc. The change of these variables may impact on our estimation of infections and deaths in the UK. Lastly, our model assumes a condition that there will be a reasonable growth of available hospital source as time goes in the UK after 23^{rd} March 2020. This was actually supported by latest news that Nightingale hospital that enables holding 4000 patients opened at London Excel centre on 4^{th} April 2020.[24] Our results show that taking rolling intervention is one optimal strategy to effectively and efficiently control COVID-19 outbreaks in the UK. This strategy potentially reduces the overall infections and deaths; delays and reduces peak healthcare demand. In future, our model will be extended to investigate how to optimise the timing and strength of intervention to reduce COVID-19 morality and specific healthcare demand.

3. CONCLUSIONS

This paper conducts a feasibility study by defining a mathematical model named SEMCR that analyses and compares mitigation and suppression intervention strategies for controlling COVID-19 outbreaks in London and Wuhan Cases. The model was fitted and evaluated with public dataset containing daily number of confirmed active cases including Wuhan, London, Hubei province and the UK. The experimental findings show that the optimal timing of interventions differs between suppression and mitigation strategies, as well as depending on the definition of optimal. In future, our model could be extended to investigate how to optimise the timing and strength of intervention to reduce COVID-19 morality and healthcare demand in mobile application.

4. DATA AND CODE

All data and code required to reproduce the analysis are available online at: https://github.com/TurtleZZH/Feasibility-Study-of-Mitigation-and-Suppression-Intervention-Strategies-for-Controlling-COVID-19.git

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