



Article title: An Engineering Model of the COVID-19 Trajectory to Predict Success of Isolation Initiatives

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To: Prof. Dan Osborn
Chair of Human Ecology
Editor in Chief: UCL Open: Environment
Department of Earth Sciences
University College London
London, UK

30 April 2020

Dear Prof. Osborn,
Please find enclosed an article entitled

An Engineering Model of the Covid-19 Trajectory to Predict Success of Isolation Initiatives

By
Steven King and Alberto Striolo.

My co-author and I would like to submit this manuscript for publication in *UCL Open: Environment*.

We believe this is a timely article due to the immense impact on our society that is being caused by the spread of Covid-19, clearly a pandemic. We became interested in applying a simple engineering model to the data frequently reported regarding the trajectory of the disease, and we found, with some surprise that the model indeed captures the important elements of the virus trajectory, namely the number of infected individuals as a function of time, simply by adjusting two parameters.

We do not have the ambition to relate these parameters to the ability of the virus to spread, nor to societal habits. However, despite its simplicity, the model is clearly able to reproduce the effects induced by governmental isolation/lockdown initiatives, and it also seems to correctly predict that if such initiatives are interrupted prematurely, the spreading trajectory can quickly resume. Reports from Germany, which are not included in this manuscript because they occurred after the manuscript was completed, seem to strengthen the reliability of the model predictions.

Should one believe the model, the implications are several, including that effective isolation/lockdown initiatives should reduce tenfold our usual societal interactions, and that intense measures, applied for the medium period, are likely the best approach to limit the spread of Covid-19.

We include in the manuscript a cautionary statement, at the end, as we recognise the model does not account for a variety of other phenomena, including, for example, possible negative societal effects that might be caused by extended isolation/lockdown initiatives.

As epidemiology is not our area of expertise, we cannot recommend suitable Reviewers. We are however looking forward to any comment that might help us improve the quality of this submission, and we hope the manuscript will find a home in *UCL Open: Environment* in a timely manner.

Sincerely yours,

Alberto Striolo
Professor of Molecular Thermodynamics

An Engineering Model of the Covid-19 Trajectory to Predict Success of Isolation Initiatives

Steven King and Alberto Striolo*

University College London

Department of Chemical Engineering

Abstract

Much media and societal attention is today focused on how to best control the spread of Covid-19. Every day brings us new data, and policymakers are implementing different strategies in different countries to manage the impact of Covid-19. In several countries, including the UK, policymakers opted for isolation/lockdown initiatives, with different degrees of rigours, which seems to yield the expected results in terms of containing the rapid trajectory of the virus. The affected societies are now wondering when the isolation/lockdown initiatives will be lifted. While detailed epidemiologic and economic studies would be required to find the answer to this question to maximise the control over the spread of the virus and minimise the negative impacts on the society due to the isolation/lockdown initiatives, not least the negative impact on the economy, we address here this question with a simple engineering model. The model is capable of reproducing the main features of the data reported in the literature concerning the Covid-19 trajectory in different countries, including the increase in cases in countries in which the initial isolation/lockdown initiatives were seen as successful. Keeping in mind the simplicity of the model, we attempt to draw some conclusions, which seem to suggest that a decrease in the number of infected individuals after the initiation of isolation/lockdown initiatives does not necessarily mean that the virus trajectory is under control. Within the limit of this model, it would appear that rigid isolation/lockdown initiatives for the medium term would lead to achieving the desired control over the spread of the virus.

Keywords: Virus propagation model, engineering approximations, length of intervention

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1. Introduction

The development of the Covid-19 pandemic both in terms of geographical footprint and the growth of cases and fatalities has been the subject of opportune comment and provided the news media with constant and compelling feed. Because the media-reported current state and expected future outcomes show wide variation, modelling has been attempted here using an engineering differential model to provide an evidence-based statement of future expectations.

When data were required to validate the model, those were sourced from WHO, via <https://ourworldindata.org/coronavirus-source-data>,¹ which provides current daily new case and mortality figures for most countries. Data as of April 2nd have been used for the present analysis.

The differential model employed was constructed as follows, based on a population of fixed size (P_0), in which three groups of Individuals were defined:

1. X = uninfected Individuals;
2. Y = infected Individuals;
3. REC = Individuals not able to pass on infection by virtue of recovery, or fatality.

Defining

k_1 = infection growth rate constant, which will itself be a function of the frequency of daily person-to-person contact (assumed random) and of a yet unknown efficacy of transfer;

and

k_2 = the rate constant for the recovery /mortality of the infected population (Y).

The following 1st order differential equations may be defined:

$$\frac{dX(t)}{dt} = -k_1 X(t)Y(t) \quad [1]$$

$$\frac{dY(t)}{dt} = k_1 X(t)Y(t) - k_2 Y(t) \quad [2]$$

$$REC(t) = P_0 - X(t) - Y(t) \quad [3]$$

The above non-linear equations [1-3] may be solved numerically, for example using a Runge-Kutta-Simpson technique,² with the initial conditions $X(0)=P_0$, $Y(0)=0$, $REC(0)=0$.

The development of the 3 groups of Individuals with time is shown in Figure 1 in both linear and logarithmic scaling representations. In Figure 1, the dotted line indicates an exponential growth of the infected population, which is fitted to the early part of the correspondent curve (i.e., $Y(t)$). Although a very basic model, the character of the curves is consistent with real infection transfer and other models presented in the literature. Fitting is not shown here because abundant analysis is reported on the news. The most significant feature evident from this engineering representation of the infected population Y curve is its departure from exponential growth, evidenced by the change in colour in the $Y(t)$ curve in Figure 1, as the trajectory of the disease continues. This departure evidences the possibility of reaching ‘the peak’ in the infection trajectory and eventually reaching ‘herd immunity’. In the engineering model presented here, the departure from exponential growth in the number of infected Individuals is due to larger number of contacts between infected Individuals as opposed to contacts between infected and uninfected ones, recovery or death of the infected Individuals (described by the constant k_2), and reduced total population, all eventualities which effectively terminate the growth chain.

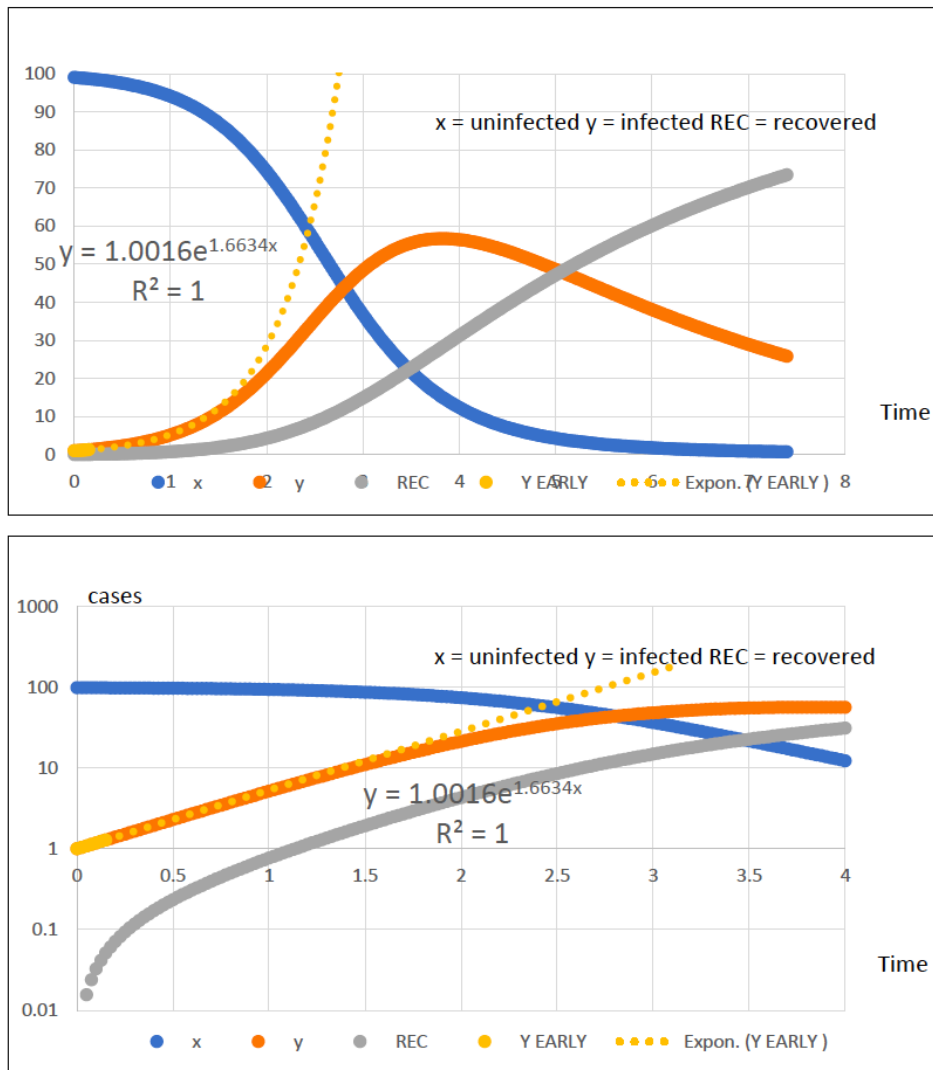


Figure 1: Differential model to describe the propagation of a virus through a total population (P_0) which is initially completely uninfected (X , blue symbols), and, as time progresses, becomes infected (Y , orange symbols) and then either recovers or dies (REC , grey symbols). The dotted line is an exponential growth model fitted to the early growth stages (yellow) of the infected population Y . The top panel the model is presented in linear representation, while in the bottom panel the logarithmic representation is used.

Analysing the results shown in Figure 1, it may be seen that prior to Y reaching 2% of P_0 , the correspondence to exponential growth approximation is very high, with Y model / Y exponential = 1.0009. It is possible to render the model a-dimensional by expressing the $Y(t)$ curve as a deviation from the correspondent exponential growth model $Y_{\text{exponential}}(t)$, under the constraint of limiting the analysis to $Y < 2\%$ of P_0 . Using the a-dimensional model it is then possible to draw generally applicable conclusions independently on the actual values of P_0 , k_1 and k_2 .

The significance of the above observation is that in examining WHO data where the infected population (Y) is a very small proportion of the total (or local) population P_0 , for unchanging rate constants k_1 and k_2 a simple exponential growth in Y should be observed. From:

$$\frac{dY(t)}{dt} = k_1 X(t) Y(t) - k_2 Y(t) \quad [2]$$

Because $X \sim P_0$ in our approximation,

$$k_{3,initial} = k_1 P_0 \quad [4]$$

$$\frac{dY(t)}{dt} = (k_{3,initial} - k_2) Y(t) \quad [5]$$

Which can be solved to yield

$$Y(t) = \exp((k_{3,initial} - k_2)t) \quad [6]$$

It is in fact possible to apply Eq. [6] to WHO data specifically for different countries and regions, until the onset of isolation/lockdown initiatives, which have the goal of slowing down, and eventually reversing the growth rate. In other words, Eq. [6] represents an un-moderated exponential growth in the number of infected Individuals.

2. Modelling the effect of isolation/lockdown initiatives

One timely question in relation to governmental initiatives designed to mitigate the spread of a virus, is quantifying the merits (and consequences) of strong and weak compliance to governmental health directives (i.e., social isolation and lockdown initiatives).

The effect of these initiatives with respect to the above engineering model is expected to introduce a stepwise down shift in the exponential growth constant for the disease, k_3 in Eq. [6]. This effect was modelled here by applying various stepdown factors ($K_{\text{step-down}}$) to the growth constant k_3 at the time when 1% of the total population P_0 was infected. In other words, at $t > t_{\text{intervention}}$, we set:

$$k_{3,intervention} = k_{3,initial} \times (1 - K_{\text{step-down}}) \quad [7]$$

Note that $K_{\text{step-down}}$ is limited between 0, which reflects an ineffective imposition of governmental initiatives, and 1, in which case said initiatives are so effective that no new Individual is infected. In our approach, the rate of recovery/mortality from the disease, k_2 , is considered unchanged.

Modelling $Y(t)$ under various scenarios for a given k_3 yields evidence that two behaviours emerge, depending on whether $K_{\text{step-down}}$ is larger or smaller than a critical value. In the former case, the number of infected Individuals declines and over time control over disease prevails. When $K_{\text{step-down}}$ is lower than the critical value, which corresponds to a lower degree of populace compliance with governmental health initiatives, $Y(t)$ resumes its exponential growth and control over disease propagation is lost. In Figure 2, the two behaviours are shown; control is achieved (blue) for $K_{\text{step-down}} = 0.94$, and not achieved (orange) for $K_{\text{step-down}} = 0.90$. This analysis yields $K_{\text{step-down,critical}} = 0.92$.

It is instructive to analyse the number of new infected cases per day as predicted by our model when $K_{\text{step-down}} = 0.90$. These results are shown in the bottom panel of Figure 2. It can be seen that while the number of new infected Individuals as a function of time (e.g., day) initially decreases, an insufficient compliance with the governmental directives eventually leads to growth in the number of newly infected Individuals.

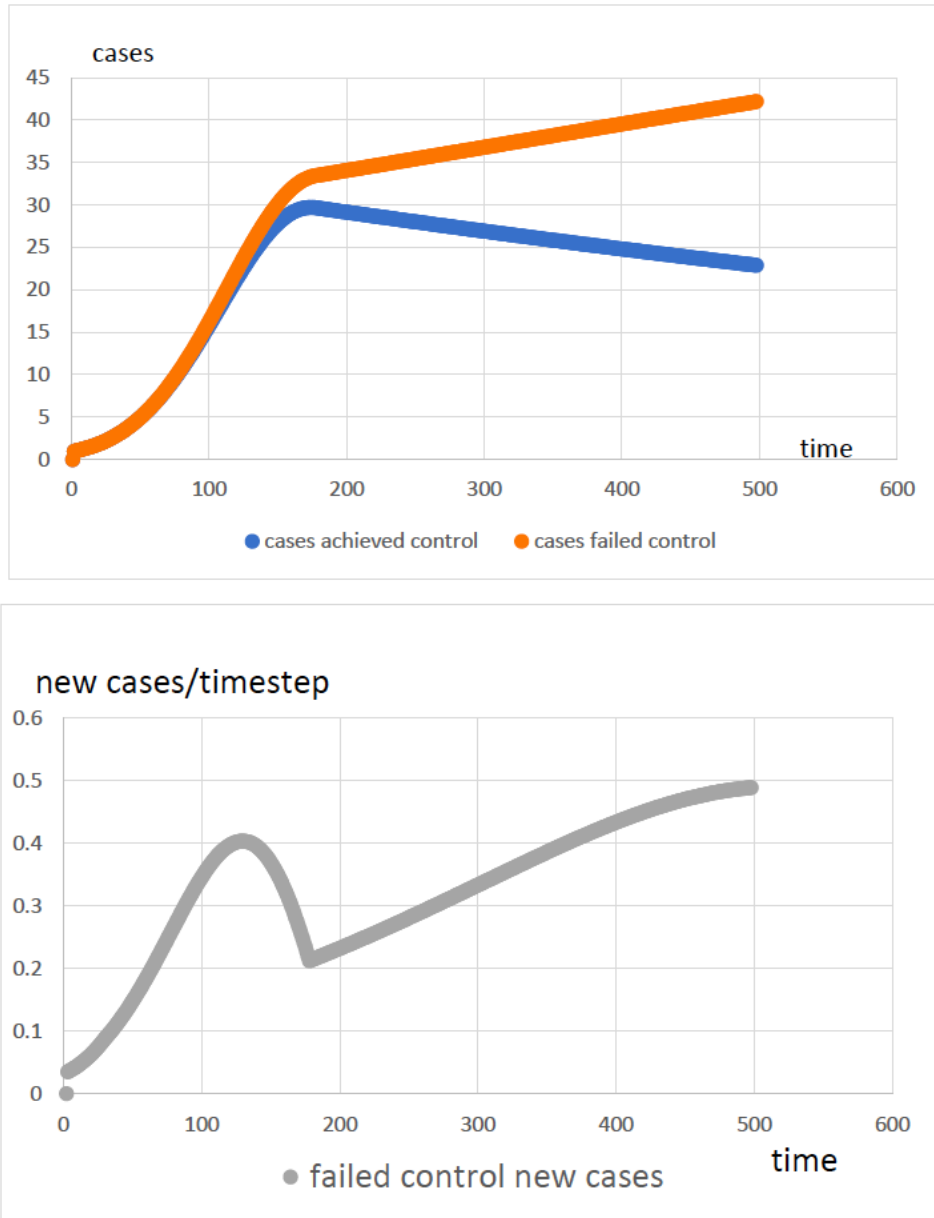


Figure 2. Top panel: Changes in the number of infected Individuals after isolation/lockdown initiatives are introduced. Two behaviours are observed, depending on the level of populace compliance with the guidelines. When compliance is high, the infected population decreases (blue curve); when compliance is not sufficiently high (orange), the exponential growth in the number of infected Individuals continues at a reduced growth rate. In the bottom panel, the number of new infected Individuals is plotted as a function of time for the case shown in orange in the top panel.

For the engineering model to be helpful, one might ask how it is possible to determine $K_{\text{step-down,critical}}$ depending on the initial population size, P_0 , and the infection growth rate, k_1 . As shown in Eq. [4], k_3 is the product of these two values. Modelling reveals a simple relation between $K_{\text{step-down,critical}}$ and k_3 :

$$(1 - K_{\text{step-down,critical}}) \times k_3 = \text{constant} \quad [8]$$

This relation holds independently of the point in time at which the isolation/lockdown initiatives are applied, although for the purposes of modelling, it is considered that the initiatives are applied during the early unmoderated exponential growth part of the curve, before significant proportion of the population is infected (i.e., $Y < 10\% P_0$). It can be seen from Eq. [8] that the smaller k_3 is, the larger

$K_{\text{step-down,critical}}$ must be to achieve control over the spread of the virus. Because, as shown in Eq. [4], as the number of uninfected Individuals X decrease, k_3 decreases, the engineering model predicts that the longer it is waited to impose isolation / lockdown initiatives after the initial appearance of the virus, the higher must $K_{\text{step-down,critical}}$ be to achieve the desired effects. A longer delay in implementing isolation / lockdown strategies will also increase the number of infected Individuals.

The consequences of applying different $K_{\text{step-down}}$ values may be modelled to assess the time frame of recovery. Such time frame can be quantified by the correspondent recovery rate constant extracted from fitting to exponential decay functions the blue portion of curves such as those in Figure 2. Sample results are tabulated in Table 1, in which only $K_{\text{step-down}}$ values above $K_{\text{step-down,critical}}$ were considered. As smaller recovery constants are consistent with a very much slower rate of decline in the population of infected Individuals, thus defining a longer period of imposed intervention, this simple analysis clearly suggests that minimum discomfort, including economic cost, is achieved by application of the most severe intervention possible, to recover control in the shortest time frame.

To quantify whether the engineering model and its predictions are reliable, one should fit the decaying functions to available datasets.

Table 1. Recovery rate constants obtained by fitting the decay in the number of infected Individuals (e.g., Figure 2) with an exponential function. The rate constants change as the $K_{\text{step-down}}$ value increases above a critical value, as shown in the datasets below.

| $k_{\text{step-down}}$ | k_{recovery} |
|------------------------|-----------------------|
| 0.990 | 1.715 |
| 0.985 | 1.574 |
| 0.980 | 1.434 |
| 0.975 | 1.296 |
| 0.970 | 1.159 |
| 0.965 | 1.025 |
| 0.960 | 0.889 |

3. Examples of Intervention: China, South Korea and Singapore

The WHO data base was examined because it provides up to date time sequences of new infective cases, total infections and deaths broken into nations. The original choice of a model dealing with infection levels rather than mortality figures was deliberate as the infective levels model is much simpler than one attempting to predict disease outcomes given the acknowledged correlation of age on outcome and the additional effect of the quality of available health care.

To assess the reliability of the engineering model, China, South Korea and Singapore were chosen as examples of intervention based on several criteria, including:

1. Early encounter with disease; proximity to the origin of the disease meant that all 3 nations experienced growth in effective numbers early, with the result that the consequences of intervention were well defined. Many other nations which had a delayed encounter with the Covid19 pandemic are still experiencing unmoderated exponential growth, and thus provide no evidence to assessing the consequences of intervention.
2. Substantial cohort numbers; in association with point 1, the examination of large national cohorts of infection will act to reduce the noise in the time sequence and allow a better assessment of the correspondence between model and actual data.

3. Cultural Similarity; the exponential growth constant defined for the disease is determined by the frequency and efficacy of transfer by immediate (person-person) or secondary (person-object/airborne-person) contact. It is appreciated that this is strongly influenced by cultural norms of social contact. Similarly, the effectiveness of disease control measures, such as social distancing, increased sanitization and enforced lockdowns will be defined by the cultural norms of the societies concerned. As such, choosing 3 nations which are acknowledged as culturally similar provides a common basis to support valid comparison. The use of Hofstede's index of cultural similarity is employed to this end, with the 3 nations concerned being defined as culturally similar.^{3,4}

For the cases of South Korea and China,^{5,6,7} the number of new infected Individuals per day was plotted vs. total number of infected Individuals. The relationship is of the form:

$$Z(t) = Y(t) \times (\exp((k_3 - k_2) \times \Delta t) - 1) \quad [9]$$

Where $Z(t)$ is the number of new infected Individuals per day, $Y(t)$ is the total number of infected Individuals, and delta Δt is the time interval between data points, usually a day. The data are presented over several orders of magnitude in a log-log plot, which shows the expected linear relationship typical of unmoderated exponential growth. Deviation from this linear relationship at low levels of infection is evidence of the control of the disease through social distancing and lockdowns, which have reduced the growth constant. In some cases, changes in behaviour can be the natural response to the perceived risk of infection, and not necessarily due to government intervention.

Comparison of the salient features of the 2 curves (un-moderated growth and moderated growth) may be achieved through quantification of two dimensionless ratios, which may be used to compare the 2 countries. The two ratios are A/B and C/D , where the letters have the following meanings:

- A represents the extrapolated number of cases per day which would have been expected from the exponential growth at the case number asymptote;
- B is the maximum encountered cases per day;
- C is the number of cases at the time of maximum number of new cases/day;
- D is the disease propagation asymptote, representing the total number of infected Individuals at the conclusion of the outbreak, when local control has been achieved.

The data reported by WHO for South Korea and China, plotted in the formalism of Eq. [9] are plotted in Figure 3. From these graphs the points A, B, C and D are extracted for these two case studies.

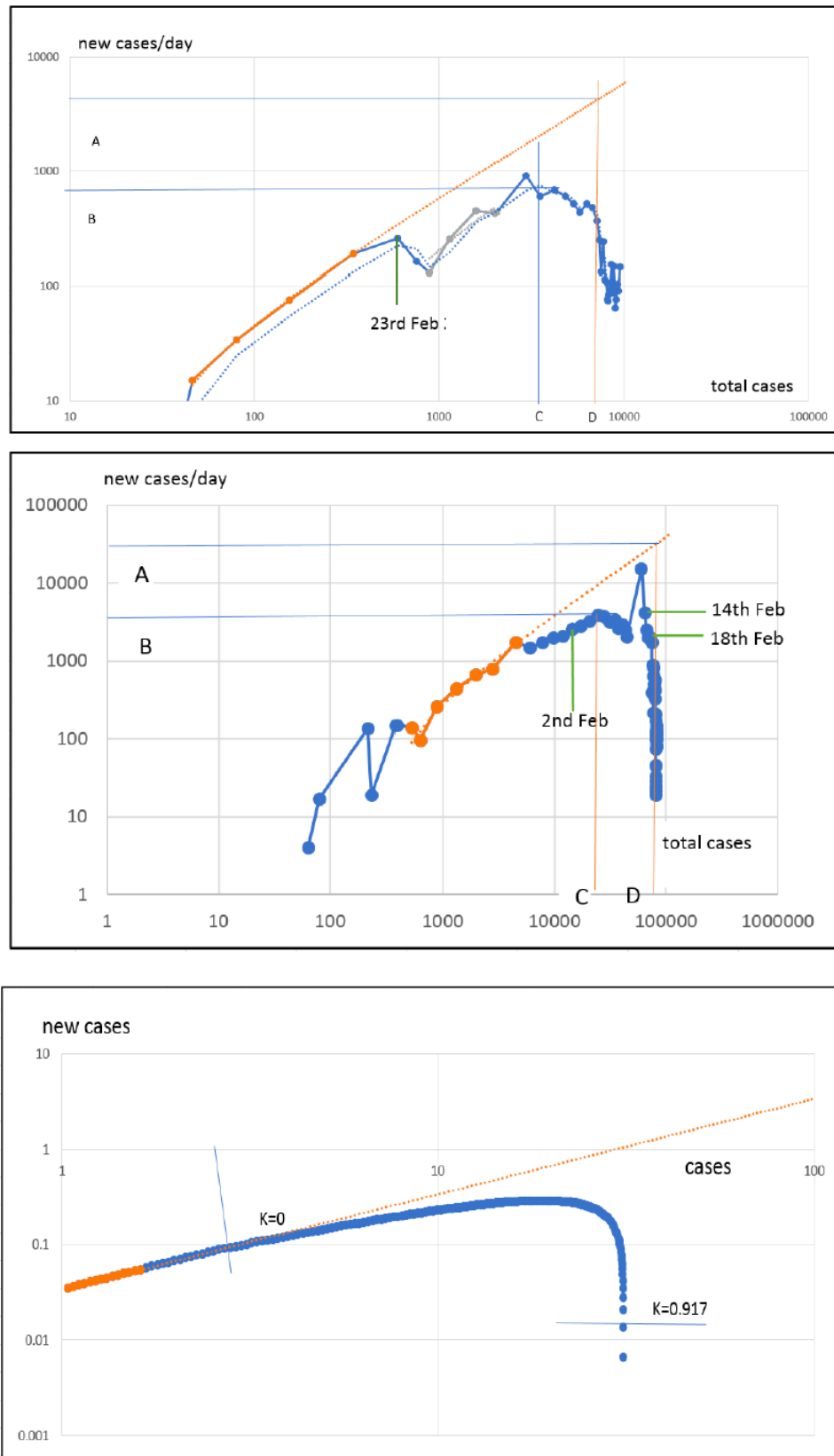


Figure 3: New cases/day versus total cases for South Korea with initial unmoderated exponential growth in orange. In blue we highlight the growth rate after the isolation / lockdown initiatives were implemented. In the left panel we report analysis for South Korea, with the 23rd February – the date of the first government self-isolation – isolated. Further initiatives were undertaken on the 14th and the 18th February, as indicated. In the middle panel we report the analysis of data from China. In the bottom panel we present model results in which $K_{\text{step-down}}$ varies linearly over time, as described by Eq. [10]. The plot clearly shows that the number of new infected Individuals per day decreases as $K_{\text{step-down}}$ increases.

4. Extension of the engineering model

In order to model the curves in Figure 3, a varying $K_{\text{step-down}}$ parameter was applied, rather than a constant value as was the case in Eq. [7], via:

$$K_{\text{step-down}} = 1 - \text{const} \times t^N \quad [10]$$

Eq. [10] reflects the fact that compliance with social distancing and lockdown directives took time to take effect and thus $K_{\text{step-down}}$ decreases with time to some final value. Fitting Eq. [10] to the data via the model detailed earlier yields the graphical results plotted in the bottom panel of Figure 3.

The results show the progression of the new cases versus total cases for $K_{\text{step-down}}$ transitioning linearly (N in Eq. [10] equals 1) with time from $K=1$ down to $K= 0.083$. Only when $K_{\text{step-down}}$ has reached values very close to 1 is control achieved.

If the time units in the simulation results of Figure 3 are scaled to match the South Korean dataset, the transitioning period required to achieve control on the spread of the disease corresponds to 5.8 days. It is encouraging to note that such time frame corresponds to WHO data.

Investigation of the effects of the rate constant, and the parameters defining the time variation of the step-down constant were explored to achieve the closest correspondence to the modelling results plotted for South Korea and China. The results, tabulated in Table 2, indicate that it is possible to scale the engineering model to reproduce WHO data. The fit of the South Korean data is more promising than the one on the Chinese data, as shown by the data in Table 2.

Table 2: Growth curve analysis salient for South Korea and China datasets.

| Country | K growth day-1 | A/B | C/D | Comments |
|-------------|----------------|--------------|---------------|-----------------------|
| South Korea | 0.6706 | 6.405- 7.205 | 0.5606-0.5706 | |
| China | 0.3364 | 8.175-8.3009 | 0.2958 | |
| Model | 0.6706 | 3.9277 | 0.6078 | Scaled to Korean data |

While the presentation of the data as shown in Figure 3 is useful in identifying the departure from the initial exponential growth, the presentation of the data in linear form enables a better comparison of WHO data to the model. For such purposes, the data are normalised to the maximum number of new cases, which also enables the comparison among different datasets. Such comparison is shown in Figure 4, where the favourable alignment of the different datasets is evident when one discards the peak in new cases reported in the dataset from China after the first maximum. The spike after the peak in Chinese data is interpreted as an influx of identified cases due to delayed identification.

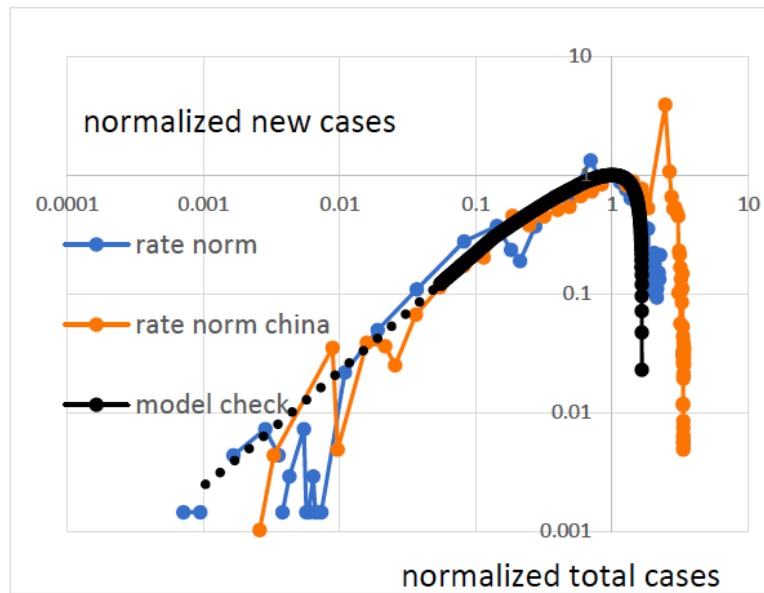


Figure 4. Normalized new cases/unit time versus normalized total cases for South Korean, Chinese and model data, with normalized new cases axis scaled to emphasize main body of data and good correspondence between South Korean, And Chinese results with model.

While in both China and South Korea the analysis suggests that the spread of the virus has been limited and the situation seems to be under control, it is possible, based on the results shown in Figure 2 (orange data), that nations achieve short-term control, but then to lose it due to a decline in compliance, or to a premature lift in the isolation / lockdown initiatives. Recent data from Singapore shows evidence of a flattening of the growth rate and new cases per day falling temporarily to zero, before growth is resumed. The WHO data from Singapore are analysed via our engineering model in Figure 5. Indeed, the increasing slope of the log total cases versus time graph for Singapore after the loss of control shows an accelerating growth rate consistent with a declining $K_{\text{step-down}}$, consistent with increasing noncompliance to social distancing and health initiatives.

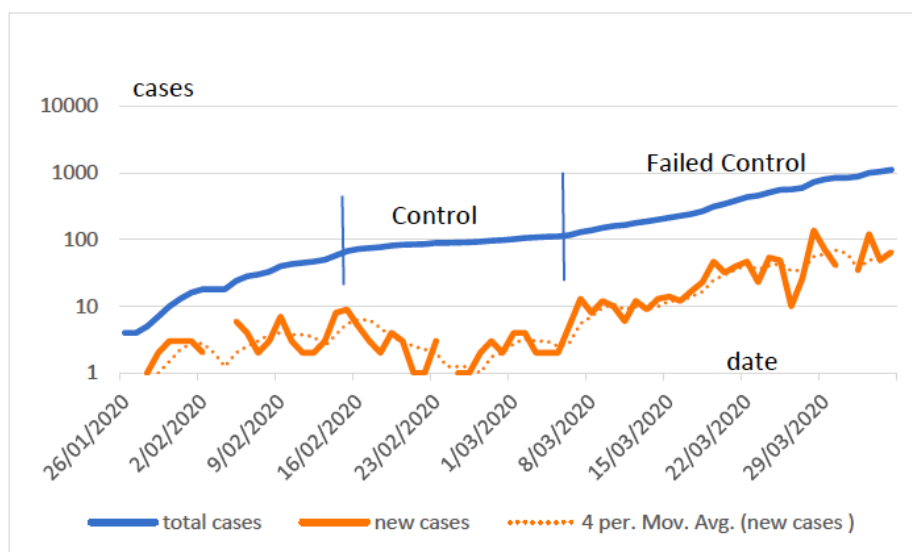


Figure 5. Total cases and new cases per day for Singapore showing evidence of control being first achieved, and then lost.

5. Discussion of Results and Conclusions

The engineering model utilizing a linear decline of $K_{\text{step-down}}$ with time to reflect increasing compliance to the application of social distancing and lockdown initiatives achieves good agreement with the South Korean and Chinese data. A late spike in new cases has been reported in China, which is not consistent with the engineering model's predictions. However, this spike is ascribed to changes in data acquisition and reporting.

The most significant conclusion is that $K_{\text{step-down}}$ needs to achieve ~ 0.92 to mitigate the spread of a virus such as COVID-19; that is to say to the frequency of social interactions needs to be reduced by more than 10-fold compared to the conditions our societies are familiar with.

In the case of South Korea, the time from reaching 100 confirmed cases to the point of maximum case numbers/day (909) was only 9 days, after which a clear decline in daily case numbers is seen.

In China, 18 days were required to reach the daily new cases maximum of 3872 infected Individuals, after which a clear decline is noted.

Examination of the model, and of its application to the Singapore case study, indicated that the application of insufficient social intervention will yield the appearance of achieving control, with a reduced number of new cases per day for a period, after which new case numbers will increase and grow. The recent data from Singapore provides evidence of control achieved and then lost, which is interpreted as consistent with a failure to adhere to health.

Analysis of the data supports the following conclusions:

- At low levels of infective presence, the number of infected Individuals may be modelled as complying to an exponential approximation, and any departures from this are evidence of changes to the growth rate constants in the propagation of the disease.
- The application of governmental intervention in social distancing and lockdowns can mitigate and control the virus trajectory, but only if a high degree, 10-fold decrease in usual social interactions (as defined by high $K_{\text{step-down}}$ values in the model) is achieved.
- For insufficient $K_{\text{step-down}}$ values control is not achieved.
- When the compliance with the governmental regulations is sufficiently high, there is a correspondence between the exponential decline in case numbers and the severity of the governmental initiatives. A very much shorter recovery time, lower numbers of infected Individuals, and smaller economic costs are achieved by applying the most severe isolation initiatives, which will need to be applied for a shorter time.
- A reduction in new cases per day does not indicate that control is achieved and can be misleading because a relaxation of compliance to health initiatives will cause a resumption of exponential growth.
- This simple analysis supports the argument that a severe but short-term lockdown will achieve the best outcome.

The analysis above was concluded on April 13th, 2020. Since then, encouraging reports have appeared in the news, suggesting that the lockdown strategies in several countries are yielding the expected positive effects. In response, some governments have initiated easing of the isolation/lockdown initiatives. While in some countries such as New Zealand the spread of Covid-19 seems to be under control as of April 28th, in other countries, for example Germany, recent reports seem to suggest that the Covid-19 trajectory has picked up momentum again. Time will tell what the best strategy will be to manage this virus, but our simple model suggests that it might still be premature to lift isolation/lockdown initiatives.

It should be recognized that the model presented here is a simple engineering model, which does not take into account the physical mechanisms by which Covid-19, or any other virus, spreads. The model also does not explicitly quantify the economic nor societal implications of isolation/lockdown

initiatives. It instead implicitly assumes a correlation between the number of infected individuals and the negative effects due to Covid-19.

Funding Statement

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Declarations and Conflicts of Interests

The Authors declare no conflicts of interest. Mr King developed the model and conducted the analysis. Dr Striolo contributed to the discussion and helped write the manuscript.

References and Notes

¹ Our World in Data: <https://ourworldindata.org/coronavirus-source-data>, website accessed on 02/02/2020.

² B. Carnahan, H.A. Luther, J.O. Wilkes, Applied Numerical Methods, Reprint, Krieger Pub. Co., 1990; originally published: New York: Wiley, 1969.

³ Hofstede comparison, from the website: <https://www.hofstede-insights.com/country-comparison/china,singapore,south-korea,the-uk/>, accessed on 02/04/2020.

⁴ Hofstede's index examines 6 parameters as definers of public and private culture:

- Power distance; expectations within a society of the distribution of authority;
- Individualism; perception of society as defined by individual or collective interests;
- Masculinity; balance between competitive versus caring;
- Uncertainty avoidance; degree of focus on security;
- Long term Orientation; focus on future planning;
- Indulgence; immediate versus delayed gratification of wants.

⁵ A Timeline of South Korea's response to Covid-19; Centre for Strategic & International Studies Victor Cha, Dana Kim, accessed on 27/03/2020: <https://www.csis.org/analysis/timeline-south-koreas-response-covid-19>

⁶ https://en.wikipedia.org/wiki/Timeline_of_the_2019–20_coronavirus_pandemic_in_February_2020#Events,_reactions,_and_measures_in_mainland_China, accessed on 27/03/2020

⁷ http://www.xinhuanet.com/english/2020-04/06/c_138951662.htm, accessed on 02/04/2020.