COVID-19: measuring the impact on healthcare demand and capacity and exploring intervention scenarios

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1 Introduction

The resurgence of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) (now commonly known as COVID-19 [11]) and its mutant variants (for example, the UK variant known as VUI–202012/01) are putting National Health Systems (NHS) in most western countries under significant pressure/strain due to an increase in COVID-19 hospitalisations and the provision of critical care for patients in need. The new UK variant, VUI–202012/01 or lineage B.1.1.7, was first announced by M. Hancock, the UK Health Secretary, on 14th December 2020. Subsequently confirmed by Public Health England and the UK’s COVID-19 sequencing consortium [27], its origins were then traced through databases of SARS-CoV-2 to the county of Kent on the 20th September 2020. Since then, cases of the new variant have been confirmed in the UK and mainland Europe and is thought to be a key driver of the resurgence of COVID-19 infections across many parts of the country. The UK government has responded to this new surge in infections by placing some regions, including Greater London, under new stricter coronavirus restrictions, known as Tier 4. For example, people in Tier 4 areas or regions are not allowed to gather with anyone outside their household, while those in the rest of the country can only gather under less stringent conditions. Tier 4 represents a stay at home order, where non-essential shops, gyms and hairdressers are closed. Proposals to move into Tier 5 are currently under consideration and this will be the equivalent of the national lockdown experienced during the first wave of COVID-19. It is reported that the new variant could increase transmission of COVID-19 by as much as 70% and increase the reproduction number $R_t$ by 0.4.

As a result, critical care in most western countries is currently undergoing enormous strain due to a rapid increase in healthcare demand and capacity for COVID-19 patients [3]. In the UK, NHS hospitals are at their most vulnerable during the winter period and COVID-19 is contributing significantly to huge strains on the provision of critical care. The bed capacity for non-COVID patients is being diverted at an alarming speed to provide invasive ventilated and/or critical care
bed capacity for COVID-19 patients. This implies that vacant and/or available bed capacity is also under huge demand and in some cases, is fast running out. In some cases, emergency responders seek to find the closest bed available rather than the closest hospital due to shortages of COVID-19 critical care capacity. Hence, it is imperative that local hospitals have clear and well-defined interventions to understand and mitigate the impact of COVID-19 hospitalisations as well as critical planning on death management, mortuary and funeral care provision. As of 28th December 2020, the UK has seen over 70752 deaths, and more than 2.3 million COVID-19 cases. In this study, we present plausible intervention measures within the Sussex region of the UK where hospital bed capacity and demand are currently experiencing enormous strain from COVID-19 patience and burial capacity is at an all time high.

As local NHS Hospital Trusts are seeing record numbers of people with COVID-19 requiring hospitalisation and subsequently critical care, NHS managers, planners and healthcare analysts are struggling to make robust and accurate predictions due to the lack of a national model applicable at regional levels. This study plugs this gap by proposing an SEIR-D model that is fitted to local NHS datasets and is driven by novel statistical methods and techniques for parameter estimation [4]. The resulting computational framework allows us to predict and forecast COVID-19 hospitalisations and deaths in a more quantitative approach that allows NHS managers and Public Health Analysts to plan accordingly. Our aim is to provide scenarios and situational awareness driven by an epidemiological model using real-time data to simulate the effects of various public policy interventions.

In the literature, there is a plethora of pre-prints and peer-reviewed articles that present work on forecasting COVID-19 dynamics [4, 7, 10, 11, 12, 14, 16, 18, 21]. However, most of these works use national datasets which are then averaged for regional purposes [24]. Furthermore, very few studies couple dynamical models with statistical inference techniques in a rigorous approach [25, 26]. The novelty of our approach is reflected in two strands: (i) we couple innovatively a data-driven SEIR-D model such that the flow compartments are directly linked to the available data and (ii) an observational model, in terms of rewriting the SEIR-D model purely in terms of the observable and obtainable data, is derived that allows to fit the model to data and rigorously justify uniqueness of the parameters and their identifiability [4]. Our computational modelling approach is then rigorously validated with current datasets as well as with subsets of the data to demonstrate the forecasting capability of our techniques. Such an approach has the capability to make forecasting long into the future with high accuracy provided the parameters do not undergo changes, like a change in average transmission due to the region going from tier 3 to tier 4 for example. In this work, we will use this approach to measure the impact of COVID-19 hospitalisations on healthcare demand and capacity through COVID-19 forecasting as well as exploring intervention scenarios under which bed capacity may be breached. This allows for robust and agile NHS planning and management.

2 A data-driven SEIR-D model

In this section we will present a simple data-driven susceptible-exposed-infected-recovered-dead (SEIR-D) model proposed in [4] which breaks down the typical infectious compartment of an SEIR-
D model into two compartments, one strand to model individuals who become infectious with COVID-19 and will be going to hospital, and the other strand to model individuals who will not need to go to hospital and thus remain undetected by hospital healthcare requirements. Using this model we will explore some theoretical uses of these models by modelling an intervention as a social distancing effect, by reducing the average transmission rate, as well as modelling early warning indicators. Throughout this study we will be measuring the “success” of an intervention by the percentage of individuals who have died throughout the simulation, in the sense that reducing this statistic means a more successful intervention. Note, although the parameters are inferred using Sussex regional datasets, the results and outputs in this study are hypothetical and are used for theoretical purposes to gain an insight on plausible management or policy-related scenarios.

As part of the national COVID response, all the National Health Service (NHS) hospitals in England treating COVID-19 patients submitted a Daily Situation Report to NHS England. The Sussex regional data was then sent to the Sussex Clinical Commissioning Group (CCG) who aggregated the data and combined it to occurrences of deaths per week in the death data from the Office of National Statistics (ONS). This is the main reason as to why the model is configured using the two strands, as demonstrated in Figure 1. The hospital dataset contained daily hospital admissions, the red dashed arrow from the $I$ compartment to the $H$ compartment in Figure 1, daily discharges, the red dashed arrow from the $H$ compartment to the $R_H$ compartment in Figure 1 and daily occupancy, the red dashed $H$ compartment in Figure 1. The death dataset contains the weekly number of deaths recorded outside of hospitals, the red dashed arrow from the $U$ compartment to the $D_U$ compartment in Figure 1 and the weekly number of deaths recorded within hospitals, the blue double dashed arrow from the $H$ compartment to the $D_H$ compartment, with COVID-19 as the underlying cause of death.

The mathematical model takes the following form of a simple temporal epidemiological dynamic sys-
tem of ordinary differential equations, governed by the interactions depicted in Figure 1, supported
by non-negative initial conditions

\[
\begin{align*}
\dot{S} &= -\beta \frac{U + I}{N} S, & t \in (0, T], & S(0) = N - 1, \\
\dot{E} &= \beta \frac{U + I}{N} S - \gamma_E E, & t \in (0, T], & E(0) = 1, \\
\dot{U} &= p \gamma_E E - \gamma_U U, & t \in (0, T], & U(0) = 0, \\
\dot{I} &= (1 - p) \gamma_E E - \gamma_I I, & t \in (0, T], & I(0) = 0, \\
\dot{H} &= \gamma_I I - (\gamma_H + \mu_H) H, & t \in (0, T], & H(0) = 0, \\
\dot{R}_U &= (1 - m_U) \gamma_U U, & t \in (0, T], & R_U(0) = 0, \\
\dot{R}_H &= \gamma_H H, & t \in (0, T], & R_H(0) = 0, \\
\dot{D}_U &= m_U \gamma_U U, & t \in (0, T], & D_U(0) = 0, \\
\dot{D}_H &= \mu_H H, & t \in (0, T], & D_H(0) = 0.
\end{align*}
\]

Here, the dot above the notation denotes the time derivative. In this setting, let \( N \) denote the
total regional population in the Sussex region of the UK (with \( N \) approximately 1.7 million, as per
the ONS Mid-Year Estimates in 2018). Then, \( S(t) \) denotes the proportion of the total population
\( N \) who are susceptible to the disease, COVID-19. Susceptible individuals become exposed to
the disease, i.e. they are carrying the disease but are not currently infectious, to form the \( E(t) \)
subpopulation at rate \( \lambda(t) \) which represents the current infectivity. The rate \( \lambda(t) \) is the product
between \( \beta \), the average transmission rate, and the probability of meeting an infectious person
\((U(t) + I(t))N^{-1}\). The \( E(t) \) subpopulation is an incubation compartment and further evolves in
two ways. A proportion of \( E(t) \) becomes infectious but, in the spirit of the hospital healthcare
demand, remains undetected with probability \( p \), denoted \( U(t) \), at a rate \( \gamma_E \), or a proportion of \( E(t) \)
becomes infectious and will require hospitalisation in the future with a probability of \( 1 - p \), denoted
\( I(t) \), at a rate \( \gamma_I \). The \( I(t) \) subpopulation that does not require hospitalisation can either progress
to recover with a probability of \( 1 - m_U \), at rate \( \gamma_U \), to form the recovered population, denoted
by \( R_U(t) \), or die with a probability of \( m_U \), at rate \( \gamma_U \), to form the dead population, denoted by
\( D_U(t) \). Considering the infectious population that will be going to hospital, these individuals will
become hospitalised, denoted by \( H(t) \), and thus be in hospital care at rate \( \gamma_H \). We assume that once
a patient has been admitted into hospital, they are no longer infectious or rather they no longer
transmit to other non-COVID-19 patients, visitors or workers. Once in hospital, patients can evolve
in two separate pathways, a proportion of the hospitalised population can fully recover at rate \( \gamma_H \)
to form the subpopulation denoted by \( R_H(t) \). Alternatively, if they can not recover, then they
die while in hospital at rate \( \mu_H \), to form the dead population denoted by \( D_H(t) \). The outbreak is
regarded to have been contained at a time \( T > 1 \) such that \( E(T) + U(T) + I(T) < 1, \mathcal{R}_t < 1 \) and
there is no ongoing intervention. This implies that there are no more infectious individuals within
the population and thus the system has reached its steady state.

As is standard for epidemiological models of this nature, \( \beta \) denotes the average transmission rate,
\( \gamma_E^{-1} \) denotes the average incubation time, \( p \) denotes the proportion of infectious individuals who
will not require hospital treatment, \( \gamma_U^{-1} \) denotes the average infectious period for those not needing
hospital treatment, \( m_U \) denotes the infected fatality ratio for undetected cases, \( \gamma_H^{-1} \) denotes the
average infectious period from becoming infectious to being admitted to hospital, \( \gamma_I^{-1} \) denotes the
average hospitalisation period for those who recover and $\mu_H^{-1}$ represents the average hospitalisation period for those who die.

In [4] we use the equations (2.1)–(2.9) to infer values of the model parameters which best fit the available NHS England datasets provided at the time. These are displayed in Table 1. The data used to fit the model was recorded during the first lockdown in March 2020 within the UK and is reflected in the value of $R_0$. Using the method of next generation matrices [9], we derive the formula for $R_0$ as the following

$$R_0 := \beta \left( \frac{p}{\gamma_U} + \frac{1-p}{\gamma_I} \right) \approx 0.85. \quad (2.10)$$

Progressing through this study we will scale $\beta$ so that there will be an epidemic.

| Parameter | Value          | Epidemiological meaning                              |
|-----------|----------------|------------------------------------------------------|
| $\beta$   | $0.151 \text{ days}^{-1}$ | Transmission rate                                      |
| $\gamma_E^{-1}$ | 6.51 days     | Average incubation period                            |
| $p$       | 0.929          | Fraction of undetected cases                         |
| $\gamma_{U}^{-1}$ | 6.10 days   | Average infectious period (undetected cases)         |
| $\gamma_{I}^{-1}$ | 6.28 days   | Average infectious period (hospital cases)           |
| $\gamma_H^{-1}$ | 19.74 days | Average hospitalisation period (recovered)           |
| $m_U$     | 0.022          | Infected fatality ratio (undetected cases)           |
| $\mu_H^{-1}$ | 12.91 days   | Average hospitalisation period (deaths)              |

Table 1: Description of the SEIR-D model parameters in (2.1)–(2.9), and their estimated inferred values as presented in [4].

We numerically approximate the solutions to the system (2.1)–(2.9) by using the SciPy implementation of the Fortran ODE solver lsoda, which is a combination of the Adams methods and the Backward Differentiation Formula (BDF) family of methods [3, 15, 23]. Given the multi-step approach of the ODE solver, each time we manipulate the parameters during a simulation, to initiate an intervention, we stop the current solver and start it again using initial conditions as the final values of the last solver. This bypasses difficulties of having a discontinuous ODE system. One notes that this can also be bypassed by using a much simpler solver, like the forward Euler scheme, however this would result in the need for significantly smaller timesteps.

3 Intervention measures based on hospital occupancy

3.1 The “do-nothing” approach

As a reference point to how the interventions are working, we use this section to demonstrate the “do-nothing” approach, which is simply to let the disease take its course. This will provide us with statistics to compare to the interventions later on to demonstrate their effectiveness. In reality, we are aware that this approach will not be implored and an intervention will occur, as has
happened all over the globe with national level lockdowns and social distancing measures. Since the parameters presented in Table 1 depict a lockdown scenario, we scale \( \beta \) accordingly to several values to establish an epidemic, i.e. so that \( R_0 > 1 \). An increase in average transmission rate can simply be interpreted as more individuals meeting each other and spreading the disease. In Table 2 we measure the maximum hospital capacity needed, the day in the simulation that maximum is reached and the percentage of dead individuals at the end of the outbreak. In Figure 2 we demonstrate the effective reproduction number \( R_t \), calculated by

\[
R_t := R_0 \frac{S(t)}{N}.
\]

As intuitively expected, as \( R_0 \) increases the maximum number of patients in the hospital increases, the day of that peak is sooner and the percentage of dead individuals increases. Similarly, the actual outbreak is much shorter in length and reaches much smaller values of \( R_t \). This description follows the notion that the larger the value of \( R_0 \), the more aggressive the disease is following the exponential growth of those who are infectious, as can be seen in Figure 2 by the steep decline in \( R_t \).

| \( R_0 \) | Max hospital occupancy | Day of peak of hospital occupancy | % dead individuals |
|---|---|---|---|
| 1.3 | 2135 | 564 | 2.67% |
| 1.4 | 3328 | 451 | 3.23% |
| 1.5 | 4593 | 379 | 3.68% |
| 1.6 | 5882 | 330 | 4.05% |
| 1.7 | 7161 | 294 | 4.36% |
| 1.8 | 8411 | 266 | 4.63% |
| 1.9 | 9620 | 244 | 4.84% |
| 2.0 | 10781 | 226 | 5.03% |

Table 2: Measurements using the “do-nothing” approach.
Figure 2: $R_t$ using the “do-nothing” approach.

3.2 Intervention

In the following sections we want to investigate how one can use hospital capacity as a measurement for whether interventions are put into place. We aim to model the situation where an intervention is triggered when hospital capacity is almost full, and then finish the intervention when the hospital capacity has reached an “opening” threshold, denoted $\beta_t$, of significantly lower patients. For ease of computation we will simply set a threshold that once breached will trigger the intervention. It is well known that post-intervention spread of an infectious disease is actually sub-exponential [20], in the sense that contacts will still be reduced from the pre-intervention amount for a period of time after an intervention has finished, however we do not consider this here as it will simply elongate the outbreak. For this investigation we will initiate an intervention once 800 patients are in hospital. This takes the form

$$\beta(t; \ell) := \begin{cases} 
\beta & \text{if } H(t) > 800, \\
\beta & \text{if } H(t) > \beta_t \text{ and } \ell = 1, \\
C_{R_0}\beta & \text{otherwise,}
\end{cases}$$

where $\beta$ is defined as in Table I, $\ell$ is set to 1 when $H$ goes above 800 and is then set to 0 when $H$ drops to below some threshold $\beta_t$, and $C_{R_0}$ is the scaling constant that allows the system to be in an epidemic. One thing to consider with this study is that we are considering the capacity of all the hospitals in Sussex as one due to modelling constraints and data access. This means that we are assuming hospitals can move patients around throughout Sussex due the physical constraints of each hospital, in response to the bed capacity of each individual hospital.
3.3 Changing $R_0$

In this section, we will be changing $R_0$ and setting $\beta_\ell = 200$ or $\beta_\ell = 400$ patients for the threshold to finish the intervention. In Tables 3 and 4 we measure the number of interventions needed, the length of each intervention, the day of the initiation of the intervention and the percentage of total deaths at the end of the epidemic. We demonstrate a few of the simulations in Figure 3 and illustrate the effective reproduction number over each outbreak in Figure 4. The black (dashed) lines in each plot depict when the intervention has occurred.

Comparing Table 2 to Tables 3 and 4 we can see that the intervention has dramatically decreased the percentage of total deaths for larger values of $R_0$, as expected. We can see that as we increase $R_0$, the number of interventions needed increases and also the length of the initial intervention increases. This is due to the number of future patients in the exposed compartment $E$ and the infectious compartment $I$. This is emphasised by the fact that the initial intervention is sooner for a larger value of $R_0$ due to the increased average transmission. It can also be seen that the time between each intervention decreases as $R_0$ increases. We can also see, by comparing Figure 2 with Figure 4, that the epidemic actually lasts significantly longer. These observations are realistically expected, however there are some results which are not necessarily expected or intuitive like the percentage of total dead for $R_0 = 1.9$ being smaller than for $R_0 = 1.8$ in Table 3 but not in Table 4. This is not specific to this value of $R_0$, rather to the circumstance that this simulation finds itself after the final intervention. Namely, at this stage of the simulation for $R_0 = 1.9$, herd immunity has almost been reached, i.e. $R_t$ is only slightly larger than 1. A value of $R_t$ slightly larger than 1 means that although there is still an increase in the number of infectious individuals, the rate of that increase is much slower comparatively to an $R_t$ value of, say, 1.5. At this stage, the number of incubating and infectious individuals in the case of $R_0 = 1.9$ is also small which means that the final bump in the simulation for $R_0 = 1.8$ is much larger than the respective bump for $R_t = 1.9$ (the bump for $R_0 = 1.9$ reaches no more than 300 individuals rather than over 600 for $R_0 = 1.8$). This interplay between parameter values, herd immunity and $R_t$ is difficult to analyse and demonstrates that intuition is not necessarily enough to predict the best plan of action.

| $R_0$ | Length and # of interventions | Day of intervention initiations | % total deaths |
|-------|-------------------------------|--------------------------------|---------------|
| 1.3   | 152 days                      | 466                            | 2.19%         |
| 1.4   | 155, 128 days                 | 337, 604                       | 2.35%         |
| 1.5   | 158, 118, 60 days             | 292, 515, 755                  | 2.46%         |
| 1.6   | 159, 114, 111 days            | 249, 461, 653                  | 2.97%         |
| 1.7   | 161, 112, 103, 154 days       | 218, 423, 595, 798             | 3.00%         |
| 1.8   | 162, 111, 98, 106 days        | 195, 396, 558, 727             | 3.40%         |
| 1.9   | 163, 112, 97, 99, 174 days    | 177, 375, 530, 685, 881        | 3.35%         |
| 2.0   | 163, 113, 95, 92, 110 days    | 162, 357, 508, 652, 815        | 3.69%         |

Table 3: Measurements using the hospital capacity intervention approach, changing $R_0$ and fixing $\beta_\ell = 200$. 
| $R_0$ | Length and # of interventions | Day of intervention initiations | % total deaths |
|-------|--------------------------------|--------------------------------|---------------|
| 1.3   | 103, 47 days                   | 406, 645                      | 1.98%         |
| 1.4   | 106, 89, 37 days               | 357, 506, 696                 | 2.25%         |
| 1.5   | 110, 86, 96 days               | 292, 433, 566                 | 2.75%         |
| 1.6   | 112, 84, 82, 132 days          | 249, 388, 507, 645            | 2.88%         |
| 1.7   | 115, 83, 76, 83, 31 days       | 218, 356, 468, 582, 747       | 2.98%         |
| 1.8   | 117, 84, 74, 76, 103 days      | 195, 333, 441, 546, 668       | 3.35%         |
| 1.9   | 120, 84, 74, 73, 80, 29 days   | 177, 315, 420, 520, 628, 776  | 3.37%         |
| 2.0   | 120, 85, 73, 71, 75, 112 days | 162, 299, 403, 499, 599, 718  | 3.66%         |

Table 4: Measurements using the hospital capacity intervention approach, changing $R_0$ and fixing $\beta_\ell = 400$.

Figure 3: Number of patients in hospitals using the hospital capacity intervention approach, changing $R_0$ and fixing $\beta_\ell = 200$ or $\beta_\ell = 400$. 

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3.4 Changing $\beta_\ell$

In this section, we will be changing $\beta_\ell$, the lower threshold of patients that signals the ending of the intervention, and setting $R_0 = 1.4$ or $R_0 = 1.5$. In Tables 5 and 6 we measure the number of interventions needed, the length of each intervention (measured in days), the day of the initiation of each intervention and the percentage of the total deaths at the end of the epidemic. We demonstrate a few of the simulations in Figure 5 and we demonstrate the effective reproduction number over each outbreak in Figure 6. The black (dashed) lines in each plot depict when the intervention has occurred.

Comparing Table 2 to Tables 5 and 6 we can see that again the intervention has dramatically decreased the percentage of total deaths compared to the “do-nothing” approach. Interestingly, changing the threshold $\beta_\ell$ does not have that much of an effect on the percentage of total deaths, unlike the difference we saw in Tables 3 or 4 when changing $R_0$, but it does have a large effect on the length of the outbreak. This can also be seen by looking at the length of the interventions, considering $\beta_\ell = 20$, say, the length of the interventions are much longer than for those with $\beta_\ell = 600$. Similarly to the previous section, in Table 5 we see that a threshold of $\beta_\ell = 400$ actually
decreases the percentage of total deaths, whereas the trend would suggest otherwise. Likewise we see this in Table 6 with $\beta_\ell = 200$. If we look at the purple line ($\beta_\ell = 400$) and the dashed red line ($\beta_\ell = 200$) in Figure 5 we see that, after the third intervention, the value of $R_t$ is only slightly above 1 which implies a very slow increase in infections and, as alluded to previously, the state of the system is very close to herd immunity. This slow increase is demonstrated by the difference in the length of the outbreaks and the sharpness of the increase after the final intervention in Figure 5.

Both conclusions made in this section and the previous imply that the timing of interventions and the lengths are extremely important. Getting closer to herd immunity when ending an intervention has the potential to save a huge amount of lives. However, calculating $R_t$ in real life is in general very challenging which leaves the process of timing for herd immunity difficult. One also notices that, although the percentage of total deaths decreases with an intervention, the length of most of the interventions is large due to the criteria set. This is mainly due to the fact that the average hospitalisation period is large and that the scenario we are simulating means that intervention will be in place until hospitals go from full capacity to between 2% and 60% capacity. Fortunately, we see that as the target capacity percentage increases, the percentage of total deaths does not increase dramatically, and the length of interventions decreases from the best part of 10 months to the best part of 3 months. Similarly, as the outbreak progresses, one would expect the average hospitalisation length to decrease, since awareness of the disease and treatment gets better, as well as an increase in resources. This final point is important as it means realistic interventions can be implemented as circuit breakers and still maintain a large decrease in the number of total deaths. However, one aspect of this which is overlooked in this study is the potential for outbreaks within hospitals, whereby the probability of an outbreak increases with a larger number of infectious patients.

| $\beta_\ell$ | Length and # of interventions | Day of intervention initiations | % total deaths |
|-------------|-------------------------------|-------------------------------|----------------|
| 20          | 300, 238 days                 | 357, 906                      | 2.11%          |
| 50          | 243, 201 days                 | 357, 788                      | 2.16%          |
| 100         | 200, 168 days                 | 357, 698                      | 2.23%          |
| 200         | 155, 128 days                 | 357, 604                      | 2.35%          |
| 400         | 106, 89, 37 days              | 357, 506, 696                 | 2.25%          |
| 600         | 75, 66, 78 days               | 357, 450, 541                 | 2.52%          |

Table 5: Measurements using the hospital capacity intervention approach, changing $\beta_\ell$ and fixing $R_0 = 1.4$. 11
| $\beta_\ell$ | Length and # of interventions | Day of intervention initiations | % total deaths |
|------------|-----------------------------|-------------------------------|---------------|
| 20         | 301, 212 days               | 292, 766                      | 2.74%         |
| 50         | 245, 175 days               | 292, 668                      | 2.77%         |
| 100        | 202, 147 days               | 292, 593                      | 2.81%         |
| 200        | 158, 118, 60 days           | 292, 515, 755                 | 2.46%         |
| 400        | 109, 86, 96 days            | 292, 433, 566                 | 2.75%         |
| 600        | 79, 64, 64, 86 days         | 292, 395, 474, 560            | 2.77%         |

Table 6: Measurements using the hospital capacity intervention approach, changing $\beta_\ell$ and fixing $R_0 = 1.5$.

Figure 5: Number of patients in hospitals using the hospital capacity intervention approach, changing $\beta_\ell$ and fixing $R_0 = 1.4$ or $R_0 = 1.5$. 

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3.5 Early warning indicators based on hospital capacity

In this section we will discuss how we can use the above notions of interventions to generate some early warning indicators. We ask the question, how many patients can the hospital take before an intervention needs to be initiated so that the maximum capacity of 1000 patients is never reached? The answer is not as simple as 1000, since there will be a significant number of people in the incubation stage before the intervention occurs, thus going above the 1000 mark, as seen by the red lines ($R_0 = 1.9$) in Figure 3 for example. In this section we measure what that number is for different values of $R_0$ and also how long it takes from the moment there is an intervention to when the occupancy reaches 1000 patients. These two measurements are depicted in Figure 7. We can see that as $R_0$ increases, the cap on the occupancy for the intervention decreases, which is as expected. This measurement is useful as depending on the value of $R_0$, one can know what the cap is on occupancy and thus can judge when to take steps to reduce transmission. We also see that as $R_0$ increases, the time from the initiation of an intervention until the peak also increases, which is not to be expected. This is, however, intuitive since the larger the value of $R_0$ the more patients are expected to be hospitalised, as demonstrated in Table 2. Hence, the quicker the threshold for initiating an intervention is met, as can be seen in the first plot of Figure 7. This means that, in
the intervention phase, a lot more patients need to be admitted to reach the 1000 patient capacity in comparison to a smaller value of $R_0$ but at a similar rate, hence the longer time. The final plot has a larger implication for modelling, namely that we need accurate two-three week forecasting in order to be able to use early warning indicators in this manner.

Figure 7: Early warning measurements considering hospital capacity.
4 Conclusion

In this study, we have presented a computational approach for measuring the impact of healthcare demand and capacity due to surges in COVID-19 infections and hospitalisations. We have used the notion of hospital capacity as a measure for exploring intervention scenarios that will allow hospitals to predict and forecast when demand and capacity are close to being bridged and therefore allow resource allocations where necessary.

The key findings are:

- we have demonstrated that interventions will make a significant impact of the percentage of individuals who will die as a result of COVID-19;
- we have described an easily definable and understandable method of introducing an intervention which doesn’t depend on prior knowledge of when the peak of infections will be;
- we have computationally shown the number of interventions expected for different values of $R_0$;
- we have described a method of using epidemiological SEIR-D systems to derive early warning indicators as to when hospital demand and capacity could be breached.

Our approach is built around using a simple SEIR-D model coupled with novel statistical methods for parameter estimation to allow us to explore various plausible hypothetical scenarios that are of interest to the NHS local planners and death management teams [4]. The theoretical and computational approach has a strong interplay between data and the model, whereby data drives the optimal parameter estimates and these in turn drive model predictions through a dynamic SEIR-D model.

5 Further Work

Given the simplicity of the mathematics for models like (2.1)–(2.9), extra compartments can be added to model other aspects of the outbreak like the use of intensive care units (ICU) or care homes, both useful to have in the model for death management services, provided reliable datasets become available. ICU services will have its own notion of maximum capacity, especially due to the dangerous nature of the units and the increased need for extra resources such as ventilation assistance, and the results here can easily be extended to include conditions on the ICU compartment that can be included in the equations.

Another aspect of the outbreak which we have not included in this study is the possibility of re-infection post recovery [27, 28]. This would turn the model from an SEIR-D type model into an SEIS-D type model [1], which brings forward a whole host of new questions to be asked and answered. On a similar vein, the current research into vaccines will prove pivotal in the role to stop COVID-19 [2, 19]. Mathematically, the addition of a vaccine into the model has been undertaken...
in previous works of this nature [13], but as with the other aspects we have mentioned, getting reliable data and understanding the appropriate mathematical additions remains the challenge.

An oversight of the work here is that the county is not homogeneous with respect to age. Different age-groups have different social structures, something which we have not explored in this work. In general, the lockdown we impose on our system is a total lockdown of all ages, similar to the national lockdown during the first wave, however utilising age-groups within the model will allow for dedicated forecasting into the effect some social events like schools opening or returning to offices will have on interventions [8, 17, 22].

Sticking to the model presented here, we can take steps forward to consider that maximising capacity and having longer lockdowns might not be more beneficial than small “circuit breaker” lockdowns when one considers the cost of hospital use and the local economy. For example, by associating a cost to hospital usage or to a lockdown in general, we can find the threshold $\beta_f$ or maximum capacity threshold to go into a lockdown such that, for a specific value of $R_0$, we minimise the total costs by using some of the measurements we presented here such as the length of lockdown, number of lockdowns, and the time until the peak from the initiation of a lockdown. A similar study was conducted in [10] where they calculated the cost of capital (e.g. extra hospitals, provision of hand-washing stations) and one-time costs (e.g. hiring consultants to adapt policy, prepare online training courses), the cost of commodities (e.g. extra single use masks, specific increase in drugs) and the cost of human resources (e.g. extra doctors, extra cleaners) and combined it with the estimated number of cases from the Imperial College model [11] after four weeks and twelve weeks, using an increase and decrease of 50% transmission rate for an interval of costs. Since their model is on a national scale and uses national derived parameters, one can extend their results to Sussex by using our fitted model.

From a practical perspective, the next question to ask is: now we know what levels the hospital can take, what about the recovery procedure? It is well known that recovering from COVID-19 is not as easy as recovering from the common cold [5, 29]. In this sense, it is natural to extend the model here to include, what the Clinical Commission Group (CCG) label as, the discharge pathways, which describe the nature of the discharge of a patient and what recovery services they will need. Each pathway describes the level of need of a discharged patient, each level having an associated requirement and cost. Hence the following question arises: what will the burden to healthcare across the country be in one year, five years, and so on? Understanding the pressure on the discharge pathways due to COVID-19 may give an indication on recovery costs post COVID-19 infection and/or hospitalisation.
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