An Interactive Tool for Enhancing Hospital Capacity Predictions Using an Epidemiological Model

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ABSTRACT

Hospital managers have limited resources, and they have to plan on how best to allocate these resources based on predicted demand, which is often based on linear or exponential models. In this paper, we propose an interactive tool that produces a forecast of bed occupancy based on an epidemiological model. We optimise this model to fit recently observed data, and interactivity is conferred through a controllable parameter of the model such that users can readily investigate hypothetical scenarios for planning purposes. This study was designed with the Welsh National Health Service, and was born out of their practical need of accurately modelling hospital occupancy during the ongoing Covid-19 pandemic.

CCS CONCEPTS

• **Human-centered computing → Interactive systems and tools**.

KEYWORDS

SEIR model, hospital occupancy, Covid-19, multimodal problem.

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1 INTRODUCTION

As a manager of a hospital, how do you make decisions on organising your resources when you are faced with a pandemic and increasing influx of severely sick patients? One approach is to look at the recent data on the number of hospital occupants, and extrapolate to forecast the expected numbers in the short term and allocate resources accordingly. This issue becomes critical when one expects a sharp increase in bed occupancy that could strain the health service, as it has been the case in several countries during the ongoing COVID19 pandemic. For forecasting, our stakeholders originally used linear, and sometimes exponential, regressors. Here the linear model gave a best guess, while the exponential model indicated the worst case scenario. As they had to respond to the pandemic quickly, these *ad hoc* measures were necessary, and this approach helped make solid plans in the short term. Nonetheless, it is desirable to utilise an epidemiological model of the disease for forecasting instead. In this short study, we present an application of the well-known SEIR compartmental model [2] for Covid-19 to aid resource allocation planning in a hospital. Furthermore, the tool developed in this work enables users to interactively change a controllable parameter of the model, and investigate hypothetical scenarios for contingency planning.

2 SEIR MODEL

The SEIR model for infectious diseases consists of four compartments: Susceptible (S), Exposed (E), Infectious (I) and Recovered (R). Typically, everyone will start their journey through the model in the S compartment, where they are susceptible to the disease. At least one member of the population gets infected, and at this point they become *exposed* to the disease, but not yet *infectious*. After some period of time α^{-1} exposed individuals will become infectious, and now the disease can start spreading at full swing. Anyone in S compartment coming into contact with an individual in I, would get the disease with multiplier β, which represents the average number of contacts per person per time multiplied by the disease transmission probability. So, there would be a continuous flux of people to E and then to I without any interventions to stop the contacts. Depending on the disease, after a certain period of time γ^{-1} *infectious* individuals will *recover*, and complete their journey through the model.

Treating each compartment size as a proportion of the total population, i.e. it can only vary between 0 and 1, the overall influx at each compartment can be described by the following derivatives with respect to time t: $\dot{S} = -\beta SI$, $\dot{E} = \beta SI - \alpha E$, $\dot{I} = \alpha E - \gamma I$, and $\dot{R} = \gamma I$. These derivatives allow us to create a next state model, that can estimate the compartment size at time $i + 1$ given we know the compartment sizes at time i as follows:

$$S_{i+1} = S_i + \dot{S}_i = S_i - \beta S_i I_i \tag{1}$$

$$E_{i+1} = E_i + \dot{E}_i = (1 - \alpha)E_i + \beta S_i I_i, \tag{2}$$

$$I_{i+1} = I_i + \dot{I}_i = (1 - \gamma)I_i + \alpha E_i, \tag{3}$$

$$R_{i+1} = R_i + \dot{R}_i = R_i + \gamma I_i. \tag{4}$$

It should be noted that generally an SEIR model will incorporate birth and death rates, but for simplicity we exclude these parameters here. As a consequence, the total population is conserved, and therefore we have $S + E + I + R = 1$. Also, in this case, the basic reproduction rate is $r = \frac{\beta}{\gamma}$.

With the next state model, we can simulate the disease progressing through a population for any length of time, starting from a given set of initial conditions. Thus it can indicate where we might be heading given the data observed in the last few time steps.

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It should be stressed that not all of these compartment sizes are observable. For instance, it is implausible to measure exactly what proportion of people are currently in infectious state without mass testing at every time step. It is possible to explicitly model observable variables, such as the number of cases, instead, as an additional compartment with an associated influx. However, here we adopt a simple heuristic: we assume that the number of beds occupied in a hospital at a time step i is equal to the *one-tenth* of the the size of the infectious compartment at this time step, i.e. the observed number of beds $\hat{H}_i = \frac{I_i}{10}$. This allows us to construct a dataset consisting of the measured number of hospital beds in the last n time steps and locate a set of initial conditions that may have given rise to the data, which in turn can help us forecast the demand in the future. This model fitting process is described next.

3 MODEL FITTING

Suppose we construct a dataset $\mathcal{H} = (H_1, \ldots, H_k)^\top$ that consists of hospital bed occupancy numbers for k consecutive days. A decision vector $\mathbf{x} = (S_1, I_1, E_1, R_1, \alpha, \beta, \gamma)^\top$ incorporates the initial compartment sizes on the first day, contact rate β, and disease specific parameters α and γ. For an arbitrary $\mathbf{x}$, using the forward simulation model described in (1)–(4), we can compute $I_2, \ldots, I_k$, which in turn produces our estimates of occupancy $\hat{H}_i = I_i/10$. With this, we pose the model fitting as a minimisation of mean squared error:

$$\min_{\mathbf{x}} f(\mathbf{x}) = \frac{1}{|\mathcal{H}|}\sqrt{\left(H_i - \hat{H}_i\right)^2}, \tag{5}$$

subject to $S_i + E_i + I_i + R_i = 1$, and $\alpha = 0.25$ and $\gamma = 0.1$ that are Covid-19 specific estimates. Note that the first constraint of conserving population forces S_1, I_1, E_1, and R_1 on a simplex. To tackle this constraint, we therefore consider a three-dimensional continuous space within range $[0, 1]$ for searching, and then project any member of that space onto a four-dimensional simplex as described in [3]. This is a multimodal optimisation problem: different $\mathbf{x}$s may produce similarly good fit to the data $\mathcal{H}$. We therefore use Niching Migratory Multi-Swarm Optimizer (NMMSO) with default settings for 50000 iterations [1]. This results in a range of solutions that we pass on to the user of the tool.

4 AN INTERACTIVE TOOL

To use the tool, the user would first select a dataset for training the SEIR model, and they will get multiple solutions from model fitting in Section 3. Using either ancillary information, or expert knowledge, the user will select one of the potentially many sets of parameters that may have given rise to the observed data. With this selected solution, they can now use the interactive visualisation in Figure 1, and make appropriate contingency plans based on their exploration of hypothetical scenarios.

5 CONCLUSIONS

In this paper, we presented an interactive tool for hospital managers. We focused on using an epidemiological model in deriving predictions on hospital bed occupancy in the near future, which is an improvement over the use of näive linear or exponential models. In addition, we enabled the user to interact with the model by changing controllable parameters, and the tool reacts in turn to produce the associated forecast. They can then make a decision on how to prepare for the likely hypothetical scenarios based on their organisation's need and policies. Future work will incorporate improving the epidemiological model to include hospital occupancy as a compartment, and also conducting an extensive user study.

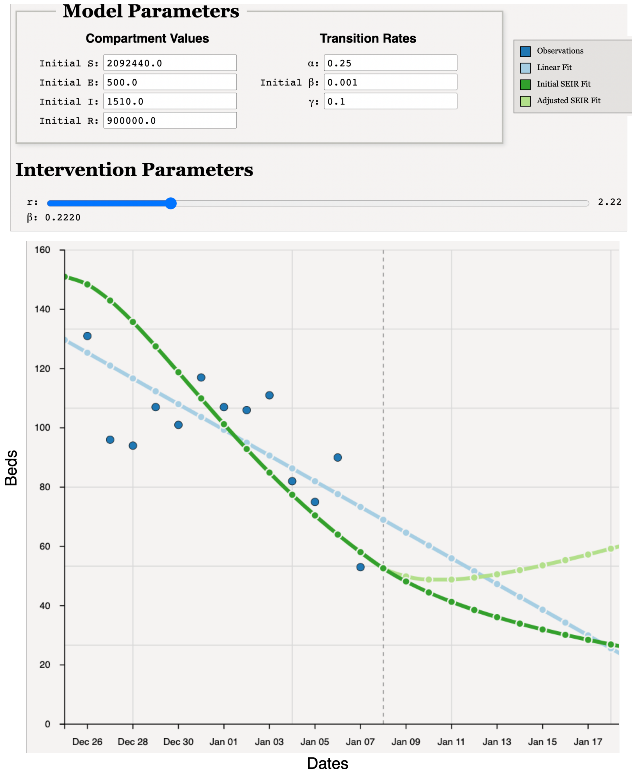

Figure 1: Illustration of the developed interactive tool for hospital managers. It has editable textboxes for model parameters (top-left), and an interactive slider for changing the basic reproduction rate r, and consequently β. The training data is shown with blue dots. The dashed vertical line portrays the marker for today. The tool depicts the estimated future given the a linear fit to the data, shown in light blue. The dark green line shows the potential future with SEIR model with the fitted solution. Finally, the light green line shows the result of a deviation in β. Here, we changed β from 0.001 to 0.222. Hence, we observe an immediate increase in the light green line over the dark green line.

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