Optimisation and Visualisation for Medium Term Projections in Response to COVID-19

Alma Rahat* Carla White* Noemi Picco* Gibin Powathil* Daniel Archambault*†
Biagio Lucini* Michael Gravenor*

Abstract

This bulletin describes part of the Swansea University effort in response to the COVID-19 pandemic that combines optimisation, visualisation, and epidemiology to have an impact on the Welsh Government response. During the pandemic, when the omicron variant was beginning to affect the the world, researchers in epidemiology, optimisation, and visualisation came together to produce medium term projections of COVID-19. The methodology involved measuring data from the real world such as different types of hospital admissions and deaths and fitting this time varying data to the compartments of a model. This model is reflective of the current state in the Welsh population, and is run forward for four to six weeks creating a projection for these types of hospitalisations and deaths. For over a year, these MTPs have formed an important part of informing the Welsh Government and the UK Health Security Agency about the current state of the pandemic.

1 Introduction

When COVID-19 began, the Welsh Government required a Wales specific model. Biagio Lucini and Mike Gravenor created this model by adapting existing models [1] and provided reports to the Welsh Government to estimate hospital admissions and deaths due to the pandemic in the form of hand-tuned worse-case, median-case and best-case scenarios. This process was refined over the first two years in response to the pandemic to help make data driven decisions.

In the second part of 2021, the omicron variant began to emerge. The characteristics of the disease were changing, and the model should adapt to this new variant as well as other new variants. At this time, there was a desire to produce projections more frequently and for a shorter period of time. These Medium Term Projections (or MTPs) were created in order to provide a more frequent projections of COVID-19 to help the government make data driven decisions, with improved uncertainty estimations.

2 Medium Term Projections: How They Work

Figure 1 shows the version of the Swansea University COVID-19 model used for MTPs. A compartmental model encodes each state of the disease as a compartment. The number of individuals in that state are assigned to that compartment. Edges model how individuals progress from compartment to compartment with differential equations on each edge modelling the change over time. MTPs are generated weekly, with new data typically incorporated on a Friday, the optimisation run over the weekend, outputs checked on a Monday and delivered on a Tuesday to the Welsh Government.

The model has two types of parameters: disease specific (e.g. basic reproduction rate for a variant) and population behaviour specific (e.g. scaling factors for contacts). These parameters control how the disease progresses, captured in the variables of interest, such as daily deaths. Using the errors between the simulated and observed data for some of these variables, we can estimate the optimal parameters.

Let a parameter vector $\mathbf{x}$ contain the parameters to be tuned. For ith variable of interest, if the simulator time series output is $o_i(\mathbf{x})$ and the relevant observed data vector $\mathbf{d}_i$, then we define the error as: $e_i(\mathbf{x}) = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(o_i(\mathbf{x})[j] - \mathbf{d}_i[j])^2} + \max_j |o_i(\mathbf{x})[j] - \mathbf{d}_i[j]|$, where, N is the number of days with $j = [1, N] \in \mathbb{N}^+$. Without loss of generality, the multi-objective parameter optimisation problem can be defined as: $\min_{\mathbf{x}} \boldsymbol{\varepsilon}(\mathbf{x}) = (e_1(\mathbf{x}), \ldots, e_M(\mathbf{x}))^\top$, where there are M target variables of interest. In this work, we have five target variables: ward occupancy, ICU occupancy, ward admissions, ICU admissions, and death.

We locate a range of solutions to solve this problem that optimally trade-off between the error components $e_i(\cdot)$. There are no exact solvers that can locate the Pareto front. In addition, the simulator is computationally expensive (10s to 20s to generate time series outputs). Traditional multi-objective optimisers may take more than 10 days (i.e. 100k+ model runs), which would not be acceptable to our stakeholders who require results within 2-3 days of receiving the data. Therefore, we use a multi-objective, Bayesian optimiser from [2] that is known to produce good estimates of the Pareto front with fewer evaluations (e.g. up to 650 in this work). Uncertainty is estimated through a bootstrapping scheme where we change the target data (e.g. $\mathbf{d}_i$) by sampling from a predefined distribution and rerun the optimiser: we repeat the process 40 times to produce a range for the projections of each variable of interest. Once the model parameters are optimised, the compartmental model can be run forward for four to six weeks in the future. These estimates are plotted with uncertainty (Figure 2). The plots have been read by policymakers, to understand how the pandemic could evolve.

3 Conclusion

We describe part of the Welsh Government response that combined epidemiology, optimisation, and visualisation. A version of the Swansea University model for COVID-19 and this methodology was used to create projections in response to COVID-19 and its variants to help policy makers make data driven decisions.

Acknowledgments

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*Swansea University, {a.a.m.rahat, c.l.white, Noemi.Picco, g.g.powathil, b.lucini, m.b.gravenor @swansea.ac.uk}@swansea.ac.uk
†Newcastle University, daniel.archambault@newcastle.ac.uk

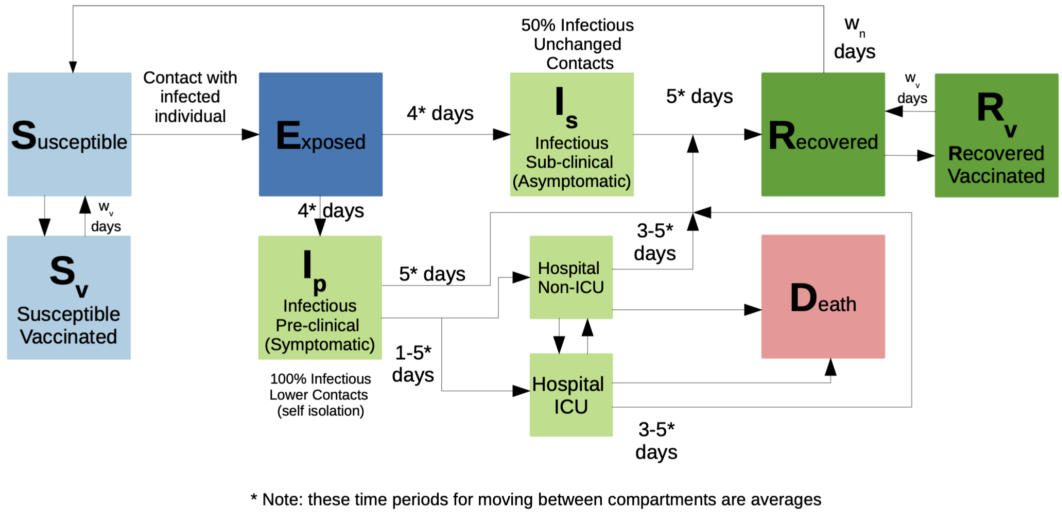

Figure 1: Schematic model used for the Medium Term Projections (MTPs). This compartmental model explicitly models compartments for various types of hospitalisations. Optimisation methods are used to fit the data to these compartments so that it can be run forwards, making a projection for the omicron variant over four to six weeks.

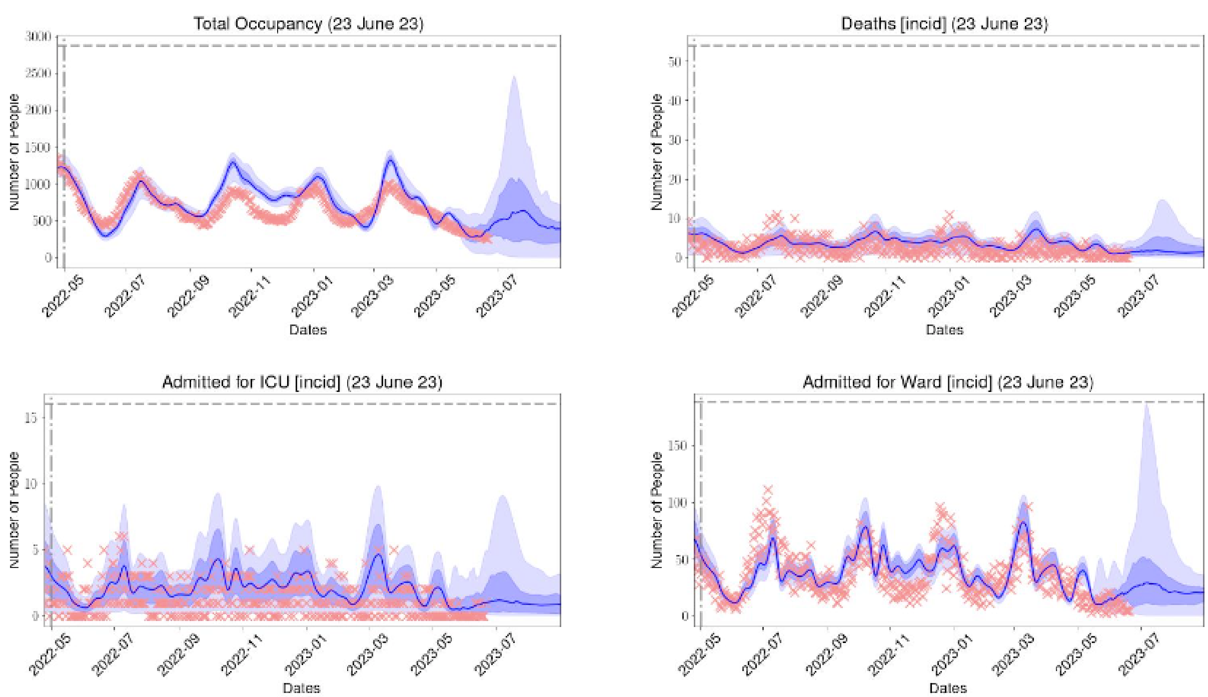

Figure 2: Example visualisations for an MTP. Plots for total occupancy, deaths, ICU admissions, and ward admissions shown. Optimisation methods fit the data to the model. The red crosses indicate the observed data since May 2022. The projections from the model are shown in blue. The dark blue line is the median projection, while the darker shaded blue depicts the area between 25th and 75th percentile of the projections, and the lighter outer shaded regions represents projections between 97.5th and 75th, or 2.5th and 25th, percentile.