



Supporting COVID-19 elective recovery through scalable wait list modelling: Specialty-level application to all hospitals in England

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Abstract

The recovery of elective waiting lists represents a major challenge and priority for the health services of many countries. In England's National Health Service (NHS), the waiting list has increased by 45% in the two years since the COVID-19 pandemic was declared in March 2020. Long waits associate with worse patient outcomes and can deepen inequalities and lead to additional demands on healthcare resources. Modelling the waiting list can be valuable for both estimating future trajectories and considering alternative capacity allocation strategies. However, there is a deficit within the current literature of scalable solutions that can provide managers and clinicians with hospital and specialty level projections on a routine basis. In this paper, a model representing the key dynamics of the waiting list problem is presented alongside its differential equation based solution. Versatility of the model is demonstrated through its calibration to routine publicly available NHS data. The model has since been used to produce regular monthly projections of the waiting list for every hospital trust and specialty in England.

Keywords COVID-19 · Elective care · Waiting lists · Mathematical modelling · Operations Research

1 Background

While the direct impacts of COVID-19 have mainly affected the acute emergency setting, the associated reduction in hospital resources has severely restricted the capacity available for elective treatments. During the first wave of the pandemic, many countries postponed all non-urgent procedures, contributing to an estimated 28 million operations being cancelled or postponed worldwide [1–3]. At the time of writing, the elective backlog in England's National Health Service (NHS) has reached 6.4 m, representing a 45% increase in the two years from March 2020 [4]. And wait times have also lengthened over this period, with the numbers waiting over 18 weeks (the constitutional target) increasing over 3-fold from 0.7 to 2.4 m, and the numbers

waiting over 52 weeks increasing a staggering 190-fold from under 2,000 to 0.3 m [4].

Long waits associate with worse health outcomes and can result in loss of independence and depression [5, 6]. Health inequalities risk further widening with those who can pay able to go private [7]. And healthcare providers face the consequence of long waits – in terms of the additional non-surgical treatments required to manage symptoms up to the point of definitive treatment [8], as well as patients converting from the elective to the more costly and disruptive emergency treatment route [9].

Despite the clear importance of effectively managing waiting lists, there is a deficit of models available in the academic literature to support decision makers. Pre COVID-19, much of the effort involved bespoke projects for individual hospital specialties or patient pathways, through application of operational research techniques such as queueing theory, system dynamics and discrete event simulation [10–14]. More recently, others have projected the effect of COVID-19 on waiting lists for particular surgical specialties [15] and at a total national level [16].

However, in none of these studies is a solution presented that is sufficiently scalable in providing healthcare managers with waiting list projections across the hospital and

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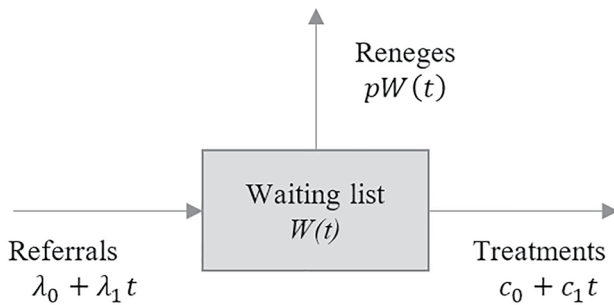


Fig. 1 Description of the modelled waiting list problem

specialty level, and which can be refreshed with the latest data on a routine basis. There is also a lack of consideration to patients leaving the waiting list before treatment. This is an important dynamical property in the current environment, given the greater likelihood of patients renegeing due to death, becoming inoperable, as well as for the aforementioned reasons (going private and converting to the emergency route).

Presented here is a simple and scalable differential equation based model that approximates the waiting list problem, and which has been routinely applied on a monthly basis to produce waiting list projections for every hospital trust and specialty in England's NHS. In terms of connection with the previous literature, the solution presented here could be viewed as a simple implementation of system dynamics (SD), given its differential equation basis. Examples of SD wait list models, albeit for bespoke exercises, are available [14], alongside a review of SD modelling and queueing theory [17].

2 A simple model for projecting waiting lists

Essentially, the future waiting list size is modelled by the difference of new referrals to treatments and reneges (Fig. 1). The future number of new referrals and treatment capacity are modelled linearly, with λ_0 and c_0 representing the respective known values at the time of the modelling (typically the time of the latest data) and λ_1 and c_1 representing the future growth rates. Reneges are assumed to be proportionate to the waiting list size at any given time, according to the constant p . This ensures greater amounts of renegeing when the waiting list is longer (a more detailed interpretation of this relationship is provided in the Supplementary Material).

The problem depicted in Fig. 1 can be expressed as a differential equation:

$$\frac{dW}{dt} = (\lambda_0 + \lambda_1 t) - (c_0 + c_1 t) - pW(t)$$

This can be solved, through the workings detailed in the Supplementary Material, to give:

$$W(t) = \frac{1}{p} \left[(\lambda_0 + \lambda_1 t) - (c_0 + c_1 t) - \frac{\lambda_1}{p} + \frac{c_1}{p} \right] + \left[W_0 - \frac{1}{p} \left(\lambda_0 - c_0 - \frac{\lambda_1}{p} + \frac{c_1}{p} \right) \right] e^{-pt}$$

where W_0 is the size of the waiting list at the time of the modelling (i.e. typically the time of the latest data).

The model can be applied to NHS waiting lists using hospital trust and specialty level data made publicly available each month by NHS England [4]. W_0 is estimated as the waiting list size at the latest month. Given the volatilities in referrals and treatments from one month to the next, λ_0 , c_0 , and p are estimated not based on the data of just the latest month, but on the data from a number of recent months. Here, the period from July 2021 onwards is used (noting that any earlier times would be subject to particular disruption given the sequential lockdown relaxations in the UK in the first half of that year [18]). Further detail on calibration of these parameters can be found in the Supplementary Material.

Finally, the remaining two parameters λ_1 and c_1 , representing future growth rates in new referrals and treatment capacity, are estimated. Given that these are essentially unknown, a multitude of values are considered within the modelling. For new referrals, annual growth rates of 0, 1, and 5% were assumed, noting historical all-specialty growth rates of 3.5%, 3.3%, and 1.9% in the three calendar years before the pandemic [4]. For treatment capacity, annual growth rates of 0, 5, and 10% considered, based upon NHS planning guidance [19].

The model was developed in close coordination with service managers at the author's local NHS system, from which the ask had originally emerged. Specifically, system stakeholders had articulated a need to understand the longer-term effect of COVID-19 on waiting lists, subject to factors within their immediate control (treatment capacity) and outside of it (new referrals and renegeing). Planners were involved in decisions regarding the calibration period as well as approving the growth rates used. Development of a generic model was identified as essential given the requirement to conduct the modelling on a routine basis, for all specialties, for each of the two trusts, and over a range of scenarios. With the data source providing national coverage of the requisite inputs, upscaling to other trusts outside the local area was readily possible thereafter.

NORTH BRISTOL NHS TRUST - Waiting list size

Projections based on actual data for referrals and treatments over the last 9 months to end Mar 2022 (shaded grey area)

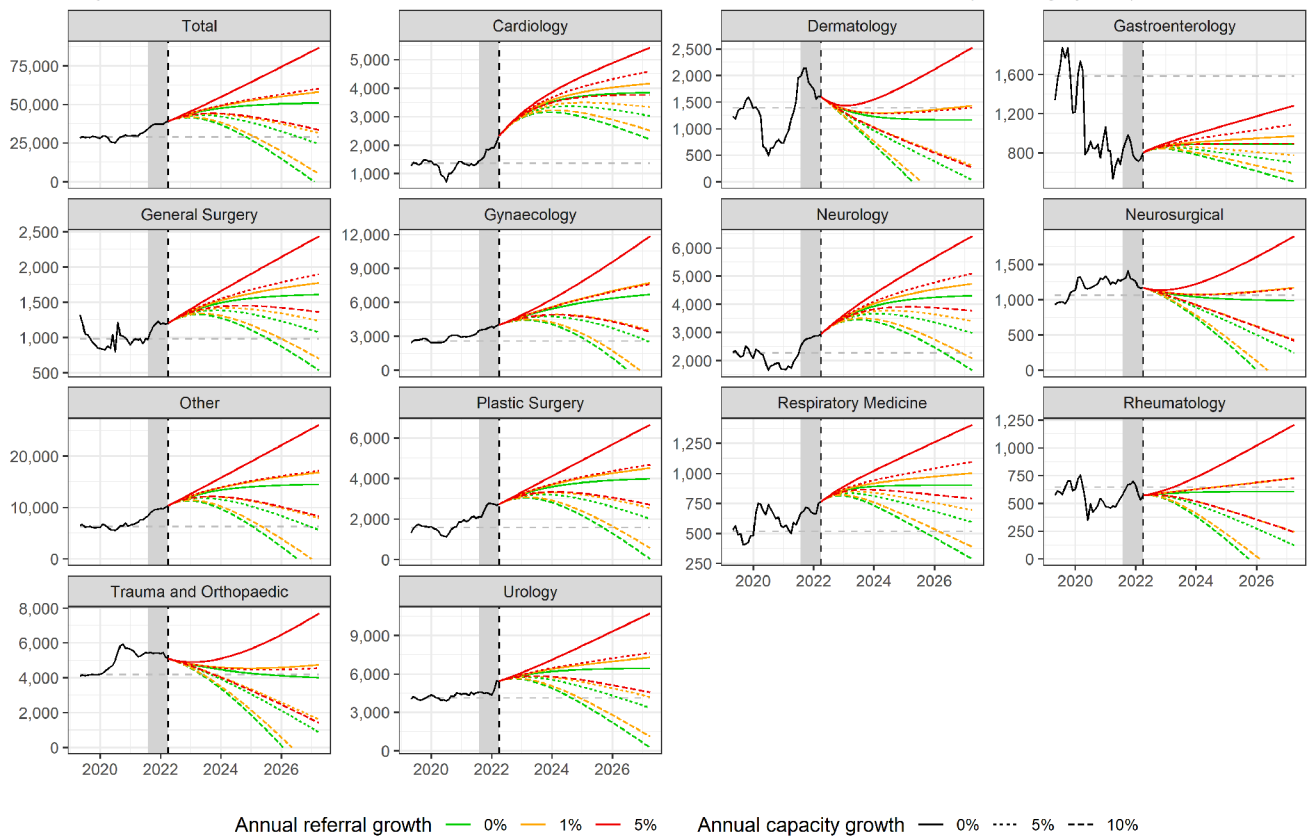


Fig. 2 Example projections for one hospital trust based upon data to end-March 2022 (made available May 2022). Note that the dashed horizontal line is used for reference in representing the mean waiting list size from April 2019 to February 2020 (i.e. the pre COVID-19 period)

3 Modelled projections

Specialty level projections for all 171 NHS hospital trusts in England are calculated each month based on the latest data [4] and made freely and publicly available on GitHub [20]. For transparency and reproducibility, the GitHub space also contains model documentation and all code (written in R) used to process the data and produce the projections. The projections have been shared with neighbouring systems, and nationally via social media, webinars [21], and conversations with the central NHS team for elective care recovery analysis.

An example of the outputs for a particular NHS hospital trust – one within the author’s local NHS system – is provided in Fig. 2. This shows the waiting list projections for all elective specialties operated by the hospital, according to the various considered growth rates in new referrals and treatment capacity. These were calculated in May 2022 based upon the latest data available at the time (to end-March 2022) [4]. Projections are also provided for the

proportion of terminating pathways due to renegeing – see the Supplementary Material.

In the author’s NHS system, the modelling has first provided a ‘do nothing’ assessment of future waiting lists assuming no changes to capacity. Modelling of additional capacity has allowed consideration of the resources required to recover waiting lists within given timescales. For instance, with 0% referral growth and 10% capacity growth, the total trust waiting list would continue to increase from its current 39,101 to a 41,619 peak by end-November 2022, followed by a reduction to 24,245 – a level more comparable to the pre COVID-19 period – by end-March 2025, i.e. three years from the latest data of the modelling (Fig. 2). Additional to the routine monthly projections, service managers have also requested specific analyses involving alternative referral and capacity growth rates – which has been conveniently facilitated through the versatile model code [20].

Strategically, the projections are being used to support long-term planning in helping to understand which specialties could be prioritised for additional capacity. This analysis is being complemented with estimates of the additional

healthcare activity consumed while waiting for treatment, to help identify particular specialties which could be targeted to prevent additional pressures. The modelling has also contributed to an improved understanding of the benefits of additional elective capacity versus the potential consequences for other services, e.g. a reduced bed-base for admitted non-elective care.

4 Further opportunities

In the wake of the COVID-19 pandemic, growing waiting lists represent perhaps the largest strategic problem facing the healthcare services of many countries, including England's NHS [22, 23]. While the problem is complex, and the current literature is lacking, the simple model presented here provides some evidence of the potential for modelling to offer scalable and interpretable solutions to healthcare managers and clinicians.

There exist many opportunities for future investigators to enhance the value of generic waiting list modelling. The sophistication of the current model could be expanded – for instance, by incorporating the effect of balking (referrals not being made due to known treatment delays) [24]. However, there is no obvious source of publicly available routine data relating to this, and consideration would also need to be given to the functional form accounting for this mechanism. Relaxing the linear restriction of referral and capacity growth may also be considered. Not least, this would allow the model to be validated through backtesting – the volatility in historical demand and capacity volumes (especially over the COVID-19 period) currently prohibits a meaningful comparison with outputs from a model assuming a steady linear profile. However, this would be at the expense of model simplicity and the closed-form solution (a numerical solution would likely be required). Any adjustments to the open-source R code of the current model could be facilitated by researchers as well as analysts within the NHS, given the recent upskilling efforts by the NHS-R Community [25].

Investigators may also wish to consider waiting time as well as waiting list size. In the interests of providing some assessment of this, additional model outputs (not shown) currently include estimates calculated via Little's Law (the division of queue length by throughput) [26]. However, this is inherently flawed, given its application to a non-stationary system (it is not possible to say whether the estimated wait at a given time is relevant for those joining the queue or leaving it). Instead, further research could consider the development of generic models based upon the stochastic DES methodology, whose event-driven nature provides the necessary conceptual appropriateness for reliably deriving

this metric [12, 16]. DES methods also have the benefit of providing confidence ranges for modelled outputs. On the other hand, their suitability for use as a routine generic model may be compromised by the greater complexity and data required to specify the input variable distributions, as well as the computational time required to perform multiple simulation replications for each trust/specialty/scenario instance.

Finally, it could be valuable to conduct a more comprehensive assessment of the trade-off between generic and bespoke models, in order to assist healthcare managers in determining the conditions under which to use one or the other. As well as scalability, such an evaluation could also feature a comparison of performance accuracy, development and computational time, data and model requirements, and the necessary technical competency of the target end user.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s10729-022-09615-2>.

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Data, materials and code availability <https://github.com/nhs-bnssg-analytics/waiting-list-projections>.

Statements and declarations

Competing Interests None.

Ethics approval Not applicable (public data).

Consent Not applicable.

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