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ABSTRACT

Objectives

A generalisable simulation model is described; intended for use by managers, clinicians, planners and policy makers to understand the effects of UK waiting time targets for hospital care that have been a feature of the English NHS for some years. It is important that their development, use and emulation elsewhere is based on evidence and the model shows the effects of such targets and the actions taken to achieve them.

Methods

Using UK Health Episode Statistics, Patient Administration Systems and local data, the simulation model can be configured to fit the activities of many UK general hospitals. The simulations capture changes made in the hospital and their effect on waiting time performance and side effects such as cancellations.

Results

The paper includes a demonstration of the use of the simulation model to investigate the activity of a UK district general hospital over a two and half year period. This shows that its success in reducing patient waiting times was based on a multi-facetted approach that is much superior to individual initiatives.

Conclusions

Building a whole hospital model of waiting time performance is feasible and offers benefits to users in understanding the effects of changes in hospitals that are large, complex and highly congested systems. This is essential if target-based policies are to be based on evidence so that side effects can be minimised.

INTRODUCTION

Waiting for healthcare

Waiting time targets are a major element of the current NHS performance assessment framework in England and play an important role in determining the performance rating of NHS Trusts. The targets have covered emergency admissions, planned inpatients, outpatients and readmissions. NHS Trusts are allowed some leeway in achieving these targets: for example, in 2002/3 up to 8 patients could wait more than 12 hours for emergency admission. Any Trust breaching that target would be labelled as 'underachieving' (9 to 50 breaches) or 'significantly underachieving (up to 50 breaches).

These targets for outpatients, standard inpatients and day-case admissions have become more demanding through time. In the UK, General Practitioners (GPs) act as gatekeepers to elective hospital treatment, which is usually accessed via a referral from the GP to an appropriate provider of tertiary healthcare. The recent 18-week Referral to Treatment (RRT) target originally specified that, by the end of 2008 no-one should wait more than 18 weeks from GP referral to hospital treatment. This target was later relaxed, and now requires that 90% of admitted patients enter inpatient care with 18 weeks and that treatment of 95% of non-admitted patients starts within 18 weeks.

Whether or not the demand for healthcare is insatiable in developed economies, availability tends to be rationed; by price in those systems that require payment for treatment, or by waiting in systems in which treatment is free when needed. Recognising the latter, Propper (1995) [1] is an example of an attempt to consider the economic value of waiting time for patients, focusing on the UK's National Health Service. Appleby and Thorby (2008) [2] is a more recent discussion, placing waiting times in the historical context of the early days of the NHS.

When the 18-week RTT target was announced, average waits were expected to be around nine weeks from GP referral to treatment, with waits for an outpatient consultation not normally exceeding six weeks [3]. When the target was announced, there was no published analysis showing how it, or others, would be achieved. If, for example, hospitals lack the resources or information and know-how to operate with such short waiting times, there would be high costs from them being in a state of permanent crisis, or having significant under-utilised capacity, or possibly both. In particular, this targeting seems to ignore possible interaction with other performance indicators and other targets – for example, the need to

balance the books and, in the case of the 18-week RTT target, the 4-hour waiting time target for A&E.

Matching supply to demand

Queues are a common feature of public services and in the NHS are seen as symptoms of system failures, but their causes are rarely understood and so policy responses tend to be crude. It is well known that it is difficult to manage a system in which demand varies stochastically. For example, providing resources to meet average demand and ignoring the variation is a recipe for poor performance, leading to long queues and overworked resources. Ideally, resource availability should vary with patient demand, but this requires surplus resources at times of slack demand unless they can be turned on and off like a tap. To economically match resources to demand requires sound conceptual understanding based on well-designed information systems and must recognise two complications.

First, most demands originate outside the hospital and it is possible that reduced waiting times could lead to increased demand. Modelling work to date has shown that the increased demand for NHS surgery resulting from reduced waiting times will in general be modest. This was the common finding of a system dynamics model of NHS waiting lists [4] and more detailed econometric work [5]. But these look at periods when waiting times were quite long: it is at least conceivable that new policies emphasising both short waiting time and increasing patient choice [6] will increase demand from NHS patients for surgery. If this were to happen, then waiting times could increase despite improved management of hospitals, making them look worse despite actually doing better.

Second, some demands for hospital services are internally generated, as patients require a sequence of treatments and investigations. This means that sound management and performance assessment of hospitals should recognise the interconnectedness of their various services: outpatients, A&E, and inpatients. For example, reducing the time to be seen in outpatients may increase demand on inpatients; and reducing time in A&E, may increase demand on theatres. The whole hospital simulation model described here offers a means of diagnosing causes of failures to achieve targets and an understanding of which remedies are likely to work and which merely shift queues around the hospital so that one target is met but others are missed. Its use should be of value to policy makers who wish to understand the likely effects of waiting time policies as well as to local managers and clinicians wishing to reduce waiting times.

Healthcare system simulation

Computer simulation is a widely used technique in management science and, as argued by Morton and Bevan (2008) [7], management science approaches can produce insights not available from more conventional health economics methods. Computer simulation has a long history in healthcare, for training as well as in planning and analysis. Here we focus on its use to understand and improve performance; that is, we focus on healthcare systems simulation, as does, for example Katsaliaki (2008) [8], which examines ways to make the UK's blood supply chain more cost-effective.

Several literature reviews that identify and classify the range of applications of healthcare systems simulation have been published in the last 30 years [9], [10], [11], [12], examining the use of simulation approaches to support resource allocation decisions and healthcare planning. Recent reviews include Jun et al (1999) [11], which examines publications in the thirty years from the late 1960s, reporting that most papers give accounts of attempts to simulate discrete parts of a hospital, such as a clinic or A&E department; and Fone et al (2003) [12], which is a systematic review that examines the literature to assess the quality of published studies and their influence, if any, on policy, rather than healthcare applications.

It is clear from these reviews that there have been many attempts, some successful, to apply computer simulation methods to help investigate and support improvement in the delivery of healthcare. However, it is also clear that the published accounts of healthcare simulations of hospital activity have two linked and rather limited foci:

1. An emphasis on a single, discrete element of a hospital. Of these, there are many accounts of simulations of outpatient clinics [13], [14] and of A&E departments [15], with a view to making better use of resources whilst provided a better experience for patients.
2. A short-tern, operational focus that aims to support managers and clinicians in the search for improved performance in a particular unit within a hospital.

That is, there are no reports of simulation models that encompass a whole hospital nor are there accounts of simulations intended to support policy analysis and regulation, rather than operational improvement.

MATERIALS AND METHODS: THE DGHPSIM PROJECT

By contrast, the DGHPSim project includes a whole-hospital simulation model that goes beyond a single unit such as outpatients or A&E and links these different functions together

so that their interactions can be understood. Details of the inner workings of the DGHPSim components and their data requirements can be found in Günal and Pidd [16], [17] and [18] and a conceptual overview of its four main components is shown in figure 1.

All DGHPSim sub- models simulate individual patients, who may be emergencies or electives. If admitted, emergencies arrive via A&E or as direct referrals. Electives may remain in the outpatient stream until discharge or be admitted as inpatients after outpatient care. The A&E and outpatient sub-models can be run separately, much like the standard healthcare systems simulation applications found in the literature. However, their power comes when linked into a single, whole hospital simulation to provide a dynamic systems view of hospital performance that allows users to see the effect of the interactions of actions taken, say, in outpatients, on, say, inpatient performance and overall performance. That is, the DGHPSim suite allows users to take a holistic view of hospital performance as measured in the waiting time of patients.

Figure 1: Conceptual overview of the DGHPSim suite

Accident and emergency department model

A&E Departments (EDs) are found in most general hospitals and accept patients who arrive themselves or are brought in by ambulance. Most A&E patients do not require eventual admission as inpatients and, often, those that do are initially admitted to assessment units for observation from which they may be discharged or fully admitted as inpatients.

As well as being part of DGHPSim whole hospital simulation, the A&E model can be run alone and, in this mode, allows users to investigate issues related to the current 4-hour A&E target [19]. In whichever mode it is run, it must be parameterised with demand data,

details of staffing levels and resources, and process times to make it fit a particular unit. Since A&E demand varies by day of week and time of day, this variation is built into the operation of the simulation, representing individual patients as they arrive for treatment until their discharge or admission to inpatient wards. It is also known that clinicians simultaneously handle several patients when demand is high and the A&E model uses established multi-tasking rates [20].

Inpatient model

The inpatient model receives simulated patients from three routes: the A&E department, direct emergencies and, finally, elective patients from waiting lists. The inpatient activity can be modelled at different levels of data; for example by individual wards, or by groups of wards. Within each ward or group of wards, a proportion of beds is assumed set aside for elective admissions but, if emergency demand is high, elective patients whose admission is planned for a particular day may be cancelled and the bed occupied by emergency patients. Thus, emergency patients, which are effectively exogenous, have preference over elective admissions. Cancelled elective patients are returned to the waiting list.

Since a proportion of inpatients changes wards during their hospital stay, the inpatient model also simulates these transfers, based either on the actual historical behaviour of the hospital, or to reflect intended practice as part of an investigation of a scenario for change. The simulated length of stay experienced by inpatients reflects the fact that, in most hospitals, a small number of patients stay for a very long time in some specialties. Operating theatre availability is not modelled in the inpatient simulator, based on advice received from the UK Healthcare Commission that theatre capacity is not a real constraint in most hospitals and that better scheduling would allow extra throughput even in hospitals that appear to operating at full theatre capacity.

Outpatient model

Elective patients are simulated in the outpatient model that takes referrals from GPs through a three stage process shown in figure 2. In stage 1, referred patients wait for an outpatient appointment, which is currently managed by the NHS Choose and Book system. The simulation maintains individual clinic diaries in which patients are allocated the first available slot. As with the inpatient model, the user can choose the level at which to simulate and could, if appropriate, simulate individual consultants, though grouping is more likely. Once the date for a patient's appointment is reached in the simulation, their interaction with the clinicians is

modelled in stage 2, which may include repeat visits if necessary. The model assumes that sufficient diagnostic capacity is available.

At the end of stage 2 in the simulation, a decision is made about whether inpatient admission is required or whether continued outpatient treatment or discharge is more appropriate. Patients who will be admitted enter stage 3, waiting for inpatient admission – which requires the eventual availability of a suitable bed.

Inpatient waiting list model

During Stage 3 a patient waits for elective admission having been placed on an admission list in the outpatient model. Patients placed on an admission list are assigned a priority, very high priority patients being given the first available admission slot immediately the decision to admit is made. The rest sit in a pool and, as they wait, their priority increases so as to ensure that none wait beyond some defined maximum and, on a weekly cycle, the highest priority patients are assigned the first available slots, with some being reserved for patients who will shortly have an immediate high priority. As mentioned in the description of the inpatient model, a patient may not be admitted on the intended day due to emergencies taking priority, leaving no available bed on the appropriate ward or ward group.
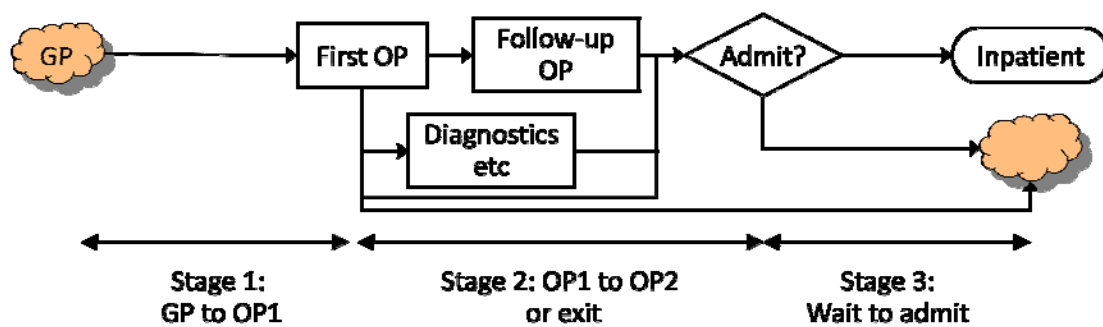
Figure 2: Conceptual overview of the outpatient sub-model

Data requirements

The DGHPSim suite is a generic simulation model, configured for a particular hospital using data appropriate to that hospital. Data parameterisation is never a wholly straightforward process but can be eased by the use of widely available data sets. Much of the data required by DGHPSim is from the UK's Hospital Episode Statistics (HES) database, in which all inpatient and outpatient episodes are recorded, and from a hospital's Patient Administration System (PAS). Combining these two data sets provides a full view of inpatient and outpatient interactions over a defined period. The Hospital Activity Data Analyser (HADA) [21], created

as part of the DGHPSim project, is used to merge the data sets and create the much of the data required to simulate individual patient flows.

In addition, the user must specify details about the particular hospital that will depend on the level of detail required in a simulation. These include the number of specialties (or groups of specialties), the number of wards (or groups of wards), the links between wards and specialties and the outpatient diary slots. Finally, since the simulation aims to show the effect of different actions on patient waiting times, current waiting lists and waiting times are required for the start of the simulation.

RESULTS: USING THE DGHPSIM SUITE

As discussed earlier, two modes of use are possible for DGHPSim. In the first mode, a user may wish to investigate different options for improvement; for example to meet and to continue to meet, the 18-week RTT target. The second mode of use, the reason for the DGHPSim project, is for commissioners and regulators to investigate whether claimed performance improvements are valid and sustainable and for policy makers to check the feasibility of policy proposals. This is particularly important, since it would be unwise, though understandable, to encourage a hospital to meet a short-term target at the expense of its long-term, sustainable performance. The remainder of this section shows this second mode of use for an English hospital with the following characteristics:

- District General Hospital also serving as a national centre for neurosurgery, neurology and nephrology
- 19 specialties and functions on 34 wards/units with 840 beds.
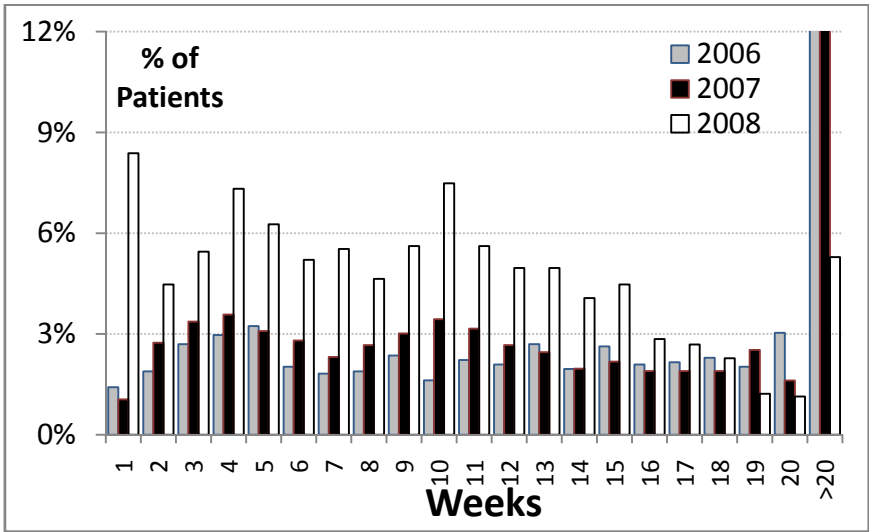- On a typical day, sees 1000 outpatients, 190-250 A&E cases and 74 day cases

Figure 3: Improved18-week RTT performance

The focus in this simulation is the apparent improvement in RTT performance as the hospital works towards the 18-week target. Figure 3 shows the RTT performance of this hospital across all specialties, over 2006, 2007 and up to July 2008. It is clear from figure 3 that the RTT performance of the hospital has improved markedly over the period from January 2006 to July 2008. The issues of interest are: how was this improvement achieved, were there any downsides to this improvement and is this improvement sustainable?

In considering these questions, we must ask what actions are open to hospital managers and clinicians in striving to reduce RTT waiting times. The first action available that might have an effect is more active management of the waiting lists. This begins by ensuring that only patients who are actually waiting for care are on the lists –some may have died, some may have moved away and some may have sought private treatment. Linked to this, there is also the possibility of diverting GP referrals to other providers, such as the private sector. Both actions reduce number of referrals to be seen and thereby the demand for both outpatient and inpatient care. In addition, it may be possible to divert people already on the inpatient waiting list to other providers.

The second set of actions relate to the availability and use of outpatient slots. The number of slots could be increased either by increasing the number of clinicians and clinics or by processing people faster in a clinic by reducing the slot length. Given the trend to one-stop outpatients in some specialties, it may also possible to increase the number of slots devoted to first referrals.

The third set of actions relate to inpatient care, particularly making better use of beds. Options here include reducing the lengths of stay, varying the proportion of beds allocated to emergency and elective patients and increasing the proportion of surgery done as day cases.

The DGHPSim suite can be used to investigate the effect of these different policies to see what happens to the performance against the 18-week RTT target. It can be used to see which of the policies has the greatest effect and which generate undesirable side effects. Hence it can be used to check whether any of the policies could have led to the reported performance improvement, or whether other factors were at work.

Experimentation using the DGHPSim suite

The various actions listed above can be translated into a set of scenarios with which the DGHPSim suite can be used to simulate their likely effect. In doing so, it is important to realise that the simulations are not intended to produce precise predictions but to indicate the

directions and magnitude of the changes in performance that would result if the actions were taken in practice. That is, the DGHPSim suite should be regarded as a *tool for thinking* [22], rather than as a predictive calculator; it does not provide precise predictions of performance but indicates the approximate degree to which performance may improve and thus serves as a basis for debate about feasible and desirable change. This distinction is very important and is based on a view that a precise estimate that is precisely wrong is of no value, whereas an indication of the effects of policies can be very valuable.

Scenario	Approach	Detail
1	Reduced referrals	20% reduction in OP backlog
2 (a/b)		10 or 20% diversion in GP referrals for the final 6 months
3		20% reduction in the inpatient backlog
4 (a/b)	More outpatient capacity	10 or 20% increase in OP processing rate
5		Allocate 60% of OP capacity to first referrals
6	Better use of beds	20% increase in day-cases
7		20% reduction in length of stay
8		30% more elective beds (taken from emergencies)

Table 1: Summary of experimental scenarios

The 8 scenarios selected to represent the actions open to clinicians and managers are summarised in table 1. Here we consider how the hospital is meeting the 18-week RTT target and the effect that these actions have on the number of elective patients treated, the number of elective cancellations, the ward occupancy and the percentage of emergency outliers. The simulations start at January 2006 and run through to July 2008. The results of running simulations of these scenarios are shown in tables 2 to 5 and cover the entire two and a half year reporting period. Since the simulations include stochastic elements, the resulting statistical variation requires each scenario to be run several times with different random number seeds and, in these experiments, the simulations were each run 20 times.

Table 2 shows the results of scenarios related to reducing the number of referrals and diverting people on the inpatient waiting list to other providers. Each scenario is simulated separately and it is clear that none have much effect on the 18-week RTT performance of the hospital or on the other performance measures shown. Table 3 shows the results of simulating each of the scenarios that are summarised as increasing outpatient capacity. As with Table 2, none of the individual policies seems to have much effect. Table 4 shows the simulation results from scenarios related to the better use of beds and these do seem to have some effect,

though not enough to explain the reported increase in performance against the 18-week RTT target. Note that, in all cases, the ward occupancy figures include programmed investigation units and short stay wards, on which occupancy is typically low.

Measure	BASE CASE	Reduced referrals			
		1	2a	2b	3
RTT wait > 8 wks	88%	86%	88%	88%	86%
RTT wait > 18 wks	55%	52%	55%	55%	53%
Elective admissions	4395	4351	4376	4371	4488
Elective cancellations	9%	8%	9%	9%	4%
Av ward occupancy	80%	80%	80%	80%	70%
% emergency outliers	9%	9%	9%	9%	9%

Table 2: Results of running scenarios 1, 2 and 3

Measure	BASE CASE	More outpatient capacity		
		4a	4b	5
RTT wait > 8 wks	88%	87%	86%	81%
RTT wait > 18 wks	55%	52%	51%	51%
Elective admissions	4395	4407	4463	4284
Elective cancellations	9%	9%	9%	9%
Av ward occupancy	80%	80%	80%	80%
% emergency outliers	9%	9%	9%	9%

Table 3: Results of running scenarios 4 and 5

Measure	BASE CASE	Better use of beds		
		6	7	8
RTT wait > 8 wks	88%	84%	82%	83%
RTT wait > 18 wks	55%	48%	44%	45%
Elective admissions	4395	4080	4488	4529
Elective cancellations	9%	8%	4%	7%
Av ward occupancy	80%	80%	70%	80%
% emergency outliers	9%	9%	7%	9%

Table 4: Results of running scenarios 6, 7 and 8

This is very puzzling: according to the simulation, none of the individual policy changes seem to have a large enough effect on RTT performance to explain the improvements seen in practice. We must, though recall that the performance measures shown in the tables relate to the entire two and half year period. It takes time for improvements to have an effect and so the average performance over the period will be worse than that at the end, if performance is improving. However, even that does not explain the discrepancy, so perhaps a multiple assault is needed to effect these improvements? That is, what happens if the hospital attempts all improvements simultaneous by combining scenarios 1, 2(b), 3, 4(b), 5, 6, 7 and 8? The results of this are shown in table 5, where we do see a significant performance improvement that tallies with that reported by the hospital. It seems that no single action has enough power to produce significant improvement, but their combined, holistic effect does. We also see that reducing the availability of emergency beds by using them for elective patients has no discernable effect on the percentage of emergency outliers, which suggests that the hospital can safely do this.

Measure	BASE CASE	All scenarios combined
RTT wait > 8 wks	88%	54%
RTT wait > 18 wks	55%	19%
Elective admissions	4395	4430
Elective cancellations	9%	4%
Av ward occupancy	80%	70%
% emergency outliers	9%	7%

Table 5: Results of combining scenarios 1 to 8 simultaneously

DISCUSSION AND CONCLUSIONS

The DGHPSim suite can be used to model the waiting time performance of general hospitals that include inpatients, outpatients and A&E. The models are configured using generally available datasets with a limited need for specially-collected data. The example discussed in the paper is a general hospital that has improved its performance by the simultaneous application of policies that manage demand, increase outpatient resources and improve bed use. We do not know how confident its managers were that this set of policies would work or whether they tried everything they could think of. Whether by accident or design, the hospital has appropriately balanced capacity across the inpatient and outpatient parts of the pathway, which is an indication of a well-managed hospital. The managerial implication is that in such

a well-managed hospital there is no "silver bullet" intervention - instead there is a need for continuous and coordinated improvement along the patient pathway, lest some part of the process become a bottleneck.

It is, perhaps, obvious, that models can be of help to local managers and clinicians in their efforts to develop sound plans and to make better decisions. The DGHPSim suite is a useful addition to their armoury because it offers a holistic approach; that is, it represents the main features of a hospital to enable managers and clinicians to see what trade-offs are possible when striving for improvement, whether on a continuous basis or as part of a blitz. Since the performance of a hospital is very much situation dependent, the need for tools to allow exploration within that context seems clear. More general approaches run the risk of generating significant side effects such as cancellations whilst seemingly meeting targets.

General hospitals are large, complex and highly congested systems that must cope with a variable emergency load whilst ensuring that elective patients receive high quality care without waiting too long. It is a well-known rule of thumb [23] that people find it hard to understand more interacting factors than seven, plus or minus two. Not surprisingly, then, introducing changes and understanding the effects of those changes within a hospital is difficult; intuition will occasionally work OK, but often not. Models such as the DGHPSim suite, can contribute to better health policy as well as to better local management.

It addition, though, the DGHPSim suite and approaches like it can be of use to commissioners, regulators and policy makers. It is an example of a management science approach that can be of great value to policy makers and commissioners by providing a test-bed on which policy and commissioning options can be assessed before their introduction. This is particularly important in systems with stochastic behaviour in which common-sense approaches may lead to outcomes that seem, initially, counter intuitive. It offers commissioners a way to understand the efforts that service providers need to make to meet whatever service level agreements are in place. If allows regulators to investigate performance improvement claimed by service providers as part of accreditation and quality management processes. It allows policy makers to see whether proposed targets are too tight or too slack. If such tools are not used before policy is announced, there is a risk that target-based initiatives are shooting in the dark – with the risk of collateral damage.

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