Meeting the four-hour deadline in an A&E Department

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Abstract

Purpose: A&E departments experience a secondary peak in patient Length of Stay (LoS) at around 4-hours, caused by the coping strategies used to meet the operational standards imposed by government. We aim to build a discrete-event simulation model that captures the coping strategies and more accurately reflects the processes that occur within an A&E department.

Design/methodology/approach: A Discrete-event simulation (DES) model was used to capture the A&E process at a UK hospital and record the LoS for each patient. Input data on 4150 arrivals over three one-week periods and staffing levels was obtained from hospital records, while output data was compared with the corresponding records. Expert opinion was used to generate the pathways and model the decision-making processes

Findings : We were able accurately to replicate the LoS distribution for the hospital. The model was then applied to a second configuration which had been trialled there, again the results also reflected the experiences of the hospital.

Practical implications: This demonstrates the coping strategies, such as re-prioritising patients based on current length of time in the department, employed in A&E departments have an impact on LoS of patients and therefore need to be considered when building predictive models if confidence in the results is to be justified.

Originality/value: As far as the authors are aware this is the first time that these coping strategies have been included within a simulation model, and therefore the first time that the peak around the four-hour has been so accurately analysed using a model.

Keywords

A&E department; Coping strategies: Simulation; Emergency Department; Four-hour operational standard; Length of stay

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1. Introduction:

The flow of patients through Accident and Emergency (A&E) Departments has received sustained attention over the past decade. Since 2004, A&E Departments in the UK have been required to ensure that at least 98% of patients are either discharged or admitted to hospital within 4 hours of arrival. Although extra resources were made available at the time (Department of Health 2001), the introduction of this reform saw a huge increase (18.29%) in first-time attendees at A&E departments over the previous year, and has seen an overall increase of 41.38% increase since its introduction (Department of Health 2009).

This mix of heightened demand and more stringent requirement has driven the search for ways to streamline the pathways of patients through A&E, rather like the business process re-engineering that took place in the '90s (Hammer and Champy 1993). In particular, it was hoped that the 4-hour operational standard could be met systemically, without resort to coping strategies in which patients nearing the 4-hour mark are identified and then fast-tracked onto a hospital ward; into a medical assessment unit; or through to discharge. Nonetheless, patients are coded according to their stay in A&E, usually in colour on the information displays – red indicating the approach of a breach. This remains an integral part of the NHS (National Health Service) system, and a secondary discharge peak close to 4 hours is visible in most distributions that capture the length of stay of A&E patients (Locker and Mason 2005; Mayhew and Smith 2008), indicating widespread use of coping strategies.

While there is an extensive literature reporting simulation and modelling of A&E and Emergency Room (ER) throughput, there is, to our knowledge, nothing in the literature that addresses or replicates the impact of such strategies. In this paper we model the A&E Department of a District General Hospital, motivated initially by a desire to set up a baseline against which a number of streamlining strategies could be assessed. The exercise has turned out to be more complex than initially anticipated – which may, in part, explain the gap in the literature – for several reasons. Firstly, the practice of A&E queue management, on the ground, is based, as noted, on identifying patients as they approach the 4-hour mark, which can be difficult to capture in many modelling tools, and indeed in practice. A second problem with providing an accurate model lies in simulating the behaviour of staff. Breaks, for instance, are not static: most managers waiting for either a quiet spell or at least until specific tasks are completed before allowing or encouraging staff to take a break. Moreover, judgements are made, either by individuals or their managers, in deciding to move from one area to another, as the loading moves around the system (e.g. from Major Injuries to Minor Injuries). The former effect we have not really modelled, sticking to fixed breaks (providing the current task is completed). To imitate the latter effect, we have constructed simple rules, which may reflect the judgement of a manager, for instance, in determining whether an area is busy or not.

2. Literature Review

Healthcare and A&E departments in particular, have attracted attention from the discrete-event simulation (DES) modelling community. Jun et al (1999) conducted an extensive review of the literature in 1999, and Fletcher and Worthington (2009) and Brailsford et al. (2009) provide more recent reviews of the literature. Reasons for A&E departments featuring so prominently may include the relatively short timescales required for data collection as well as the comparatively self-contained nature of the facility. Moreover, as a front line of the care system, these departments attract a lot of interest from the public and policy makers. Models range from being relatively simple and accessible (e.g. Kumar and Shim 2007; Hoot et al. 2008) to being highly complex (e.g. Duguay and Chetouane 2007). A key trade-off lies in capturing the detail to address the problem at hand, while retaining sufficient simplicity to support an intuitive understanding of the key mechanisms in play (Chwif, Barretto and Paul 2000).

Other techniques have also been used in modelling the healthcare environment. For instance, Asplin et al (2006) used statistical and queuing theories examine how patient census and hence throughput times can be affected for the 10 hours following a small but unexpected surge in patient arrivals. Lane et al (2000) use systems dynamics to show the interaction between the A&E department and the rest of the hospital. In particular, by highlighting the need to discharge patients quickly, they linked emergency care to elective care and the bed management of the entire hospital.

Setting aside any issues associated with operational standards and their deployment, these standards exist as ‘data for judgement’ (Lilford, Brown and Nicholl 2007) at a national level, and it is necessary for hospitals to conform to them. In the case of A&E throughput, this means dealing with patients and either admitting or discharging them within four hours. The most visible feature of such strategies is the secondary peak in discharges occurring around the 4-hour mark. The feature is described by Mayhew and Smith (2008) but not modelled, while Locker and Mason (2005) report a similar feature in their survey of 122 A&E departments in England and Wales. At times the use of coping strategies (or gaming) and even data manipulation has been reported in achieving these results (British Medical Association 2005; Locker and Mason 2006; Radnor 2008).

As this paper is concerned with the four-hour operational standard, introduced in 2004, and applied in A&E departments within the UK, we conducted a more in-depth analysis on papers published after 2004 that dealt with simulation models of A&E departments in the UK that specifically dealt with patient throughput issues. A review of this literature reveals that only 6 of the papers even make mention of the 4-hour standard (Codrington-Virtue et al. 2006; Gunal and Pidd 2006; Davies 2007; Bowers, Ghattas and Mould 2009; Gunal and Pidd 2009; Maulla et al. 2009) and of these only two include it in their analysis of the throughput times. Maulla et al (2009) conclude that “…it is not a case of medical staff misreporting the LoS [Length of Stay] but of adapting their behaviour to meet the 4 h target” while Gunal and Pidd (2009) state “…it is reasonable to suppose that the looming breach point caused the department to find ways to quickly complete the processing of a small proportion of their patients.” Though these papers show that such coping strategies are being used in A&E departments and account for some discrepancies of their results, no detailed models that incorporate systems that meet the metric or the coping strategies employed were found.

So long as these operational standards are in place, it is hard to see how such coping strategies will cease without radical changes to the system. While the current scene prevails, attempts to modify or improve the system will be complicated by the coping strategies, which are themselves poorly understood. Modelling the system with an attempt to understand the coping strategies, therefore, brings great benefit.

Wolstenholme et al (2007) report on the difficulty in modelling the coping strategies adopted by healthcare staff to make the system work. One reason is that such strategies are, to some extent, unofficial, and therefore generally unrecorded. At the same time, they also note the, ‘deep-seated nature of the coping philosophy.’ In general, the paper takes a negative view of such strategies, deeming them ‘detrimental to patients and costly to the organisation.’ Other surveys (British Medical Association 2007) take a more even-handed view, noting that 85% of respondents report that care of seriously ill and/or injured patients was ‘never or rarely’ compromised by the implementation of the strategies.

This paper takes the study of A&E management forward by creating a model of the department that captures patient throughput accurately and thus replicates the 4-hour peak.

3. Modelling the A&E Department

Operational Context

We report on a district general hospital in West London that handles approximately 1350 patients in its A&E department each week, although this fluctuates with the season.

Some patients arrive at the A&E department by ambulance, while others present as ‘walk-in’ patients who have referred themselves, are referred by their General Practitioner (GP) or through NHS Direct (a telephone advisory service). When a walk-in patient arrives in the department they see the receptionist who records their arrival time, takes their details, and allocates them a priority based on the severity of their case. In general, the 4-hour period is intended to start as soon as the patient crosses the threshold. Since arrival times are recorded by the receptionist, in many hospitals during busy periods patients may wait until a receptionist is free.

Patients are then directed to the appropriate area within the A&E department or to the resident GP in the A&E department. The GP service is intended for those patients who do not require emergency treatment, but need to see a GP promptly (often to obtain a prescription), and may not be able to see their own GP in an acceptable timescale (due to opening hours and appointment availability). The GP service has been introduced, but time spent with the GP is not part of the 4 hours, unless the GP refers a patient on into A&E, in which case, the clock started on first arrival and registration. Hence the slightly ambiguous position of the GP service and its inclusion in the model even though it is not strictly part of the A&E Department.

Walk-in patients under the age of 16 are directed to the paediatric area. Adults with less severe complaints are sent to ‘minors’, and those with more severe cases are sent to ‘majors’. Occasionally someone may be a ‘walk-in’ arrival with a life-threatening complaint and will be sent to the resuscitation area. Once a walk-in patient has registered with the receptionist (and assuming that they do not require resuscitation) they wait in the appropriate area until both a nurse and a cubicle are available, where they are assessed – a doctor may be involved – and their priority rating may be altered. Once the assessment has been made the patient continues through the A&E system, receiving diagnostic tests and/or treatment as their case demands. When these are complete the patient will be re-assessed and discharged or admitted to the observation unit (OBS), the emergency assessment unit (EAU), or a ward in the hospital (see Fig. 1 for an overview). The clock monitoring patient time in A&E continues to tick until the patient has received the discharge paperwork or is admitted as described above.

A patient who arrives by ambulance (or their companion) may have provided their details in the ambulance, or may be in too serious a condition, and will therefore bypass the reception and be directed to the most appropriate area – usually majors or the resuscitation unit depending on the severity of the case.

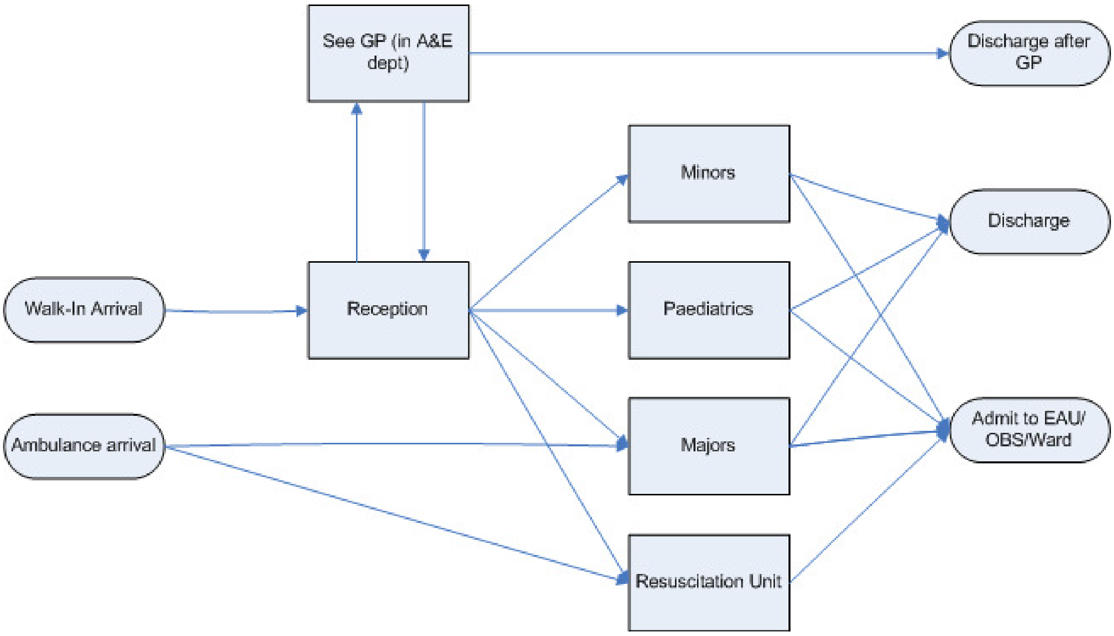

Fig. 1 Overview of model

Modelling and Implementation

A detailed model of the system was generated using Simul8 v15.0 software. In each of the 4 treatment areas (minors, majors, paediatrics, or resuscitation) shown in Fig. 1, patients receive a selection of diagnostic tests and/or treatments depending on their case. It would not be possible to model every individual case, so all diagnostic tests were combined into a standard activity with a statistical distribution to provide a wide range of times for the duration of that activity, representing the range of tests performed. Treatment processes were dealt with in a similar fashion to diagnostic tests in that they were grouped into a single activity, but in this case any treatment requires the use of a nursing resource.

The minors area is shown in Fig. 2, the white squares containing the two black squares represent the queues, whilst the other icons represent the activities. On arrival at the A&E department if a patient is directed to the minors area then their card is placed on a pile for the nurse to deal with, or in some instances to be seen by the doctor. The order in which the cards are placed are based on the patient's priority rating, but as most patients in minors have a low priority rating the queue effectively works as a first-come-first-served queue. When the card appears at the top of the pile, and there is a cubicle free in which to see the patient, the nurse assesses whether she can treat the patient (extreme right in Fig. 2). In very few cases the nurse is unable to treat the patient and the card is placed on the pile of cards indicating which patients the doctor has to assess. Normally however the patient will be assessed by the nurse in a cubicle and a decision is made about whether the patient needs diagnostic tests (out of department), point-of-care (POC)/bedside tests, treatment, or nothing.

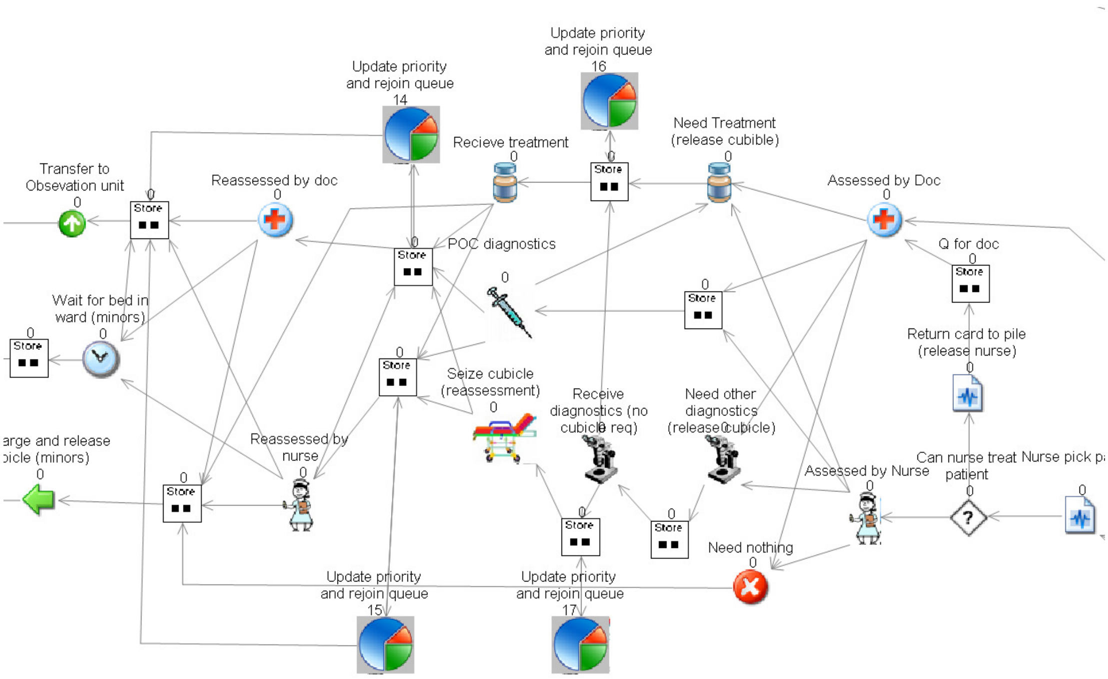

Fig. 2 Minors area of model

If the patient needs nothing further then they are reassured that there is nothing wrong and await their discharge note.

If a POC test is required this is performed by a nurse. The results may indicate that the patient needs treatment, but if not they are reassessed by the nurse or doctor, who then decides to discharge them, to admit them to the OBS unit for further observation, or to admit them to a hospital ward.

If patient's need diagnostic tests outside the A&E department i.e. an x-ray, then they are directed to where the test will be performed, while the cubicle they were using is cleaned and made available for another patient to use. On their return, patients will have to wait for an available cubicle and appropriate staff member, for reassurance (if nothing further is required) and/or discharge, (further) diagnostics or treatment, or admission to the OBS or a main ward.

The majors and paediatrics areas are modelled at a similar level of granularity. The resuscitation unit is at a higher level as there is not the competition for cubicles, and a nurse will remain there while there is a patient in the area, so the competition for nursing resources is limited within the resuscitation unit. A doctor will be required for some of the time, but any request for a doctor from the resuscitation unit will supersede any other request from elsewhere in the department. The effect of the resuscitation unit impacts the rest of the department by removing resources from the majors, minors, and paediatrics areas.

The OBS, EAU and the wards were outside the scope of this project so are not explicitly modelled, but in order to capture the effect of bed-blocking by these units on the A&E ward a simple limit on the number of patients that can be in either at any point in time is included.

At each stage in the patient's journey through the A&E department details on when a patient joins a queue, or starts an activity (such as a treatment or an assessment) is output to a file which records this information for every patient. In this way we create a patient diary so we can examine each patient's process through the department and compare with actual information available.

Hillingdon Hospital's own records were used as patient arrival data for the model. A selection of the data table is shown in Table 1. The table shows the arrival time and mode of the patient, whether the patient was sent to the resident GP before being sent back to the A&E department, the number of tests performed outside the A&E department, whether the patient was admitted or discharged, and at what time. Finally the time that they spent within the department is calculated. The arrival information (columns 2-5 of Table 1) provided the input data for the model. Using Hillingdon hospital's historical data allowed us to accurately model the demands placed on the A&E department over the time period. The information contained in columns 6-9 of Table 1 were used in the verification and validation of the model.

Day	Arrival time	Ambulance or walk-in	GP?	dest	Total tests	Discharged / admitted	Time departed A+E	time in A+E
Sun	20/04/2008 09:20	Walk-in	No	MIN	1	Referred to other Out-Patient Clinic	20/04/2008 13:00	03:40
Mon	14/04/2008 15:03	Walk-in	No	PD	0	Discharged - did not require any follow up treatment	14/04/2008 17:15	02:12
Thu	17/04/2008 12:50	Ambulance	No	MAJ	2	Admitted to hospital bed/became a LODGED PATIENT	17/04/2008 16:48	03:58
Sun	03/08/2008 19:32	Ambulance	No	RES	0	Admitted to hospital bed/became a LODGED PATIENT	03/08/2008 23:00	03:28
Tue	05/08/2008 22:53	Walk-in	Yes	MIN	0	Discharged - did not require any follow up treatment	06/08/2008 06:05	07:12

Table 1 Hillingdon hospital's historical data

Resources for the model were also obtained from hospital records, the number of nurses and doctors available being obtained from staff rota sheets. In practice staff members take their break in quiet moments, rather than on a strict timetable. This proved difficult to model so breaks were modelled to a timetable to ensure that the staff did have breaks in the model.

4. Why is the four-hour limit difficult to model?

Given an operational standard of discharging or admitting patients within 4 hours, an industrial approach, using the insights of queuing theory, would focus on pushing the peak of discharges and admissions well away from 4 hours, so that there would be a small minority of patients remaining in the department after 4 hours, and therefore little need for management-by-exception, or coping strategies. However, the healthcare culture has attacked the problem from the other end and tracks all patients, a strategy which is highly consumptive of resources and is therefore more difficult to model.

In reality in the hospital we can monitor the patients' progress and act to fast-track them when they approach the 4-hour limit. In DES this is more difficult. There are two methods how this could be achieved:

1) Periodically check the status of every patient in the model and instigate amended action on those exceeding a time threshold
2) Set an "expire by time" on entry to queues

Each method has advantages, as well as disadvantages. The first requires a record of each patient as they enter the system and time thresholds that apply. A global process must examine the record of each patient at periodic intervals (say every 5 minutes of model lifetime) and change the status of any patient exceeding a time threshold. A large complex model with many patients would require running the check often, and therefore would add substantially to computing time. Furthermore, implementation may be complex in how to update the record for each patient whenever they move location. However it has the advantage that the model can be built independent of the checks.

The second option reduces computation time required, but requires modification of the model to include a check at every point for the status of each patient as they pass that point. However DES suffers from limitation that it has only certain points where such a check can be made whenever a patient

1) joins a queue,
2) leaves a queue,
3) starts an activity,
4) finishes an activity

This means that during the time a patient is in a queue or involved in an activity, it is not possible to change his or her status and therefore divert their course. This is especially problematic if the queues are long, or the activities have long durations. A solution to this problem would be to implement the concept of an expiry time, where a queue is left prematurely. The "shelf life" facility within Simul8 was utilised to achieve this.

In our model each patient, as they enter the A&E department, is allocated a priority rating based on the severity of their case. This priority rating is updated at 150, 180, 210, and 240 minutes after arrival. The queuing strategy used throughout the model is based on these priorities and patients with highest priority rating are placed at the front of each queue. On entry to a queue the patient is given a shelf life, which is set so that the patient will exit the queue early at the next priority update time. If a patient exceeds 240 minutes in system then a shelf life of 999 is allocated. A patient will wait in a queue until:

1) There are enough resources for the activity to start, or
2) The shelf-life expires

If the shelf life expires the patient will drop out of their current queue and have their priority rating increased. If there is sufficient time remaining before the patient would breach the four-hour limit then they are returned to the original queue. As the queuing strategy is based on taking high priority first, then a patient may be moved forward in the queue in comparison to where they were previously positioned. If, on the other hand the patient is in danger of breaching the four-hours, they are redirected to an alternative fast-track path. This is illustrated in Fig. 3. The updating of the priorities does not advance the simulation clock, so this effectively is an instantaneous re-ordering of the queue based on the updated priorities.

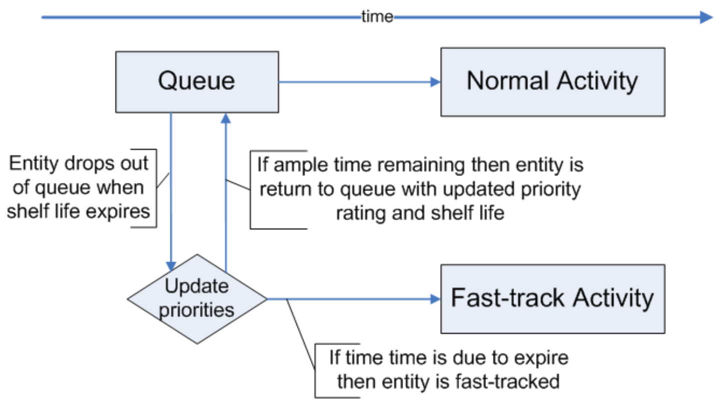

Fig. 3 How shelf life is used to fast-track patients

Whilst this approach can affect the behaviour for patients in a queue, it cannot affect behaviour for patients within an activity. In practice this does not affect behaviour significantly, as the patient continues to receive the same care that they would be likely to obtain through the alternative route, and their priority rating would be updated whenever they entered the next queue.

5. Results

Three different weeks of data were collected from the hospital, and were used to provide the input data for the model. The data collected included all patients that were in the department from Monday 00:00 through to Sunday 23:59, so those patients that arrived on Sunday night but were still present after midnight are included in the table. However, to ensure no double counting the input data used just those arriving after midnight.

	Start date/time	End day/time	No of patients
Week 1	Sunday 13/04/08 20:54	Sunday 20/04/08 22:27	1346
Week 2	Sunday 27/07/08 18:54	Sunday 03/08/08 23:07	1370
Week 3	Sunday 03/08/08 19:52	Sunday 10/08/08 22:22	1434

Simul8 has a facility to determine the number of replications necessary to ensure that the results fall within the desired confidence limits. The calculations used by the software are discussed in Hoad et al (2007). Using this feature, 20 replications were deemed necessary to ensure that the “average time in system” and the “percentage of patients in the system less than 4 hours” statistics were within 99% confidence interval.

The model was run for two identical weeks of arrival data, though the results were collected only for the second week. Although the arrival data, being drawn from the historical records, remained consistent throughout each set of runs, variability was introduced by using a different random number seed to draw durations of activities, and likelihood of requiring tests and/or treatments from their distributions.

The arrival data remained consistent because we wished to verify that the model accurately represented the hospital's A&E department by comparing the LoS for patients from historical data with the model output data.

We determined the actual frequency distribution for length of stay from the hospital data, and the results from week 1 are shown by the dotted line in Fig. 4. This has the expected form of a typical queuing system up to 3:30 hours, however beyond this time the frequency up to the 4 hour point increases significantly and thereafter falls. The results from the model are shown as the solid line in the graph. From the graph it can be seen that the model produces a similar distribution for the patient length of stay to the actual length of stay. There is a slight discrepancy at the number of patients released in the 4:00-4:30 hours time slot, which in turn means that the percentage of patients through A&E in less than 4 hours is smaller than recorded in the hospitals actual figures (see Table 2). One reason for this is could be the digit bias as reported by Locker and Mason (Locker and Mason 2006), that patients released at say, 4:01 may have their time recorded as 3:59 or rounded to the nearest 5 minutes so as not to count as a breach case. We elected not to replicate this digit bias in the model output as the aim is to improve throughput and so reduce the need for any data manipulation. Including the digit bias within the model may well distort the effects of changes made to the system.

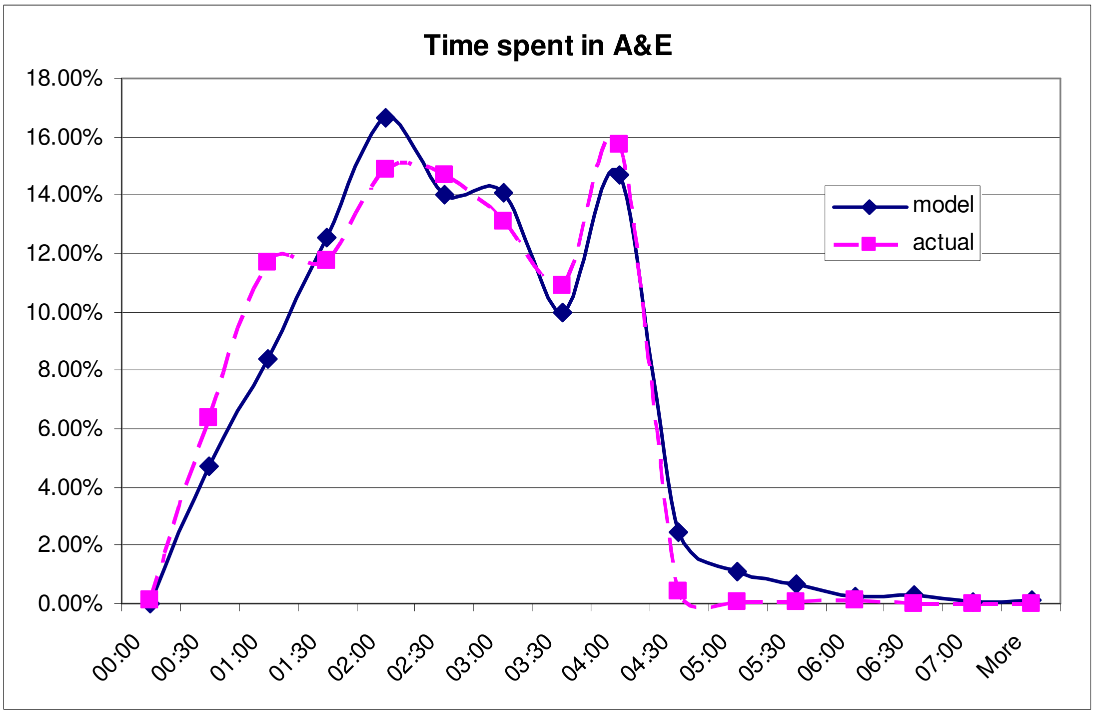

Fig. 4 Comparison of actual (dashed) and model (solid) for length of stay in A&E department (week 1)

Table 2 gives the results from each of the 20 replications for the data for week 1. The number completed in the table is less than the number of arrivals for a number of reasons. Firstly some of the patients will still be receiving treatment in the department; secondly patients that were admitted to the resus unit are not included in these results are they are exempt from the four-hour standard; thirdly some of the patients will have been directed to the GP service and discharged from there so are also not included in the results.

Trial Number	Average Time in System	Number Completed	% In System less than 4 hours	St Dev of avg time in system	Maximum Time in System	Minimum Time in System
1	154.5322	1114	88.24057	74.1152	722.4823	11.72394
2	150.3331	1105	91.9457	65.8503	447.1695	12.31507
3	152.2253	1111	90.54905	69.194	588.1491	12.18128
4	151.6169	1105	91.58371	66.9607	593.0622	13.85638
5	148.1006	1111	91.26913	67.0766	399.0393	11.4942

6	144.304	1110	93.78378	63.9478	540.8	11.89763
7	151.7715	1116	89.96416	68.8225	514.2788	11.52791
8	148.5228	1099	92.2657	68.9088	605.6329	13.20082
9	150.7361	1099	90.26388	68.4561	388.8447	12.12553
10	151.6092	1105	92.21719	69.6249	504.7466	10.84919
11	150.0119	1106	91.86257	66.9809	467.2111	13.59172
12	159.3559	1109	88.00721	71.4445	481.6793	11.71931
13	149.4745	1114	92.10054	66.6053	592.7556	13.04618
14	151.3609	1124	91.01423	71.9715	568.9392	12.29201
15	150.3348	1113	90.47619	67.6475	403.0214	13.57584
16	152.2636	1091	89.64253	69.5137	540.7102	13.32455
17	153.0026	1117	90.68935	70.713	606.8313	10.99644
18	145.9392	1100	91.90909	68.7154	485.7265	12.728
19	150.7639	1086	91.43646	69.1948	486.1605	12.57451
20	151.3619	1117	90.77887	79.1716	657.2752	11.46014
Lower 99%	148.9118	1101.677	90.12228	67.1585	473.0697	11.75534
Average	150.881	1107.6	91	69.2458	529.7258	12.32403
Upper 99%	152.8503	1113.523	91.87771	71.333	586.3818	12.89273

Table 2 Results of 20 runs

The results indicate that the model is extremely stable, with only the maximum length of stay varying noticeably between different replications, however these were within the limits that appeared in the actual data (956 minutes).

The model was also run for two other weeks, namely the weeks beginning 27th July and 3rd August 2008, and the results compared with the actual times that patients spent in the department during these weeks. Both produced similar correlations to the one illustrated.

We believe that the close correlation *(r=0.98)* between actual and predicted gives confidence in our model to provide insight into behaviour within the A&E department and to use it to determine the effect of changes in organisation.

6. Introduction of ENP system

As part of its own empirical improvement process the hospital introduced a fast-track for patients with injuries that can be dealt with relatively quickly in order to improve the four-hour breach. Such a system has been tried at a number of other hospitals, with varying success (Cooke, Wilson and Pearson 2002; Darrab et al. 2006; O'Brien et al. 2006; Sanchez et al. 2006; Nash et al. 2007). In this approach, patients presenting at the A&E department with a minor complaint not requiring assessment by a doctor are sent directly to the Emergency Nurse Practitioner (ENP). A dedicated cubicle was used for this purpose, and these patients were dealt with on a strictly first-come-first-served basis. The model was changed so that 21% of minors arrivals between the hours of 0700 and 2000 were directed from the reception to the ENP unit. To accommodate this arrangement one nursing resource and one cubicle from the minors area was dedicated to the new ENP unit, and therefore made unavailable to the minors area.

The model again used Hillingdon's actual arrival data (week starting 2nd March 2009), so that the results could be compared against existing data and again 20 replications were deemed necessary to ensure that the results were within 99% confidence interval.

Fig. 5 shows the model output (solid line) and the actual patient length of stay distribution (dashed line) for that week *(r=0.964)*. Table 3 gives the summary statistics for the replications.

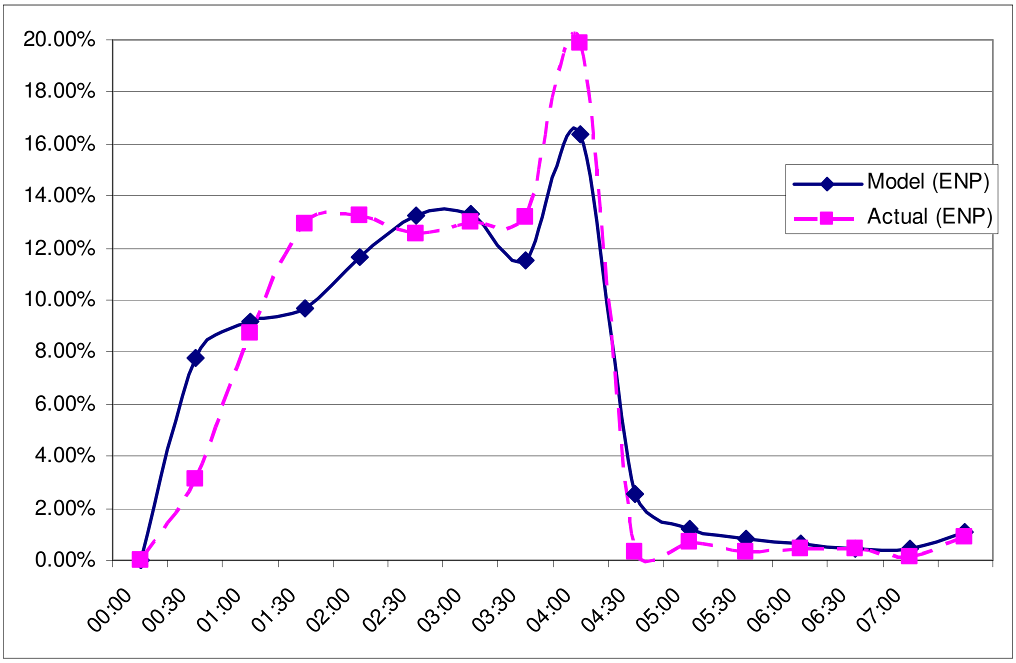

Fig. 5 Comparison of actual (dashed) and model (solid) length of stay following introduction of ENP

	Average Time in System	Number Completed	% In System less than 4 hors	St Dev of avg time in system	Maximum Time in System	Minimum Time in System
Lower 99%	152.3297	1325.266	88.0055	79.26813	572.3986	10.74031
Average	154.3044	1330.679	88.77024	81.79153	616.2479	11.52985
Upper 99%	156.2791	1336.091	89.53498	84.31493	660.0971	12.31938

Table 3 summary Results for ENP scenario

The experience of the hospital was that the change did not improve performance, and in general patients were experiencing increased time in the A&E department; most notable was the increase in those with 3:30 hours. The model predicted a similar change in times.

7. Discussion

We believe that the close agreement between the distribution of observed times and those of the model indicates that we have been able to capture with reasonable accuracy all of the critical processes that were affecting the performance of the A&E department. We determined that the majority of the processes could be described as formal and had well defined rules that could be described by a range of statistical distributions. However, as identified by Wolstenholme et al (2007), we also discovered several informal processes, with rules that were less than rigid. This meant that although the algorithms in our model were able to identify patients close to breach and fast-track them, we could not reproduce exactly the number of patients that actually breached, and we must surmise that there are some aspects of the informal processes yet to be accurately modelled.

Formal strategies that are utilised and were captured within the model included moving staff into the resuscitation area when notified of the imminent arrival of a patient and returning them back to the other areas when care was complete. However movement between other areas was less formal, with nurses moving between areas when one area was ‘busy’ and the other ‘quiet’. However the decision for ‘busy’ and ‘quiet’ is subjective, and was left to the judgement of the nurse in charge, and no attempt was made to emulate this in the model. Further informal strategies were not explicitly captured within the model, including the practice of contacting the pathology laboratory to expedite diagnostic test results when patients were approaching breach.

Wolstenholme et al (2007) point out that some of these informal processes, if continued over a period of time, can have detrimental effects on the very problems that they are trying to solve, and it is possible that the very metrics used to measure performance may disguise this fact. An example of this may be the use of the OBS ward as a 'waiting area' for patients who will be admitted to another ward when a bed becomes available. These patients do not breach the four-hour operational standard as OBS is not considered a part of the A&E department; however its use has the effect that the wards are not encouraged to make beds available. If the OBS ward should subsequently become full then patients must remain within the A&E department causing knock-on adverse effects.

In order to reduce the number of breaches in A&E departments we need a sustainable reduction in the length of stay distribution, reducing the number of occasions that the coping strategies need to be employed. One of the advantages of developing a model is the insight that can be acquired by analysis of the processes and their interactions. By gaining deeper understanding of the factors and their influence we might determine and propose alternative strategies to reduce the length of stay and improve performance.

The hospital ran its alternative strategy for six months before it believed it had sufficient data to compare approaches. Though, due to the complexity, the model took 6 months to develop, it has the advantage the new scenarios can be modelled and tested very rapidly. Using a model might give results in a fraction of the time and offers the exciting possibility to evaluate this and further innovative alternatives. These strategies may include changing staff rosters to better match the busy periods, or having staff on-call when either arrivals, or the number of patients within the department, exceeds some threshold.

More importantly these can all be evaluated without the inconvenience of the changes to staff and organisation or adverse impact on patients. Furthermore the model is able to gather a higher level of detail on events not practicable within the hospital or its IT system, such as being able to determine the actual number of nurses within the department at any one time, by being able to determine those on break or involved in transfer of a patient. This information can provide much greater insight into the mechanisms of the department and by enhancing understanding can allow improved strategies to address the problems to be developed.

However improving performance of the A&E department can bring its own problems. Anecdotal evidence (British Medical Association 2007) has suggested that reducing length of stay will entice patients to attend the hospital in preference to visiting their own GP, thus increasing the number of patients and workload. In simulation modelling we might anticipate such an increase in patients and model its effect. Through successive changes to patient numbers we might also identify the critical thresholds for arrivals that cause fundamental changes in performance.

We should recognise that the model has the limitation that it only analyses performance from a theoretical and analytical perspective - it does not have conceptual understanding of the clinical need of patients. Thus for some patients, the length of time in the A&E department is not due to logistical issues, but is a result of clinical need.

8. Conclusion

A detailed and validated model of the A&E department of a District General Hospital is reported. In the process of developing the model, important aspects of formal and informal processes have been identified. Most of the formal processes have been incorporated within the model, but informal processes have proven difficult to capture and include. We assume their effect is not significant at this time.

Our initial work, as exemplified in Fig. 4, gave us a high level of confidence in the model and its ability to reproduce all of the characteristics of the actual times. Specifically, we believe we have been able to reproduce faithfully the strategies used within the A&E department to identify patients approaching the four-hour time and reprioritise them to expedite treatment or implement a fast-track approach that removes them from the department by the four-hour time. Moreover, when the model was used to evaluate the alternative strategy of fast-tracking very minor injuries via an ENP nurse, there was excellent agreement between actual data and the predictions of the model. This gives confidence that the model can produce realistic results for other planning scenarios.

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