AN EVALUATION OF 'FAST-TRACK' IN A&E: A DISCRETE EVENT SIMULATION APPROACH

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ABSTRACT

This longitudinal study provides primary evidence on the impact that a fast track strategy in a hospital Emergency Department has on patient wait time. The study uses a Discrete Event Simulation (DES) model to predict output within a variety of triage categories and compares these to post-implementation results. The results of the study indicate a significant reduction in patient wait time with 13.2% of the population waiting longer than 4 hours prior to implementation compared with 1.4% post implementation. However, while this fast track strategy significantly improves service delivery to patients with minor conditions, service for patients with more acute conditions is not proportionately improved.

Keywords: Service Operations, Process Design, Discrete Event Simulation, Healthcare, Performance Measurement, See and Treat, Fast Track, NHS.

1. INTRODUCTION

Over the last two decades the UK's National Health Service (NHS) has been responding, in a variety of ways, to politically-led pressure to improve the service whilst containing the costs of service provision [Bolton 2002]. There has been a widespread use of performance targets set externally by government which have necessitated that both management and clinician explore strategies for improving the design and management of operational activity. For example, the NHS Plan, presented to parliament in July 2000 [H

M Government 2000] stated: ‘By 2004 no-one should be waiting more than four hours in accident and emergency from arrival to admission, transfer or discharge. Average waiting times in accident and emergency will fall as a result to 75 minutes’. To address these improvements, guidance on best practice approaches was provided by the Modernisation Agency (MA). The MA, launched in 2000 and disbanded in 2005, focused on Ten High Impact Changes [2004a] which addressed a range of issues such as managing variation, managing patient flow, and removing queues for access. To address the specific targets imposed on A&E departments the Emergency Services Collaborative (ESC) was established under the auspices of the MA. A major activity within the ESC was the dissemination of a ‘See and Treat’ (Fast Track) strategy to A&E departments across the UK [Modernisation Agency 2002, 2004b]. Although the ‘fast track’ concept is not new [Meislin et al 1988] and a variety of claims to its existence, prior to its popularity, can be found [Cooke et al 2002; Wardrope and Driscoll 2003], it has been gaining increasing attention within the literature. As this body of literature has grown, a number of variant articles have emerged which seek to address specific issues associated with this ‘fast track’ strategy: resourcing; patient satisfaction; throughput; and economics associated with implementation and improvement [for example, Fernandes and Christenson 1995; Wright 1992; Ellis and Brandt 1997; Wilson 2000; Counselman et al 2000; Cooke et al 2002]. More recently however, Lamont [2005] draws attention to the extent of adoption of ‘See and Treat’ within the UK, but also indicates emerging criticism levelled at the lack of evidence underpinning this strategy [Windle and Mackway-Jones 2003; Leaman 2003; Wardrope and Driscole 2003]. Windle and Mackway-Jones [2003], for example, raise the issue of evaluating clinical costs, especially ‘…delays in the management of the smaller number of seriously ill and injured…' While there has been an initial response to these criticisms [Castille and Cooke 2003] there is still a need for primary evidence.

This paper focuses on providing this evidence. The results presented are the product of longitudinal research with a three star foundation trust in the south west of England. The research addressed the following question: what impact does a see and treat strategy have on patient Length of Stay (LoS) in an Emergency Department? While this strategy is specifically focused on addressing patients with 'minor' medical conditions, the analyses presented in the research also evaluate the potential impact on patients with more severe (major) medical conditions. The approach utilises three data sets for the evaluation. These represent: actual pre-implementation performance, pre-implementation and post-implementation predictions derived from a discrete event simulation model, and the actual results obtained from a post-implementation analysis.

The research was structured into three phases. Phase 1 involved the development and validation of a discrete event simulation model, constructed in 2003, to represent the current processes within A&E. Phase 2 of the approach was focused on using the model to assess the impact of a 'see and treat' strategy on target wait times, as stipulated within the NHS Plan. Phase 3 of the approach, undertaken in 2005, compared pre and post implementation performance with the predicted results of the model. The results of the research indicate that prior to implementation 13.2% of patients had a Length of Stay (LoS) within A&E in excess of four hours. This was significantly reduced to 1.4% post implementation. Not surprisingly the mean time reduced from approximately 146[1] minutes to 115 minutes, the median had moved from 126 to 106 minutes and the standard deviation had reduced from 89 minutes to 68 minutes. However, while these results reflect dramatic improvements in the throughput of patients with low priority conditions, it is noticeable that service improvement for patients with more severe conditions is not commensurate. In 2002, for example, 34.4% of Triage 3 patients waited over 3 hours, whereas in 2005 this was 31%. However, it must also be noted that the overall proportion of Triage 3 patients has reduced from 34.3% (2002) to 28.5% (2005).

In addition to these findings, the paper also suggests a number of key practical issues which contribute to the successful analysis of complex dynamic systems found within healthcare services. These are included to inform future practitioner analyses and include: the identification of statistically significant time periods to model the 'actual' variation in demand and the derivation and allocation of statistical distributions to capture the variability in treatment times.

2. LITERATURE REVIEW

The assessment of a 'see and treat' strategy within an Emergency Department (ED) is problematic in that analyses must take into account the complexities inherent in the internal dynamics of the system. Harper [2002] highlights the inadequacy in the current practice of using simple deterministic approaches, often populated with an array of

[1] It is difficult to be precise because in 2002 no data was collected for the time taken to triage the patient. This was dealt with through additional primary data collection (see section 3.1.2)

averaged data, to address complex non-linear structures which correspond to a complex stochastic system. Deterministic systems utilise fixed non-random values as input which can lead to dangerous errors in output [Kelton, 1997]. Emergency Departments characterised by high variations in the demand for service, high variety in presenting condition, increasingly high volumes, combined with limited resources, necessitate the utilisation of more complex analytical and modelling methods. It is therefore unsurprising that a plethora of articles on the use of simulation methods in health services analysis and design can be identified. These articles, ranging from complex mathematical modelling to Discrete Event Simulation and System Dynamics, address a broad range of issues. Capacity issues, especially those relating to bed capacity [Bagust et al 1999; Costa et al 2003; Zilm 2004; Moore 2003; Huang 1998; Smith et al 1996] have received much attention. Specific analyses within Intensive Care Units (ICU) [Williams et al 1983; Hashimoto et al 1987, Ridge et al 1998; Ho and Lau 1999; Kim and Horowitz 2002], and a growing body of literature within drug distribution and Pharmacy practice [Dean et al 2001; Anderson et al 2002; Buchanan 2003] have also utilised the potential of simulation techniques. Other examples include focusing on cost analyses [Glick et al 2000; Dexter et al 2000], and simulations for determining workflow-based information systems [for example, Ohboshi et al 1998].

The majority of literature on the use of simulation within Emergency Departments has focused on issues associated with patient flow and resource utilisation, and often relate performance to patient wait time or Length of Stay (LoS) [Coats and Michalis 2001; Blake 1996; Connelly and Bair 2004; Braly 1995]. While there are many examples of the use of simulation methods in this setting, it is possible to identify a range of limitations in this work. Braly [1995] for example, while focusing specifically on evaluating a 'fast track' strategy in the ED, only provides anecdotal evidence and discussion. The work of Connelly and Bair [2004], while far more rigorous in approach, is limited by a small sample (a population of 682 patients in a 60,000 patient system), identified over a 4 day period. While these authors acknowledge the issue of seasonal variation in demand their approach is unable to account for this.

There is some evidence in the literature, however, of attempts to address a number of these limitations. For example, Lattimer et al [2004] use a 1 year cycle to account for seasonality, Smith et al [1996] extend this and emphasise the need for an adjusting factor at a more granular level (day of week). Costa et al [2003] challenge the use of average values for LoS, and Smith et al [1996] acknowledge the need to use statistical distributions for a more accurate representation of activity time. Their approach utilises normal distributions and associated adjusting factors. To address the issue of time distributions for activities, Kim and Horowitz [2002] use statistical tests to evaluate the 'fit' of a Poisson distribution. The grouping of patients based on common resource consumption within simulation modelling is also a factor which has been discussed [Ridley et al 1998] and which is related to identifying appropriate time distributions for activities.

A possible challenge to conducting an analysis of ED through simulation models is that the ED itself is part of a wider health service delivery system. A number of articles have addressed this issue and have focused on patient flow through a broader 'emergency medical service system'. These analyses include multiple hospitals [Su and Shih 2003] or links to other service providers (e.g. General Practitioner, Walk-in-centre, NHS direct etc.)[Lattimer et al 2003]. Brailsford et al [2003], however, compare Discrete Event Simulation and System Dynamics models and conclude that DES is an excellent tool for micro-level analysis within ED, whereas broader system issues should be addressed through system dynamics models.

In summary, while 'see and treat' practice has become widespread within the UK, there is emerging criticism levelled at the lack of primary evidence supporting this strategy. Obtaining this primary evidence within an ED is complex, due to it's characteristics as a complex stochastic system. While the use of simulation models has gained popularity, a synthesis of a number of studies has revealed a number of challenges. These challenges have been addressed in this approach and include:

1. The accurate representation of the arrival pattern of patients to the ED; accounting for seasonality and statistically significant time periods.
2. Appropriate grouping of patients by resource consumption.
3. Statistical distributions which accurately represent the variability in treatment time within each patient group.

These requirements provided the initial design guidelines for the Discrete Event Simulation model described in the following sections. While previous research highlighting sophisticated methods [e.g. CART; Ridley et al 1998] for patient grouping by resource consumption is acknowledged, this research has utilised existing triage categories to facilitate a comparison of process throughput of both pre-implementation and post-implementation scenarios. While previous research into appropriate performance measures for 'access to care' is also acknowledged [for example, Kennedy 2000; Gerard et al 2004] and that patient satisfaction criteria have recently received attention [Sitzia and Wood 1997, Williams et al 1998, Boudreaux et al 2000], the research approach described focuses specifically on the impact on wait time in Emergency Departments, as stipulated in the NHS plan [2000].

3. METHOD

3.1 Phase 1 – Model Creation and Validation

To analyse the potential impact of moving from a 'triage and treat' to a 'see and treat' strategy a discrete event simulation model was constructed based on a complete year of A&E data. The initial data, obtained from the hospital information system, included patient arrival time at A&E, time seen by Doctor, and discharge time. In total, data relating to 55,069 patients, seen during 2002, was inserted into the model. This involved mapping the data, using some relatively simple formulae, onto the basic steps of the process. A simplified process flow is shown below (Figure 1).

Figure 1

Five major questions emerged when applying the data to the model.

1. What was the arrival pattern for patients?
2. How long to Triage the patient?
3. How long to wait in reception?
4. How long to treat the patient?
5. What percentage were admitted or discharged?

3.1.1 What was the arrival pattern for patients?

To produce a representative simulation model of the system an accurate representation of the volume of demand is required. An initial statistical analysis of patient arrival times was conducted on the whole dataset (55,069 patients). The following graph (Figure 2) represents this system demand for 2002.

Figure 2

Apart from the obvious noise in the data the most striking feature is the seasonality: a rise in summer and fall in winter. While this might, at first, seem counter intuitive for an A&E department, it may be explained by the considerable population increase in the summer months due to the South West tourism industry.

The data was analysed using an analysis of variance (ANOVA) to investigate if there was any pattern in the monthly averages. These analyses revealed a complex pattern with daily variance observable both within each month and across the months. This necessitated the creation of a daily arrival pattern for patients. The clinicians also pointed out, however, that at some periods in the day wait times were longer than others. Further analyses (ANOVA) were undertaken to evaluate the significance of daily arrival times within the day. This revealed three statistically significant arrival groups: 00:00 – 10:00 AND 14.00 – 18.00 (statistically they had the same mean wait time 0.9hrs); 18.00 – 00:00 which had a mean wait of 0.81 hr; and 10.0 -14.00 which had a mean wait of 1.02 hrs. A graphical representation of these analyses is presented in Figure 3.

Figure 3

As a result of this analysis a generator of patient arrivals was developed based on the original data. The data was represented using the actual daily arrival (based on the 2002 data) and by the three statistically significant time periods within each day. In total 1095 time periods were populated to represent the arrival pattern of the 55,069 patients.

3.1.2 How long to triage the patient?

The time taken to initially triage the patients required some primary data collection as this was unavailable in the initial dataset. This was achieved by observing and monitoring a sample of 1000 patients entering the system.

Figure 4

The histogram (Figure 4) of wait times represents this data. The mean wait time was identified as 15 minutes and the standard deviation as 10.1 minutes. If we overlay a normal curve onto the histogram it is clear from observation that the data is heavily skewed; it is not normally distributed and indeed fails the normality test with a probability of greater than 99%. It was therefore necessary to identify an appropriate distribution which fitted the data. A distribution fitting function was used to ascertain the best possible fit. This resulted in the identification of a Weibull distribution with parameters, shape 1.145 and scale 16.74.

The trust's triage system categorised patients into seven groups. Triage groups 1-4 represented severity of presenting condition (Triage 1 being most severe). Triage 5 and 8 were legacies of old systems and were relatively infrequently used. A final major group was Triage 9; a category explicitly reserved for eye patients. The percentage of patients in each triage category is shown in Table 1. This clearly indicates that 80% of the total demand on the system is by patients with conditions classified as T3 and T4.

Table 1

3.1.3 How long to wait in reception and treat patient?

One would expect the wait in reception to emerge in the outcome of the model as this is, in effect, the dependent variable. In practical terms this emerged as one of the most challenging components of the simulation, not because it was itself complex but because of the difficulties inherent in identifying the resource constraints. Initial analyses indicated that the number of clinicians was the primary constraint. The identification of patient-clinician interaction is however complex due to a number of factors. To accurately account for clinician resource an estimate has to be made of the time a doctor spends with each patient. At a granular level this is complex due to the variety of patient conditions. This complexity is also compounded by a variety of skill sets and specialisms, complex working schedules, and instances where patient-clinician interaction does not conform to a one-to-one relationship.

To overcome this problem and to create an accurate representation of system performance the data was analysed to identify time distributions for both wait time and treat time. It is possible to argue that these distributions incorporate the current resource limitations of the system as these are present in the source data. This approach removes the need for modelling specific resource constraints. The limitation of this approach is that experimentation with different resource volumes and mix is difficult. For the purposes of this research however, it was assumed that the implementation of a 'See and Treat' (Fast-Track) strategy would be implemented through a dedicated patient flow with additional resource, and that resources for the triaged patients would remain constant.

The derivation of wait time and treatment time from the source data also surfaced some initial problems. There were a number of instances in the database where times had either not been recorded, or where there were obvious keying errors (negative or excessive wait or treatment times). It was therefore necessary to cleanse the data. This was achieved through discussions with senior clinicians where likely maxima were identified and applied. This cleansing of the data meant that we had reduced the original data set of 55,069 by approximately 11%.

Initial analyses revealed that the distribution of wait times and treatment times was highly dependant on the triage category. For example, a Triage category 2 patient waits very little time in reception (18 minutes), whilst a category 4 patient (46% of the total) wait on average 70 minutes. The following table (Table 2) is an Analysis of Variance across the Triage categories.

Table 2

The table illustrates that the average wait time across the triage categories creates five distinct groups. These groups are essentially the same as the Triage categories. The only undistinguishable groups are Triage 9 and Triage 5 ($p=.95$). As Triage 5 has such a small number of patients and Triage 9 is specialist eye treatment, the principle remains that triage category is an appropriate unit of analysis for determining average wait time. This approach was replicated on the treatment time data (Table 3).

Table 3

The results of the ANOVA tests necessitated that a distribution for both wait time and treatment time was derived for each individual triage category. In total twelve separate distributions were produced. A simple histogram of the data was produced for each Triage category. A typical example is provided below (Figure 5). The data was heavily skewed and in each category easily failed the test for normality ($p > .99$).

Figure 5

Appropriate distributions for each of the twelve datasets were identified by producing a probability plot against a series of standard distributions: normal; lognormal; exponential; and weibull. The following table shows the distribution and its parameters that best represented the data.

Table 4

The shape and scale parameters were then used within the model to simulate the wait times and treatment times for each triage category.

3.1.4 What percentage were admitted or discharged?

An initial assessment of the data indicated that 74.6% of patients were discharged and 25.4% were admitted (discounting fatalities of less than 1%). However, this simple rule did not apply across all triage groups. For the specialist eye patients (T9), for example, only 1.08% were admitted. This reflects the predominance of an out-patient mode of delivery for this service. In contrast, a high proportion of T2 patients, nearly 70%, were admitted to the hospital. The following table shows the percentage of patients admitted based on Triage categorisation. These calculations were incorporated into the model by inserting a series of process flow decision points for each of the triage process pathways.

Table 5

In summary, the model which was created exhibited five main features:

- A process flow combining triage-based pathways;
- An arrival pattern for each day, based on actual patient arrival, organised by three statistically significant time periods;
- A Weibull distribution for time to triage;
- Appropriate distributions (Weibull and Log Normal) for each wait and treatment time by triage category;
- Process pathways which incorporated different percentages for the admission and discharge of patients within each triage category.

3.1.5 Validation

With any simulation model of this complexity care must be taken that the results are based on an accurate representation of the data. Kleijnen [1999] (in van Dijkum, DeTombe and van Kuijk; 1999] discusses the validation of simulation models depending on three situations: no real data; real output data available; real input and output data. In this research simulated output data is being compared with real output data. The validity of the model was undertaken through a comparison of the actual data and the simulated output using a predominant test; the student t test. The results from this analysis were however inconclusive. The explanation for this lies in the size of the populations. Standard tests such as student t test or χ^2 are strongly affected by sample size because they estimate the probability that there is no difference between the two populations. We are in this case in serious danger of a Type I error; rejecting H_0 when H_0 is true. According to Newsom [2005] 'it is difficult to get a nonsignificant chi-square when samples sizes are much over 200 or so'. The total sample in this simulation is in excess of 55,000 with some instances of triage-specific populations exceeding 20,000. Small differences may be accorded a high significance simply because of a large population size. The importance of the difference between actual and simulation times is exaggerated by the sheer size of the population.

A more appropriate measure in this instance, which highlights differences in the actual and simulation results rather than estimating the probability that they are not the same, is the effect size.

Cohen's *d* (a measure of effect size) is reported as the standard approach to effect size measurement [Thalheimer and Cook, 2002]. Cohen's *d* is calculated as:

$$d = \frac{\overline{x}_t - \overline{x}_c}{s_{pooled}} \qquad s_{pooled} = \sqrt{\frac{(n_t - 1)s_t^{\,2} + (n_c - 1)s_c^{\,2}}{n_t + n_c}}$$

In this case $_t$ refers to the actual data and $_c$ to the simulation results. Cohen's [1988] convention for interpreting effect sizes suggests that an effect size of less than 0.2 is considered small. The results of calculating Cohen's *d* for each of our distributions is shown below in Table 6.

Table 6

The results are highly encouraging. In each case the effect size is small or negligible. This suggests that the simulated output is representative of the ED system being studied.

3.2 Phase 2 – Assessment of 'See and Treat'

To investigate the impact of a 'see and treat' strategy in the ED the model was used to test a number of scenarios. In the first instance, changes to the model were made to reflect the operation of 'see and treat' practice. This involved creating a process step for the preliminary assessment of the patient and formulating process logic governing process flow (Figure 6). In effect this constituted the creation of a filter which would allow a percentage of the patient population, within specific triage categories, to be directed through the see and treat activities. The 'triage' process pathway remained unchanged and serviced the residual proportion of patients as previously described. The arrival pattern and mix of variety of presenting condition also remained unchanged to facilitate the comparison of both the triage and the combined triage and 'see and treat' practice.

Figure 6

Discussions with the clinicians suggested a number of potential parameters for each scenario. Both Triage 1 and Triage 2 patients have complex acute conditions requiring immediate emergency care. These would not be serviced by the See and Treat activities. A general assumption was that a maximum of 70% of Triage 3 patients and 90% of triage 4 patients could be serviced by see and treat activities. This is a considerable proportion of the entire population; 32% and 46% respectively. The Triage 5 category, a small group of patients (0.2%), was considered an anomalous categorisation which had now been made redundant. Triage 9 constitutes 13% of patients and is the group typically represented by eye injuries. A maximum of 70% of Triage 9 patients were deemed suitable for 'see and treat'.

This guidance from the clinician team resulted in the formulation of three main scenarios for testing (Table 6).

Table 6

For each scenario we assumed no constraint from the number of practitioners or rooms. In effect switching to 'see and treat' would be using all practitioners other than those required for attendance in the 'majors' emergency room. We also assumed that the time take to 'see and treat' would have a normal distribution centred around a mean of 60 minutes. The following tables (Tables 7a – 7c) present the results of the simulations for each scenario.

Tables 7a – 7c

The results for Scenario 1 (Table 7a) suggests that a total of 1931 patients would wait more than four hours (this accounts for 3.3% of the patients). Scenario 2 (Table 7b) produced a strikingly similar result, again the number of patients waiting greater than 4 hours was around 3.4%. The third scenario indicates a reduction in the number of patients taking longer than 4 hours (triage 3 patients reduce from 919 to 604) however the improvement is small when the volume of the whole population is taken into consideration (approx. 55,000).

These simulation results were compared to the original data. However, to facilitate a meaningful comparison, the time patients wait prior to triage needed to be taken into consideration. As the reader will recall primary data was collected for this activity, as the Trust did not collect data prior to Triage. Although this distribution had a long tail and failed the test for normality, an estimate of 15 minutes (the average) was used. Although the potential error in this estimate is recognised, it provides a mechanism for the initial comparison of the two datasets. An analysis of the original data, factoring in the estimate of time before triage, and omitting the null entries, revealed that 6620 patients[*], 13.2% of the population, were waiting longer than 4 hours. A simple comparison of these results with the simulation output suggests that moving to See and Treat would have a substantial impact on the number of patients waiting longer than 4 hours; 13.2% in the Triage and

Treat system; 3.4% in the predicated See and Treat system. This prediction contributed to the decision taken by the hospital's management team to implement the See and Treat practice with A&E.

3.2 Phase 3 – Post-Implementation Performance Comparison

A post implementation analysis was conducted in 2005 (2 years later). This analysis facilitated an assessment of the performance improvement of the see and treat strategy and an evaluation of the predictive capability of the simulation model. A new dataset for the period April-September 2005 (6 months) was used as the basis for analysis. This data (Table 8) indicated an increase in patients attending A&E. For the six months April-September 2005 the number of attendees was 31,581. For the same period in 2002 this was 28,379 an increase of 11.3%.

An analysis of the data indicates a marked reduction in patient wait time. Only 451 patients out of 31581 (1.4%) in the period had a length of stay more than 4 hours. The improvement on the 2002 figure (13.2%) suggests over a 900% improvement against the government's target. This result is even more striking when the 11% increase in volume is taken into consideration.

Table 8

A second striking improvement is the number of patients now waiting less than an hour. In the new system this accounts for almost a quarter (23%) of patients. In the 2002 scenario this was 6045 approximately 12%.

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* N=55069

To facilitate a comparison of the number of patients waiting in each triage category, within time ranges in both 2002 and 2005, a summary is provided (Table 9).

Table 9

The results show that for Triage 1,2 and 3 the number of patients waiting between 3-4 hours has increased substantially. This coincides with the concerns reported in the literature on the impact See and Treat practice has on the management of the smaller number of seriously ill and injured patients. It should be recognised however, that the increase in this time category is due significantly to the reduction in the number of patients waiting more than 4 hours. In the case of Triage 4 patients waiting between 3-4 hours, the difference between the triage system and the combined triage / See and Treat system is insignificant, despite a considerable increase in the number of patients in that category. It seems safe to conclude that Triage 4 patients have benefited from a move to See and Treat practice

A more detailed analysis of patients with more acute presenting conditions (Triage 2 and 3) reveals some interesting results. Triage 2 patients have not benefited to the same extent as patients with more minor conditions. The total of triage 2 patients who wait over 3 hours in the 2005 data is 26%, compared with 30% in 2002. However to put this in perspective we estimate that based on 2005 arrivals this amounts to around 100 patients. The data on Triage 3 patients indicates a substantial increase in the number of patients waiting between 3-4 hours; 18% in 2002 compared with 29.2% in 2005. While this initially raises some concern it may be explained by a phase-shift in volume occurring from a significant reduction in the number of patients waiting longer than 4 hours; 16.7% in 2002 compared with 2% in 2005.

Figure 7

Figure 7 illustrates the effect of the four hour measure on patients' length of stay. It is immediately noticeable that a 'cliff' occurs in the results around 240 minutes (the government's four hour target). The tail is actually longer and lower than would appear, but has been compressed by the graphing application suppressing time categories containing no instances. It is worth noting that the times shown were not in the first instance recorded by medical staff as length of stay but as entry and exit times. Thus, it is not a case of medical staff misreporting the length of stay but of adapting their behaviour to meet the four hour target.

4. LIMITATIONS OF THE STUDY

There are some limitations of the approach which should be noted. Given the considerable challenges in identifying the exact allocation of resources to patients and the need to fit distributions to wait and treat times, it is very difficult to identify the impact of changing resource patterns; numbers of doctors and nurses, and their general methods of working. There is also an issue with identifying the impact on changes in volumes on wait times. Whilst it is relatively simple to change the volumes of patients entering the simulation model (on a yearly, monthly or even daily basis) the model assumes that these patients will be dealt with according to the same distribution allocated to each activity. Whilst this appears to be a considerable limitation in the model, it must be remembered that the distributions are derived from fitting to complete yearly populations (in most Triage cases this is thousands of data items). Furthermore, we discussed this limitation with medical staff and they pointed out that in practice they would modify medical practice depending upon the number of patients waiting to be seen, for example, by calling on more nurses and doctors in busy periods. Whilst it is difficult to be precise about our confidence in the overall stability of the distributions over time the volume of data analysed would tend to indicate that we have developed a robust model. We also draw attention to study's focus on evaluating the impact on patient wait time. Our analyses have not attempted to evaluate patient satisfaction, accuracy of diagnosis, or quality of treatment. The analyses of the volume of patient demand do not account for situations where patients may return to the Emergency Department due to inappropriate or incomplete care from an earlier medical event.

5. CONCLUSIONS

The conclusions which may be drawn from this research can be grouped into two categories. The first category relates to the results from the evaluation of the impact a fast-track strategy has on patient wait time in an Emergency Department. The second category relates to the method employed; issues relating to the construction and use of simulation models to inform changes to service delivery.

Our research explicitly addresses issues raised by authors such as Leaman [2003] and Windle and Mackway-Jones [2003], who request primary evidence on the impact a fast track strategy has within Emergency Departments. Central to their criticism is the issue of evidence based practice. Castille and Cooke [2003] provide an initial response to these criticisms and suggest that there is '..an increasing amount of evidence to support the principles of See and Treat'. They argue that 'See and Treat' practice is based on the triangulation of: 'empirically tested, clinician led local change; historical evidence from service provision; and professional consensus – referred to as pragmatic science'. Our research has sought to directly contribute to the existing evidence base, a direct response to the emerging criticisms, through systematic analyses undertaken on longitudinal data. The results of this work indicate that a See and Treat (Fast Track) strategy can provide a significant reduction in patient wait time for patients with minor presenting conditions. While the extent of these results were surprising, an observed improvement of over 900% against a 4 hour target, it is unsurprising that the greatest impact was on triage 4 patients; fast track strategies focus explicitly on patients with minor conditions. Windle and Mackway-Jones [2003] also raise questions regarding potential delays in the management of the smaller number of seriously ill and injured. While, as noted in the limitations of this work, we are unable to provide evidence on patient satisfaction, quality of care, or accuracy of diagnosis, which relate to the broader issues of 'clinical costs', raised by Windle and Macway-Jones [2003], we are able to report that while there is no detrimental impact on the wait time for patients with more acute presenting conditions, the impact is far more limited. It is also observable, however, that there has been a significant increase in the number of patients located in the 3-4 hour category. This is the result of the system performance being optimised against the Government target of 4 hours. This imposition of targets, and potential penalties which may ensue following underachievement, have had a dramatic effect on the behaviours of medical staff within the system.

As the government increases pressure on health care providers to improve system performance, through the imposition of specific performance measures, the requirement for practicing operations managers within the health care delivery system to understand and control their processes also increases. Simulation modelling can help operations managers in healthcare to understand the factors that affect the efficient flow of patients through their facility; it provides a mechanism for assessing the effects of changes to a system; a tool to experiment with alternative strategies and practices. While there is an obvious increase in the frequency that simulation has been used within healthcare delivery analysis and design, a degree of caution has to be exhibited in model creation. Connely and Bair [2004], for example, use a small sample of patients to draw conclusions on system performance. Our research suggests that this is grossly insufficient. While we acknowledge the difficulties in data collection and validity which may emerge, large samples of data are required to adequately model: the variation in patient demand; and accurate distributions of activity times. We agree with Lattimer [2004] that a one year cycle is required to account for seasonality, and while we concur with Smith et al [1996] that patient demand needs to be modelled at a more granular, our research has indicated that the appropriate level of granularity must move beyond day-of-week (as reported by Smith et al, [1996]) to time-of-day. Specific arrival patterns must be based on analyses which indicate statistical significance. We also agree with Smith et al [1996] that normal distributions are inappropriate. The analysis of activity times in our data failed the test for normality in every case. Previous research [Kim and Horowitz, 2002] has demonstrated the benefits of testing the fit of data to a poisson distribution. Or work has indicated significant benefits in testing the fit of activity data to a range of distributions, resulting in the identification of both Weibull and LogNormal distributions for triage-based treatment times. A comparison of output from the simulation model with the post implementation results suggests that the model was indicative of actual performance. This suggests that demand analyses and distribution fitting are integral steps in creating a representative model for the exploration of alternative practice through simulation.

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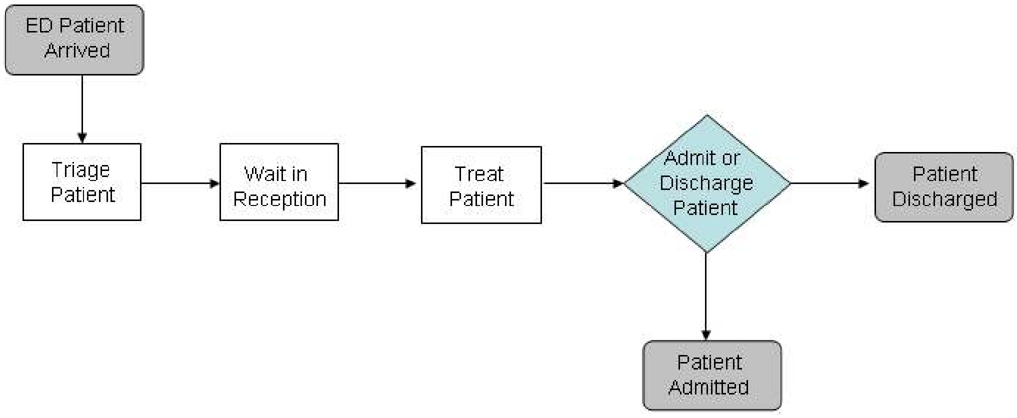

Figure 1: Simplified Process Flow Chart

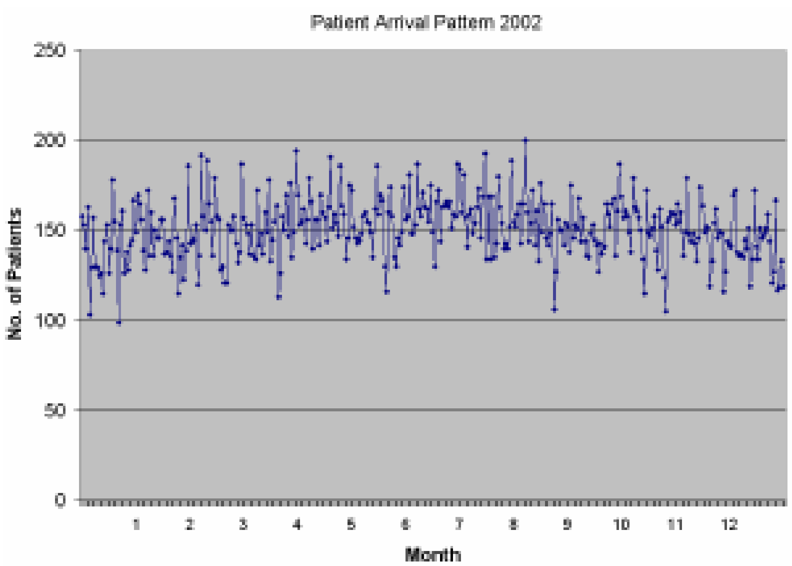

Figure 2: Patient Arrival Pattern (2002)

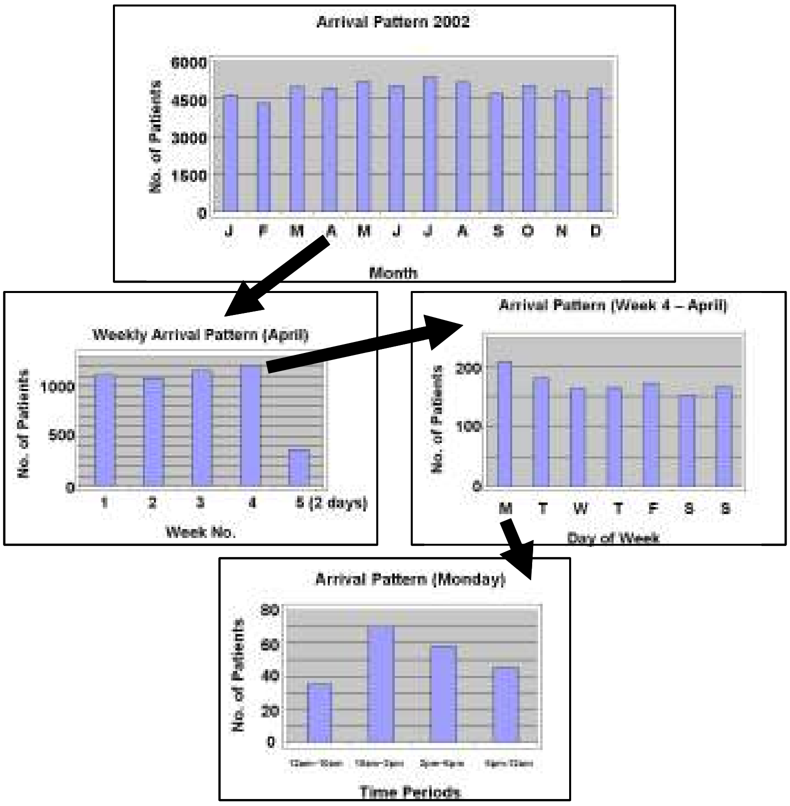

Figure 3: Volume of patient arrival by time period

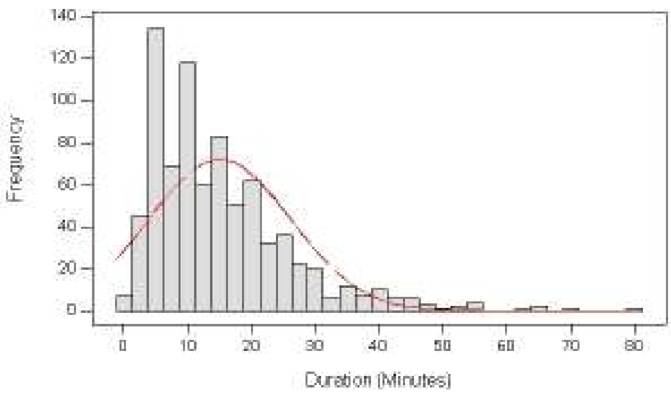

Figure 4: How long to 'triage' patient

Triage Category	% of Population
Triage 1	0.45%
Triage 2	8%
Triage 3	33%
Triage 4	47%
Triage 5	0.3%
Triage 8	0.14%
Triage 9	11.3%

Table 1 – percentage of patients by triage category

		Wait Time Alpha = .05				
Triage	N*	1	2	3	4	5
1	228	3.48				
2	3990		17.58			
3	15376			39.12		
5	114				55.2	
9	6029				57.96	
4	22281					70.44

Table 2: ANOVA of Triage wait times (average times for each triage)

		Treatment Time Alpha =.05			
Triage	N*	1	2	3	4
5	115	30.05			
9	5990	36.76			
4	22615		54.27		

* The small discrepancy in N values between the two tables is a reflection of the differences in keying errors for wait and treatment times discussed earlier.

1	215			80.52	
3	15433				107.94
2	3934				113

Table 3: ANOVA of Triage treatment times (average times for each triage)

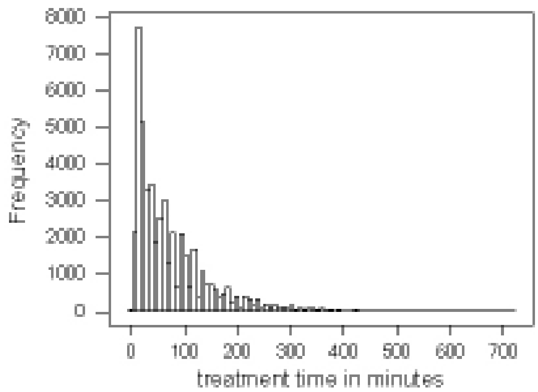

Figure 5 - Triage 1 treatment time

Activity	Distribution	Parameters (shape, scale)
Triage 1 Wait	*	
Triage 2 Wait	Weibull	0.99, 0.312
Triage 3 Wait	Weibull	1.159, 0.71
Triage 4 Wait	Weibull	1.148, 1.249
Triage 5 Wait	Weibull	0.802, 0.893
Triage 9 Wait	Weibull	1.269, 1.052
Triage 1 Treat	Weibull	0.99, 80.29^
Triage 2 Treat	Lognormal	Location 4.5, Scale 0.737
Triage 3 Treat	Weibull	1.302, 119.68^
Triage 4 Treat	Lognormal	Location 3.52, Scale 1.005
Triage 5 Treat	Weibull	0.911, 28.618^
Triage 9 Treat	Lognormal	Location 3.16 Scale 0.696

Table 4: Distributions and Parameters

* Triage 1 patients were assumed a zero wait time.

^ scale in minutes: scale for other activities in hours.

Triage	Percentage Admitted
1	53.04%
2	69.79%
3	46.04%
4	9.39%
5	1.23%
9	1.08%

Table 5: Patients admitted per Triage category

	Actual		Simulation		d_{cohen}	Effect size
	Mean	Std deviation	Mean	Std deviation		
Triage 1 wait	3.48	7.36	1.62	0.75	0.36	small
Triage 2 wait	18.07	24.04	18.29	18.60	0.01	negligible
Triage 3 wait	40.85	40.92	40.87	35.13	< 0.01	negligible
Triage 4 wait	75.62	70.98	73.08	63.81	0.07	negligible
Triage 9 wait	58.71	49.54	60.96	76.22	0.04	negligible
Triage 1 treat	80.51	79.35	82.59	87.08	0.02	negligible
Triage 2 treat	113.01	80.26	118.34	102.74	0.05	negligible
Triage 3 treat	107.94	84.25	110.15	85.41	0.02	negligible
Triage 4 treat	54.27	60.57	57.34	78.61	0.04	negligible
Triage 9 treat	36.76	44.72	36.22	42.11	0.02	negligible

Table 6 – Validity test of simulation output using effect size

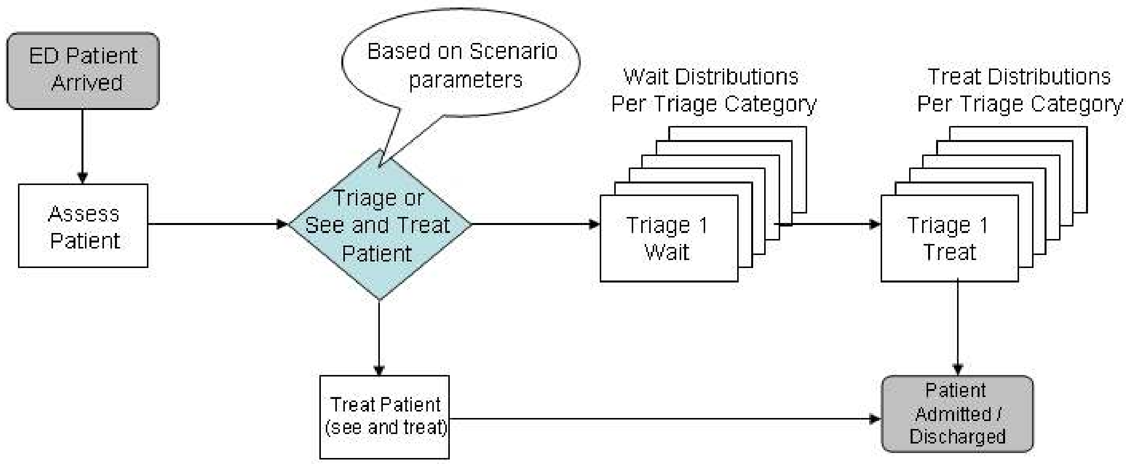

Figure 6: See and Treat process flow

Scenario	Triage 3	Triage 4	Triage 9
1	70%	80%	80%
2	70%	90%	70%
3	80%	90%	70%

Table 6: See and Treat Scenarios

	> 4 hours	> 3 hours	> 2 hours	> 1 hour
T1	19	34	62	130
T2	577	1074	2086	3869
T3	919	1849	3306	13268
T4	296	632	1242	17746
T5	18	30	45	98
T9	102	176	362	4141
Total	1931	3795	7103	39252
%	3.329%	6.54%	12.25%	67.68%

Table 7a: Scenario 1 Results

	> 4 hours	> 3 hours	> 2 hours	> 1 hour
T1	19	34	62	130
T2	577	1074	2086	3869
T3	919	1849	3306	13288
T4	296	632	1242	17673
T5	18	30	45	98
T9	137	253	546	4154
Total	1966	3872	7287	39212
%	3.39%	6.68%	12.56%	67.61%

Table 7b: Scenario 2 Results

	> 4 hours	> 3 hours	> 2 hours	> 1 hour
T1	19	34	62	130
T2	577	1074	2086	3869
T3	604	1201	2180	12848
T4	296	632	1242	17678
T5	18	30	45	98
T9	137	253	546	4077
Total	1651	3224	6161	38700
%	2.85%	5.56%	10.62%	66.72%

Table 7c: Scenario 3 Results

Table 7: Scenario Results

Month	> 4hrs	3-4 hrs	2-3 hrs	1-2 hrs	< 1hr	Null	Total
04	90	723	993	1698	1120	261	4885

05	85	844	1153	1939	1302	147	5470
06	75	830	1253	1803	1226	35	5222
07	99	991	1282	1873	1188	16	5449
08	68	1068	1398	1693	1112	5	5344
09	34	985	1276	1738	1176	2	5211
Total	451	5441	7355	10744	7214	466	31581
%	1%	17%	23%	34%	23%	1%	

Table 8: No of patients waiting (2005)

		T1	**T2**	**T3**	**T4**
2002	% of patients	0.45%	8%	33%	47%
	3 – 4 hrs	9.5%	14.2%	18%	14.1%
	> 4 hrs	5.5%	11.5%	16.6%	13.4%
2005	% of patients	1.04%	8.02%	28.5%	59%[2]
	3 – 4 hrs	18.9%	28.2%	29.2%	12.7%
	> 4 hrs	2.8%	1.7%	2%	0.9%

Table 9: comparison of patients waiting 2002 and 2005

[2] In 2005 Triage 9 patients (eye conditions) were categorised according to the standard Triage1..4 categories. Most of them were allocated into Triage 4.

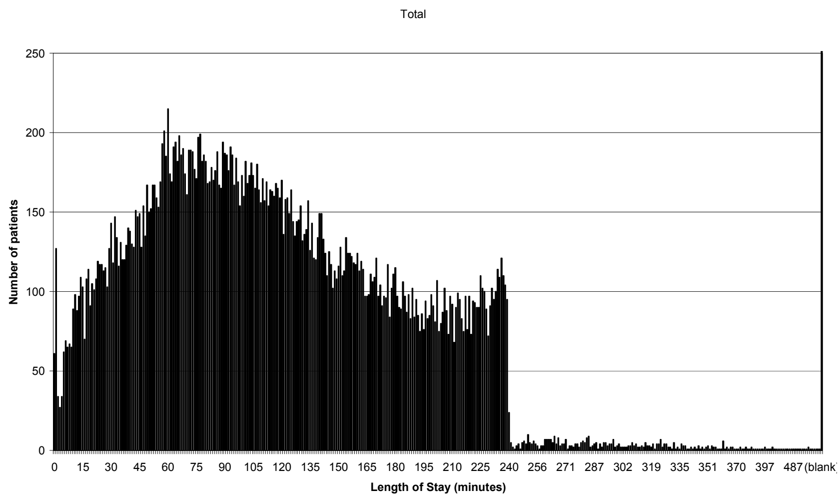

Figure 7: Patients' length of stay