Fractured neck of femur patients: Rehabilitation and the acute hospital

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Abstract

Typically, fractured neck of femur patients admitted to an acute hospital are discharged to a community hospital for a period of rehabilitation after their treatment. However, there is concern that this might unnecessarily extend the total period of hospitalisation for these patients. Using data from a local acute hospital, we used discrete event simulation to predict the practicability of fractured neck of femur patients remaining in an acute hospital for their entire superspell (the overall length of stay across hospitals). We tested scenarios in which patient superspell duration was shortened, as well as a scenario in which no reduction in superspell length was observed. The model predicts that, even assuming that the superspell of fractured neck of femur patients could be

significantly reduced, bed occupancy levels at the acute hospital would increase to operationally infeasible levels. Therefore, it is unlikely that fractured neck of femur patients could remain in a typical acute hospital unless there were sufficient increases in available resources.

Introduction

Fractures to the neck of the femur are common injuries, particularly amongst the elderly female population (Stewart, 1955). Typically, fractured neck of femur (#NOF) patients must be admitted to an acute hospital and treated surgically (Parker and Johansen, 2006). Following a period of post-surgery recovery, it is common for local #NOF patients to be discharged to a community hospital for rehabilitation because of the average age of such patients and the frequency of post-operative complications. However, until recently this "superspell", which represents the entire stay of a patient across all NHS organisations, has not been widely considered when assessing the cost of hip fractures (Royal College of Physicians, 2013), and therefore may have affected service improvement initiatives in this area.

It has been suggested that patients who are admitted as inpatients to community hospitals may face longer than necessary lengths of stay, as it is often perceived that there is a reduced urgency to discharge compared to acute hospitals (Banerjee et al, 2012). However, it has also been shown that increased hospital lengths of stay are generally undesirable for elderly patients, because of the increased risk of developing complications and loss of independence (Morton and Creditor, 1993). In addition, length of stay is the main determinant of cost of care for hip fractures, and reductions to length of stay for such patients can improve the cost-effectiveness of such care (Royal College of Physicians, 2013).

An acute hospital local to our research group wanted to explore the possibility of conducting an empirical pilot study that assessed the impact on length of stay of keeping fractured neck of femur patients in the acute hospital, with no subsequent discharge to a community hospital unless made necessary by a patient's comorbidities. However, they wanted to investigate the operational feasibility of such a scheme in terms of resultant bed occupancy levels.

Discrete event simulation is a modelling technique that is useful for assessing the impact of process changes and service reconfigurations (Babulak and Wang, 2010). In a healthcare context, discrete event simulation is often used to predict the impact of changes to a clinical pathway (Cardoen and Demeulemeester, 2007; Sobolev et al, 2011; Monks et al, 2012). This type of simulation also allows clear visual representations of current pathways and proposed changes to them, and can be a helpful means to facilitate understanding of the model for non-specialists, allowing them to challenge elements of the model that they feel do not adequately represent the real world system. In this paper, we describe how we used discrete event simulation and data from the acute hospital to build a model of the current admissions of fractured neck of femur patients, and then adapted the model to predict the impact of undertaking the entire superspell (total length of stay across hospitals) in the acute hospital for these patients.

Methods

The Data

The acute hospital in this study requested that their anonymity to be retained when publishing these results. Therefore, we shall refer to the hospital simply as "the acute hospital", and the 13 surrounding community hospitals by letters A-M.

We obtained anonymised patient data for all patients either admitted to the acute hospital, or to one of the surrounding community hospitals following an admission to the acute hospital, between 10th January 2006 and 21st January 2013. This represented 1,022,577 unique episodes for 253,227 unique patients. We identified #NOF patients as those with an ICD-10 code prefix of S72 recorded as their primary diagnosis, which represented 7,759 episodes, or 0.76% of the dataset.

The trauma ward of the acute hospital is the ward into which #NOF patients are admitted if there is sufficient capacity. In the seven years of data, there were 10,783 admissions to the trauma ward, and 6,241 #NOF admissions to the acute hospital, of which 3,042 (48.74%) were admissions to the trauma ward. On average, there were 2.84 #NOF admissions per day to the acute hospital, and 3.5 non-#NOF admissions per day to the trauma ward. The inter-arrival time of patients represents the time between the arrivals of patients. Therefore, the average inter-arrival time is 0.35 days for #NOF patients and 0.29 days for non-#NOF patients.

The average length of stay of #NOF patients in the acute hospital was 7.48 days, and 7.45 days specifically for those admitted to the trauma ward. The average length of stay of non-#NOF patients in the trauma ward was 3.39 days. Figures 1 and 2 show the distribution of lengths of stay of #NOF and non-#NOF patients admitted to the trauma ward, respectively. The superspell of #NOF patients was calculated as the sum of their length of stay at the acute hospital and any subsequent length of stay at a community hospital, where the patient's discharge from the acute hospital was on the same day or the day prior to their admission to a community hospital for a primary diagnosis of #NOF. The average #NOF superspell length was 20.07 days. 19.51% of #NOF admissions to the acute hospital resulted in a subsequent discharge to a community hospital with a primary diagnosis of #NOF.

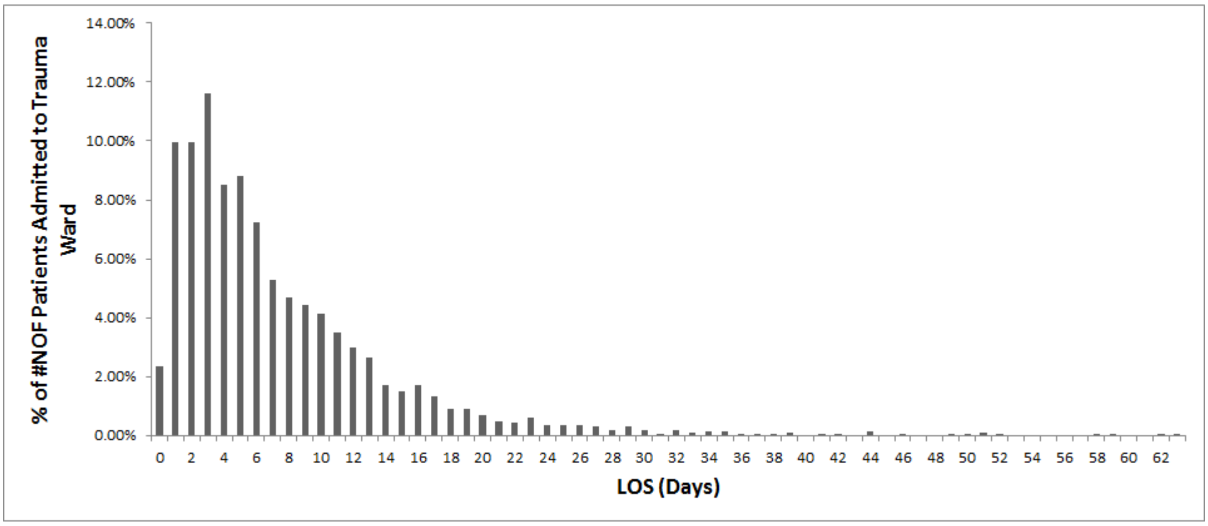

Figure 1. Length of stay distribution for #NOF patients admitted to the trauma ward of the acute hospital.

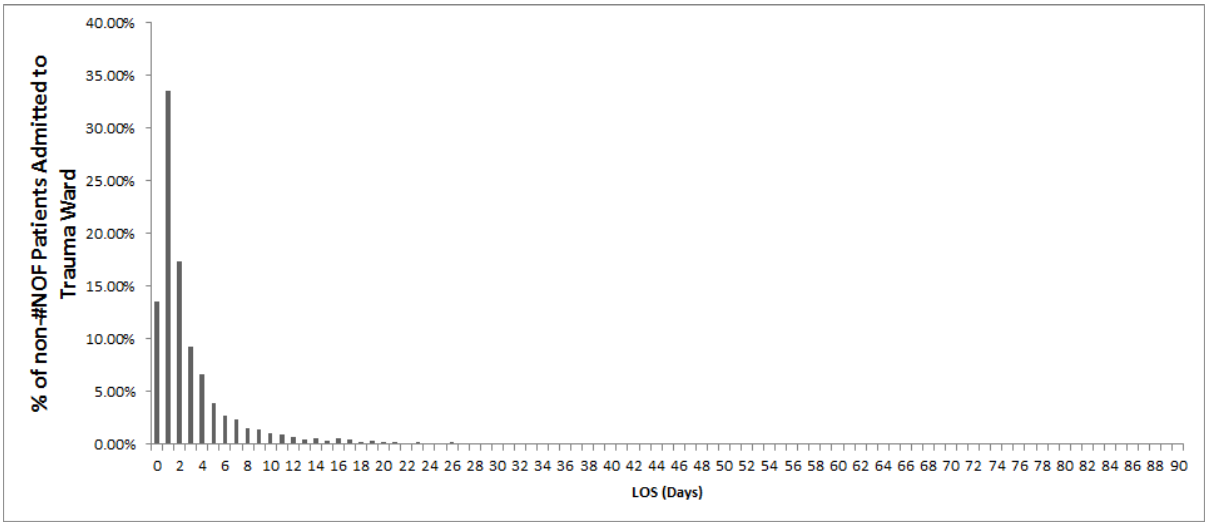

Figure 2. Length of stay distribution for non-#NOF patients admitted to the trauma ward of the acute hospital.

The Model

In a discrete event simulation model, we simulate patients flowing through a series of individual processes, each of which takes a certain amount of time, and may require a number of resources. If a process is full to capacity, a queue for the process may form. In the context of our model, our processes represent stays in beds in the ward and community hospitals. Patients are either #NOF or non-#NOF patients. Figure 3 shows an overview of the structure of the model.

Poisson distributions are used to calculate the probability of something happening that is independent from the outcomes before or after. Such distributions can be used to model the arrival of patients, because the arrival time of one patient is not typically linked to the arrival time of the patients arriving before or after them (Wolff, 1982). Therefore, the inter-arrival time of #NOF patients into our model is determined by a Poisson distribution, with a mean of 0.35 days between arrivals. #NOF patients are admitted to the trauma ward if there is a free bed at the time of their arrival, otherwise they are sent to another ward and effectively exit the model, because their admission to the hospital would not affect the bed occupancy of the trauma ward. We only model those non-#NOF patients who are admitted to the trauma ward, and their arrival is also determined by a Poisson distribution, but with mean inter-arrival time of 0.29 days. Non-#NOF patients in the model will queue for a bed in the trauma ward until one becomes available, because they represent the real-world blocking of bed capacity in the trauma ward from the perspective of #NOF patients.

Currently there are 35 beds in the trauma ward, and we represent this in the model. The length of time a patient stays in the trauma ward is dependent on whether they are a #NOF or a non-#NOF patient, and is drawn randomly for each patient from the relevant length of stay probability distribution extracted from the data (see figure 1 for #NOF distribution and figure 2 for non-#NOF distribution). Therefore, those lengths of stay that occurred more frequently in the data have a higher probability of being drawn as the length of stay of a patient in the model.

In the base case scenario, 19.51% of #NOF patients in the model are discharged to a community hospital after their stay in the trauma ward. The specific hospital to which they are discharged is randomly drawn according to the distribution of discharge destinations obtained from the real-world data.

We developed the model using Simul8 software (SIMUL8; SIMUL8 Corporation, Boston, MA; www.Simul8.com) and ran the simulation for two years for each tested scenario, taking results only from the second year to allow the simulation model sufficient time to "warm up" from a starting state in which the ward is empty. Each scenario was also run five times, with average results taken over these runs.

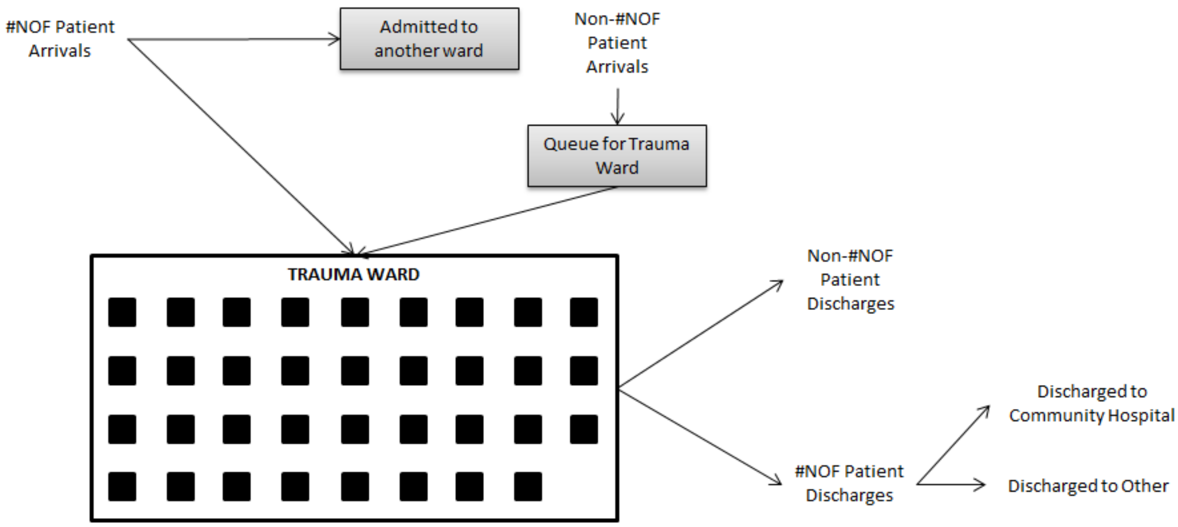

Figure 3. Overview of the structure of the model. #NOF patients are admitted to the Trauma Ward if a bed is free, otherwise they are moved elsewhere. Non-#NOF patients queue for a bed in the Trauma Ward. On discharge, #NOF patients may be discharged to a community hospital in the base case scenario.

"What if" Analysis

In order to predict the potential impact on bed occupancy levels in situations where the entire #NOF superspell takes place in the acute hospital, we simulated a number of potential future scenarios in the model. In these scenarios, no #NOF patients are discharged to a community hospital, and their length of stay in the trauma ward represents their total superspell. We looked at varying assumed reductions in superspell length (including a scenario in which there would be no reduction in superspell length). In addition, at the time of the study the trauma ward had recently lost five beds.

We therefore looked at how the predicted results would change if these beds were returned. Table 1 contains details of the eight scenarios we tested.

Results

Table 1 shows the predicted bed occupancy levels for each tested scenario. The base case (Scenario 1), predicts beds in the trauma ward are occupied around 86% of the time, which staff at the acute hospital felt was an accurate reflection of their actual bed occupancy levels in the trauma ward. For the simulated scenario where #NOF superspell is undertaken entirely in the trauma ward of the acute hospital, the model predicts that beds would be occupied 100% of the time if there was no associated reduction is superspell length (Scenario 4), and would remain extremely high at 97.5% even if total superspell length could be reduced by 8 days (Scenario 2).

If the five removed beds were returned to the trauma ward, there would be a small reduction in bed occupancy levels to 79% if #NOF patients continued to be discharged to community hospitals (Scenario 5), but undertaking the entire #NOF superspell would still result in very high bed occupancy levels, ranging from 94.2% if superspell length was reduced by 8 days (Scenario 8) to 99.8% if no reduction in superspell length was observed (Scenario 6).

Scenario #	Description of Scenario	Bed occupancy (as average % of time beds are occupied)	95% Confidence Interval (CI)
1	Base case scenario. 35 beds in trauma ward, patients discharged to community hospital for rehabilitation, 20 day mean superspell.	85.9%	82.6% to 89.2%
2	35 beds in trauma ward, superspell entirely at acute hospital, 8 day reduction in mean superspell	97.5%	95.9% to 99%
3	35 beds in trauma ward, superspell entirely at acute hospital, 4.5 day reduction in mean superspell	99.6%	99% to 100%
4	35 beds in trauma ward, superspell entirely at acute hospital, 0 day reduction in mean superspell	100%	100% to 100%

5	40 beds in trauma ward, patients discharged to community hospital for rehabilitation, 20 day mean superspell.	79%	74.4% to 83.6%
6	40 beds in trauma ward, superspell entirely at acute hospital, 8 day reduction in mean superspell	94.2%	90.9% to 97.6%
7	40 beds in trauma ward, superspell entirely at acute hospital, 4.5 day reduction in mean superspell	97.8%	96.5% to 99.1%
8	40 beds in trauma ward, superspell entirely at acute hospital, 0 day reduction in mean superspell	99.8%	99.3% to 100%

Table 1. Details of scenarios tested in the model, and the corresponding predicted average (and 95% Confidence Interval) bed occupancy, expressed as the average percentage of time beds are occupied.

Discussion

Our model predicts that, even if there were clinical benefits to keeping #NOF patients in the acute hospital for the duration of their post-surgical rehabilitation, it would be operationally infeasible for the trauma ward of the acute hospital to do this, at least with the availability of resources to which the hospital realistically has access, and given the competing demands for the trauma ward from non-#NOF patients. Typically, it is recommended that hospitals operate at a maximum bed occupancy of 85%, to allow for variability arising from fluctuations in demand (Bagust et al, 1999; Jones, 2011). Therefore, bed occupancy levels of 95% and above are likely to be infeasible, and lead to severe problems during periods of higher demand.

Furthermore, superspell reductions of 8 days would represent a significant reduction for #NOF patients and may not be realistic, particularly given there would be a minimum level of recover required post-surgery, although Enhanced Recovery strategies could help (Malviya et al, 2011). However, even assuming such significant reductions, the predicted bed occupancy levels in the trauma ward would remain infeasible.

Whilst our model only predicts the operational impact for the specific acute hospital studied in this project, it is likely that other hospitals would see similar results, since the acute hospital in our study is currently operating at the recommended level of bed occupancy, and resource constraints are common across acute hospitals in the NHS. Nevertheless, we would recommend others considering a similar scheme to investigate discrete event simulation modelling as a means of predicting the potential impact on their own trauma wards, in order that an evidence-based decision can be made.

Acknowledgements

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An anonymised version of the full data used to parameterise the model, along with the full outputs of the model, may be provided on request.

Key Points

- We built a discrete event simulation model to predict the impact of #NOF patients remaining in an acute hospital for their rehabilitation
- The model predicts that such a scheme would lead to operationally infeasible bed occupancy levels in the trauma ward of the acute hospital in our study
- Bed occupancy levels would remain infeasible even if superspell length could be significantly reduced
- It is likely that other hospitals would see similar results, because the study hospital is currently operating at recommended bed occupancy levels

Literature Cited

Babulak E, Wang M (2010) Discrete Event Simulation: State of the Art. Discrete Event Simulations Aitor Goti (Ed.), ISBN: 978-953-307-115-2, InTech, Available from: http://www.intechopen.com/books/discrete-event-simulations/discrete-event-simulation-state-of-the-art

Bagust A, Place M, Posnett J W (1999) Dynamics of bed use in accommodating emergency admissions: stochastic simulation model. British Medical Journal 319:155-158

Banerjee J, Conroy S, O'Leary V, Rawstorne S, Wenman J, Walker A et al (2012) Quality Care for Older People with Urgent and Emergency Care Needs. http://www.bgs.org.uk/campaigns/silverb/silver_book_complete.pdf

Cardoen B, Demeulemeester E (2007) Evaluating the capacity of clinical pathways through discrete-event simulation. Faculty of Economics and Applied Economics. Available from: https://lirias.kuleuven.be/bitstream/123456789/120479/1/KBI_0712.pdf

Jones R (2011) Hospital bed occupancy demystified. British Journal of Healthcare Management 17(6):242-248

Malviya A, Martin K, Harper I et al (2011) Enhanced recovery program for hip and knee replacement reduces death rate: A study of 4,500 consecutive hip and knee replacements. Acta Orthopaedica 82(5):577-581

Monks T, Pitt M, Stein K, James M (2012) Maximizing the Population Benefit from Thrombolysis in Acute Ischemic Stroke. Stroke 43:2706-2711

Morton C, Creditor M D (1993) Hazards of Hospitalization of the Elderly. Annals of Internal Medicine 118:219-223

Parker M, Johansen A (2006) Hip fracture. British Medical Journal 333:27-30

Royal College of Physicians (2013) National Hip Fracture Database annual report 2013. London: RCP, 2013

Sobolev B G, Sanchez V, Vasilakis C (2011) Systematic Review of the Use of Computer Simulation Modeling of Patient Flow in Surgical Care. Journal of Medical Systems 35:1-16

Stewart I M (1955) Fractures of Neck of Femur. British Medical Journal 1(4915):698-701

Wolff R W (1982) Poisson Arrivals See Time Averages. Operations Research 30(2):223-231