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Measuring and modelling surgical bed usage

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Surgical departments treat two groups of inpatients – the simple and the complex – consequently a single average fails to describe the use being made of the occupied beds. Using decision support techniques, we show why indicators such as the average length, the average occupancy and the average admissions mislead. Furthermore, by analysing the fluctuating pattern of weekly admissions we show how weekends and the Christmas holiday periods impact on bed usage. Next, we demonstrate that flow process models can be used to describe how the in-patient workload concerns two groups of patients. On an average day, 71.4% of the beds contained patients who will have an average (exponential) stay of 4.8 days, and the other beds, 28.6%, contain patients who will have an average (exponential) stay of 22.8 days. The article concludes by demonstrating the short and long-term impact on daily admissions of a 10% change in four different parameters of the model. The data used come from a surgical department in Adelaide, as UK data sets report finished consultant episodes rather than completed in-patient spells.

Key words: Surgical bed usage – Measures – Models

Mistakes are being made in the allocation and use of surgical beds because the methods used to measure and report hospital in-patient activity are numerically flawed.[1] In this article, we explain why performance measures – such as the average length of stay, the average occupancy and the average turnover per allocated bed – give misleading information and explain how some of these problems can be overcome. The surgical data used to illustrate the problem come from a hospital in Adelaide, Australia. We chose these data, rather than UK data, because they show how emergency and non-emergency patients interact to effect bed occupancy. Furthermore, current NHS activity data concern finished consultant episodes, rather than patient spells, so it is difficult, if not impossible, to get an accurate picture of hospital bed usage.

Measuring and reporting length of stay

Estimating length of stay

The average length of stay in hospital beds can be estimated by multiplying the average bed occupancy by the days in the year and dividing by the annual

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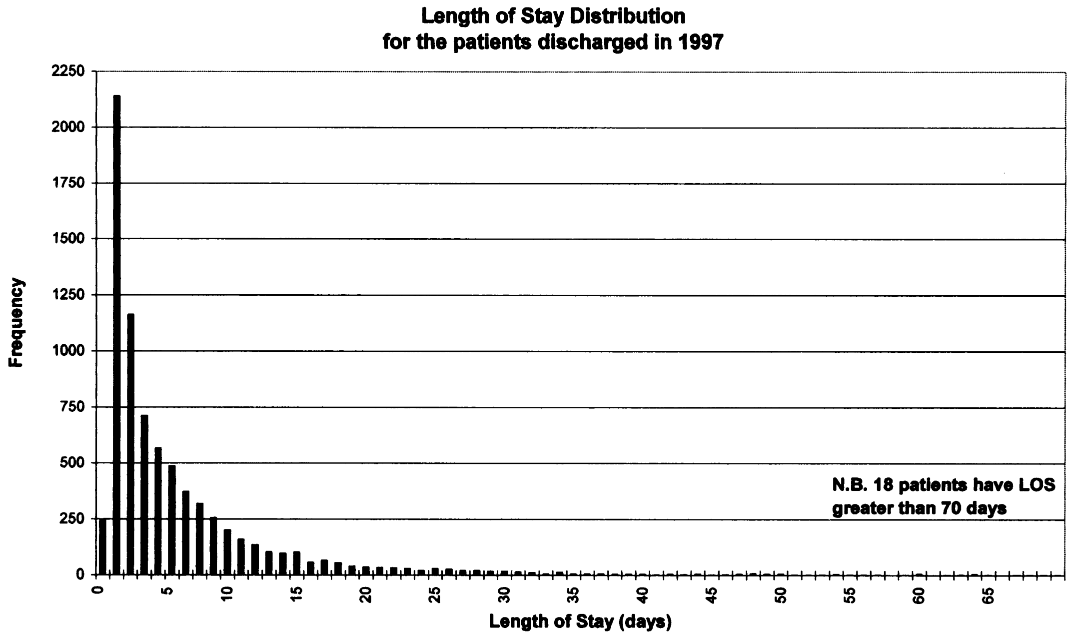

Figure 1 Length of stay distribution for the surgical patients discharged in 1997

number of admissions.[2] In geriatric medicine, the main problem with this method, and with the turnover per allocated bed, is that the specialty provides beds for long stay care so turnover occurs in only a proportion of the beds. In general, surgery problems arise because the bed occupancy is usually counted at midnight (at the hospital in Adelaide at 7.00 a.m.) whereas the work function is done during the day.

Length of stay at discharge

The average surgical length of stay in hospitals is usually calculated by dividing the sum of the individual lengths of stay of discharged patients during the year (month or week) by the total number of discharges. Three problems arise with this method. First, because bed occupancy is counted at midnight, the average length of stay count concerns the nights, not the days, of occupancy. To overcome this, either the admission and discharge dates should be counted as one day, or plus 1 should be added to the night-time length of stay. Second, patients have to be discharged to be counted. Given the short length of stay in surgical beds, this is usually not a problem; however, in geriatric medical services providing long stay care, a proportion of the patients occupying beds for long period of time are ignored. Third, and most importantly, the distribution of individual lengths of stay is skewed. Consider the following series of 7 numbers: 1, 1, 2, 2, 2, 3, 3. The total is 14, the most frequent number (the mode) is 2, the middle number (the median) is 2 and the average (the mean) is 2. In this case, the average describes the data because the data are normally distributed. However, if we add the numbers 7 and 15 to the sequence the total has now become 36 and the average 4, yet the mode and the median have not changed. It is this lack of relationship between the average stay and the skewed distribution of the data that explains why a single average fails to represent the reality of surgical care.

PHM's interest in this subject is best shown by the following series of numbers: 9, 10, 15, 21, 21, 30, 43, 91, 462. The mode is 21, the median is 21, but the average is 78. Consultants in geriatric medicine have responsibility for the provision of rehabilitative and long-stay services, but their work is reported and performance targets are set, using the average length of stay. Not surprisingly, the quickest way to achieve the target of shortening length of stay is to refuse to admit complex patients or to send them elsewhere.

Surgical length of stay in the Adelaide data set

Examination of the length of stay of the 7,681 surgical in-patients who were discharged from the Adelaide hospital between 1 January and 31 December 1997 confirms that surgical length of stay is not normally distributed. The mean length of stay was 5.68 days, the mode was 1 day, the median was 3 days and the range was 0–179 days. The standard deviation from the mean was 9.02 days which is consistent with a skewed distribution. Similar distributions were found for patients discharged during 1998. Figure 1 shows the distribution of the length of stay data in 1997. The importance of taking into account the use of resources by complex patients is shown by the fact that 10% of admitted patients stayed for more than 13 days.

Admissions and discharges

Figure 2 shows how the interaction between planned and unplanned surgical admissions establishes a weekly cyclical pattern of surgical admissions. The figure demonstrates the pattern of admissions between October

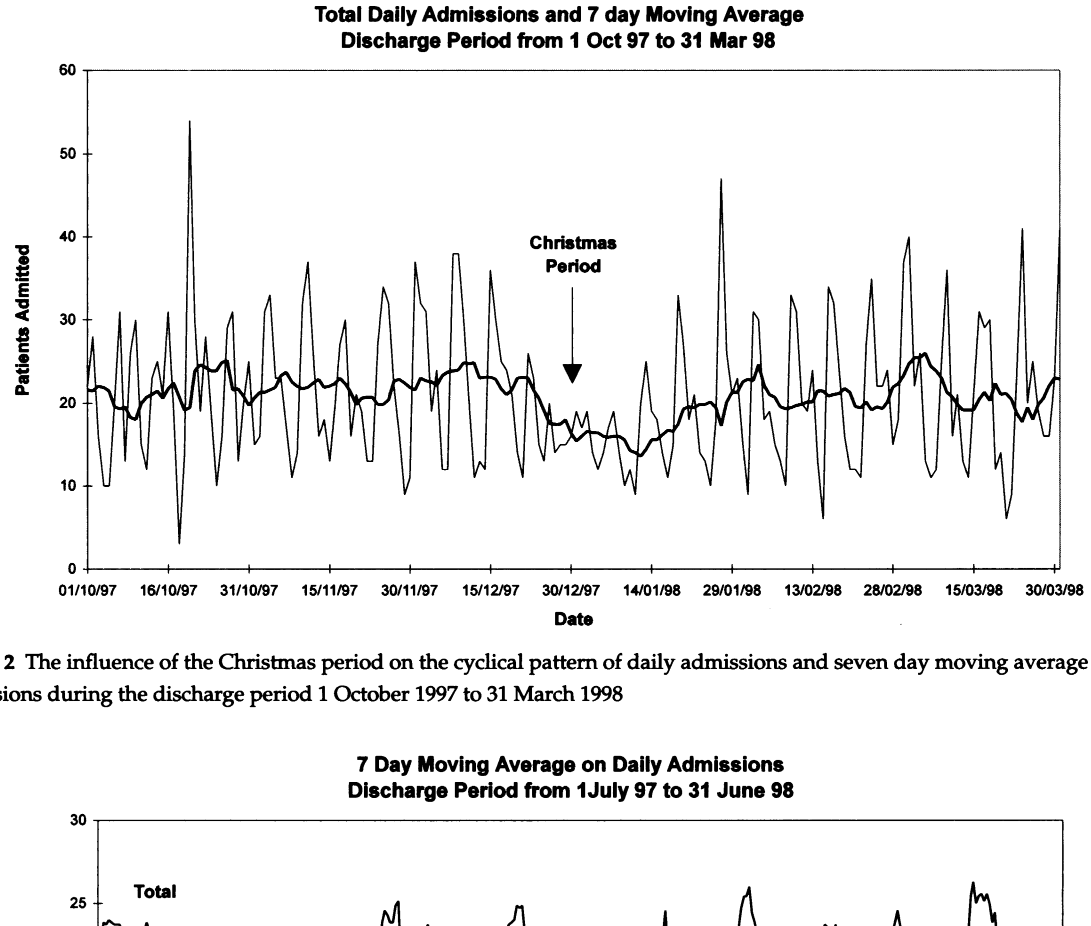

Figure 2 The influence of the Christmas period on the cyclical pattern of daily admissions and seven day moving average for admissions during the discharge period 1 October 1997 to 31 March 1998

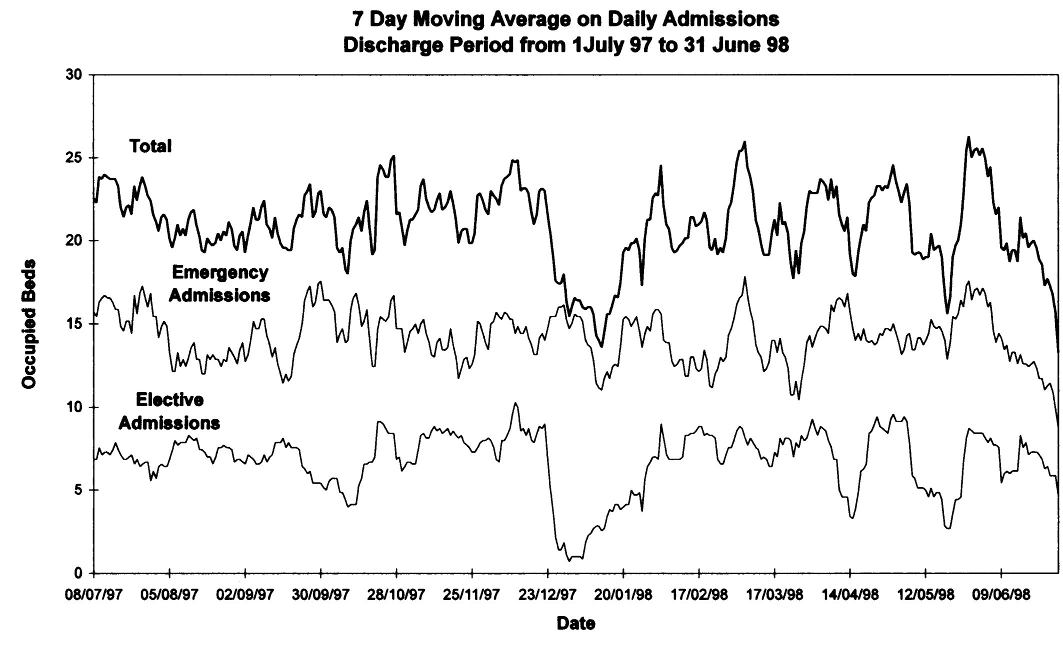

Figure 3 Seven day moving average of emergency and elective admissions for the discharge period 1 July 1997 to 31 June 1998 showing how elective and emergency admissions interact to influence the daily surgical inpatient workload

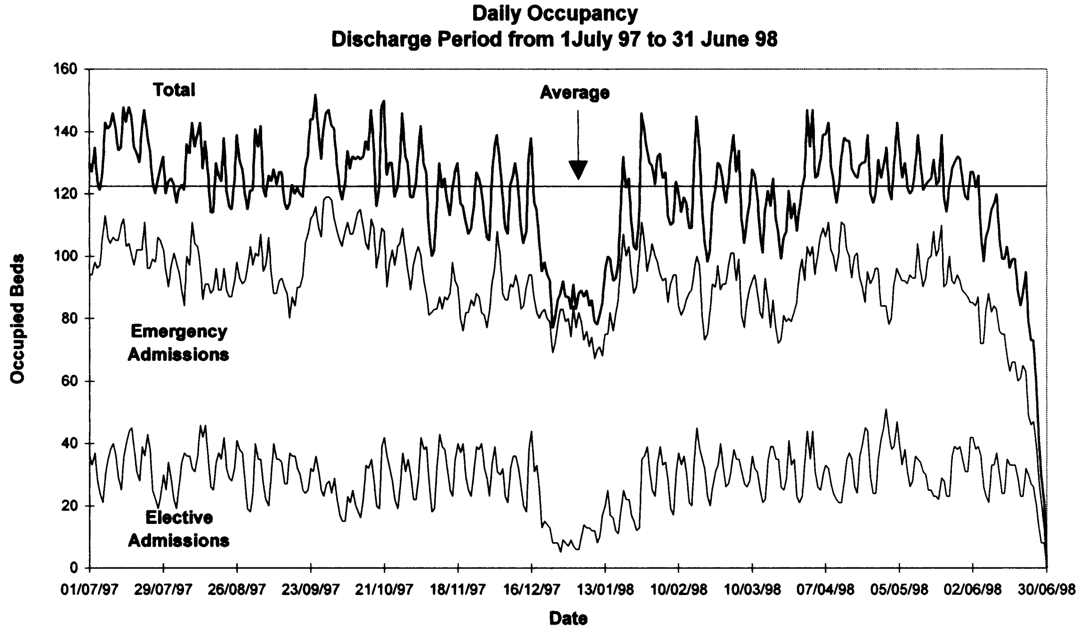

Figure 4 The interaction of emergency and elective admissions and discharges on bed occupancy. The figure shows the effect of decreasing elective admissions on overall bed occupancy, and illustrates why the use of average bed occupancy misleads. Data concern admissions and discharges during the discharge period 1 July 1997 to 31 June 1998

1997 and March 1998 in order to show the impact of the Christmas holiday on surgical admissions. During 1997, the mean daily number of admissions was 21, the mode was 13 admissions, and the median 21 admissions. That considerable daily swings in surgical admission activity can occur is shown by the difference between the minimum number of daily admissions during 1997 of 3 and the maximum of 54, with a standard deviation from the mean of 8.2. Less than 12 patients were admitted on 10% of the days and more than 32 on 10% of days. Figure 3 shows how a 7 day moving average smoothes the daily pattern of admissions and identifies that the collapse in surgical activity that occurs at Christmas is primarily attributable to the reduction in planned admissions. A cyclical pattern also occurs for discharges.

During an average working week, 9% of admissions occurred on Sundays, 19% on Mondays, 18% on Tuesdays, 15% on Wednesdays, 16% on Thursdays, 13% on Fridays and 8% on Saturdays.

Bed occupancy

Figure 4 shows how admissions and discharges interacted between July 1997 and June 1998, to establish the on-going daily pattern of surgical bed usage. During 1997, the maximum number of occupied beds was 152, the minimum bed occupancy was 70 beds and the mean bed occupancy was 120.5. The similarity between the mean occupancy and the mode of 122 beds and the median of 122 beds, coupled with the standard deviation of 14.7 beds shows that 95% of the daily bed occupancy roughly lies between 90 and 150 beds. Figure 4 also shows how the reduction in planned admissions that occurred at Christmas mainly effected the use of surgical beds by planned admissions.

Modelling the process of care

The question 'how can we make more efficient use of our current resources while maintaining (and/or improving) the standards of care?' is one that puzzles all health industry professionals. In this section, we show how exponential analysis of occupancy data can give useful insights into the use being made of surgical beds. The method used was developed in collaborative research involving mathematicians, decision scientists, planners and clinicians in different parts of the world.[3–6]

Flow models are created in the following way. First, information concerning the use being made of occupied beds is collected, either manually by a one-day census or electronically, using the midnight bed state. In this case, we used the 1997 admission data to create the pattern of bed occupancy in the Adelaide surgical beds on an

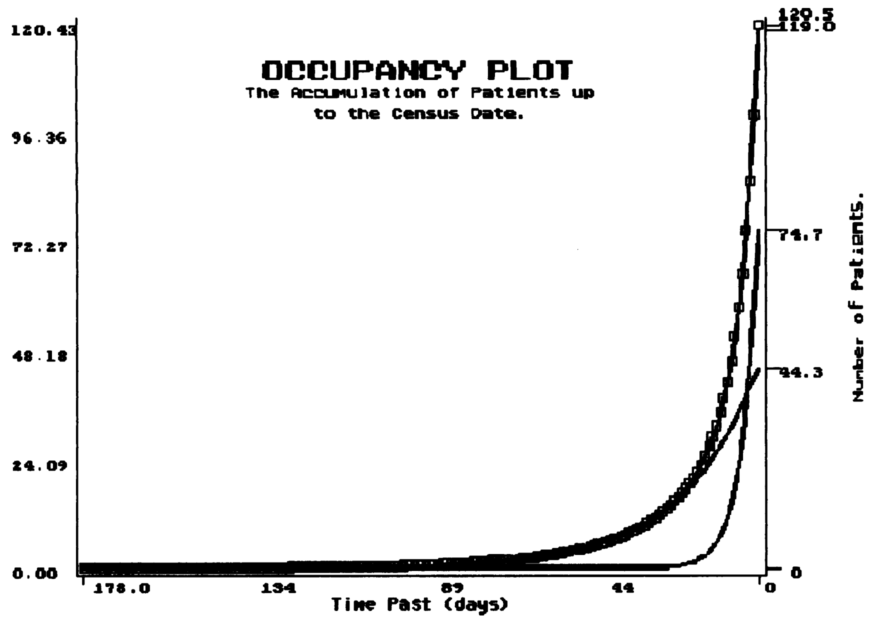

Figure 5 The relationship between the best fit exponential curve and the observed average daily surgical bed occupancy during 1997. The curve is based on 119.0 beds, while the actual occupancy was 120.5. The data points are plotted backwards to reinforce the fact that the method uses prevalence data. The curve that fits the observed data is derived from the parameters of a two component mixed exponential equation: the first component strikes the right hand side y-axis at 74.7; the second component at 44.3

Table 1 Flow modelled bed usage in Adelaide surgical data for an average day during 1997

Surgical bed usage		
Overall		
	Average daily occupied beds	119.0
	Admissions (day)	17.8
	Expected length of stay (days)	6.7
Group 1		
	Percentage of occupied beds	71.4
	Expected length of stay (days)	4.8
	Half-life (days)	2.9
	Percentage of patients treated	90.7
Group 2		
	Percentage of occupied beds	28.6
	Expected length of stay (days)	20.4
	Half-life (days)	13.8
	Percentage of patients treated	9.3

average day. The time of individual patient bed occupancy up to the census date is sorted; then, the best-fit between a one, two or three component exponential curve and the observed occupancy pattern is determined (Fig. 5 shows the fit obtained in the Adelaide data set for an average day in 1997). Next, the numerical values of the best-fit equation are used to generate a one, two or three compartment model that describes the resource utilisation by the inpatients present on the census day.[7]

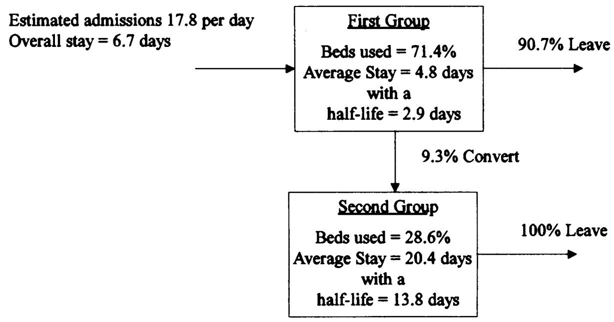

Figure 6 Two compartment flow model of surgical bed usage for an average daily census during 1997

Modelling the Adelaide surgical data

The results obtained by modelling the average daily pattern of bed occupancy during 1997 in the Adelaide surgical beds are shown in Table 1. Figure 6 shows how the two compartments of in-patient care interact. On an average day, 71.4% of the occupied surgical beds were used for those patients who would stay on average for 4.8 days: 20% of these patients would leave in less than one day, 50% within 2.9 days, 75% by 5.8 days, 87.5% by 11.4 days and 93.75% within 22.8 days, etc. The remaining 28.6% of the beds contained the patients who would stay on average for 20.4 days: 20%

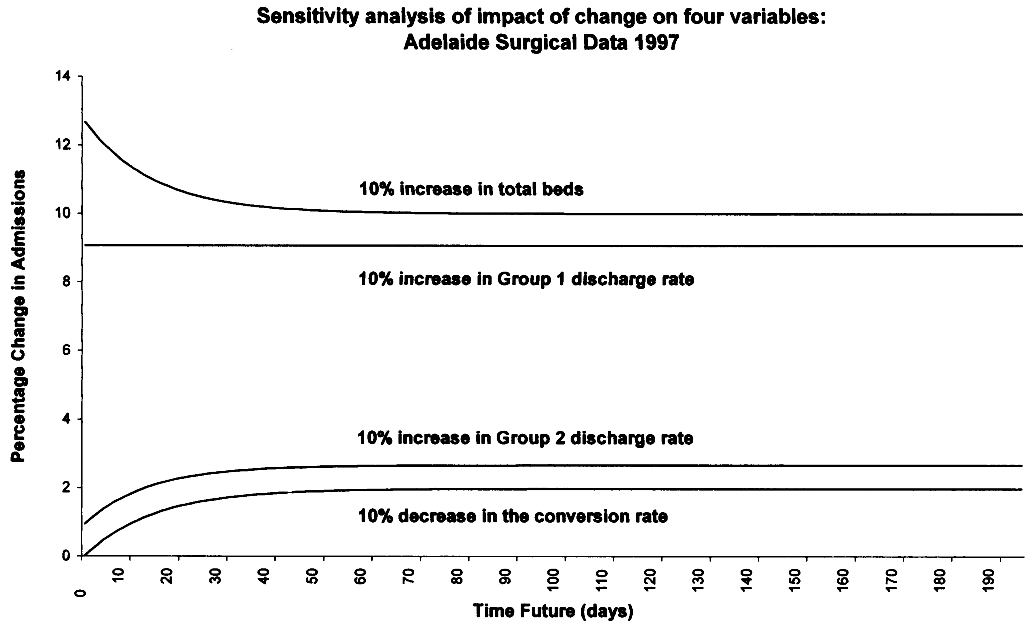

Figure 7 Sensitivity analysis of the impact of a 10% change in four variables in the two compartment model of flow for the Adelaide surgical beds

of these patients would leave within 4.4 days, 50% within 13.8 days, 75% in 27.6 days, 87.5% in 41.4 days, 93.75% in 55.2 days, 96.875% in 55.2 days. Accordingly, the process of surgical care within the Adelaide surgical beds contained two streams of patient. Understanding the interactions between these two streams of flow is key to the optimal control of resources.

Comparing the results with the actual data

The model predicted that 17.8 surgical patients would be admitted on an average day, whereas, the actual daily number of admissions was 21.3. Also, the model predicted that the average length of stay at discharge would be 5.9 days for the whole data set, whereas the model predicted the length of stay to be 6.3 days. Nevertheless, the proximity between actual and real means that it is possible to gain useful insights into the on-going, day-to-day, workload in the Adelaide surgical unit.

Changing behaviour

Given that the overall pattern of daily surgical bed usage represents the interaction between two different streams of patients, one representing the simpler patients and the other the complex, there are several different ways in which the overall surgical performance can be changed. The advantage of creating a dynamic model of flow is that the impact of different changes in the way that the workload is undertaken can be pre-tested. For example, Figure 7 shows the hypothetical results of a 10% change in four different parameters of the Adelaide model. Notice that a 10% increase in beds creates an immediate surge of admissions activity up to 14%, before eventually settling to a 10% increase. In contrast, a 10% reduction in the conversion rate from short-stay to long-stay, e.g. by improving in-patient management, eventually gives a 2% increase in admissions.

Thus the model shows that early gains made, for example by shortening length of acute stay or increasing beds, are not sustained. In contrast, methods directed at improving in-patient care bring longer term gains. This is why concentrating on the prevention and management of complexity is far more important than speedy discharge. Indeed, if the speedy discharge of a post-surgery older patient in 2 days, precipitates a fall, a fracture, re-admission and prolonged stay, then the costs that were saved by the early discharge of 20 patients are frittered away on the care of one.

Comparing units

Flow models of occupancy data can be used to demonstrate differences between units. However, many problems need to be resolved before models can be created that enable one surgical unit to be compared with another. In order to compare units, four problems, external to the system under study, need to be overcome. First, discharge is directional, so more than one number needs to be used to describe the use being made of the surgical beds. Second, speed (i.e. length of stay) does not, necessarily, indicate quality of care. In all branches of medicine, it is the impact of the medical or surgical intervention on the person that is of prime importance, not the speed with which it is done. Third, any performance comparison has to take into account the degrees of difficulty.

Here Copeland's work in Warrington is of considerable importance,[8] for he has shown that differences in length of stay and outcome between surgeons can be eliminated if degrees of difficulty embracing operative severity and physiological status are taken into account. Clearly, breast surgeons should have different lengths of stay and outcomes than colonic surgeons. Similarly, the work being done by Treasure on cardiac surgery[9] at St George's Hospital, London, points the way forward. In Adelaide, severity indices have been developed to enable comparison of the work undertaken by hospitals. These indices, which are based upon a range of factors, provide a mechanism to identify those hospitals that undertake the more complex work, which is usually associated with longer patient length of stay.[10] The method is, however, only suitable for making comparisons at the hospital level and not at the departmental level.

Finally, factors external to the system understudy effect performance. For example, geriatricians in Sussex treat their patients faster than those in Surrey, who in turn are faster than those in London, because they find it easier to send their longer stay patients elsewhere.[11] Could the same be true in surgery?

Sorensen showed that it is possible to introduce the patient's destination following discharge into bed modelling.[12] Sorensen proposed the multi-phased model for determining hospital bed requirements, which incorporated the probability of patients being discharged to a particular destination. To illustrate the importance of knowing the destination at discharge, we analysed the impact of destination on average length of stay in the Adelaide data set; 87% of the patients discharged went home within 4.6 days (SD 6.6 days). In contrast, 6% were discharged to other hospitals in 11.6 days (SD 12.0 days). The 1% who were discharged to other health care accommodation occupied beds for 20.9 days (SD 25.5 days), indicating that factors external to the surgical system are influencing performance.

Clearly not only are there a number of possible destinations to which patients may be discharged, but the average length of stay of the patient groups based upon discharge destination varies from a low of 1 day (unknown destination) to 20.9 days (discharged to other health care accommodation, which is not a hospital, nursing home or hostel). Differences in length of stay were also observed between the elective and emergency patients discharged to the same destination. There is a range of plausible and reasonable reasons why such differences should exist, including factors relating to patient age, and the number and types of cases included in each discharge destination category.

While Sorensen's approach to bed modelling is different to that used here, the linking of patient destination to the modelling developed by PHM is possible. Clearly, such modelling would be useful to determine the implications arising from changes external to the hospital milieu on bed management. For example, if nursing home bed shortages occurred, it would be likely that the length of stay of patients waiting for a nursing home bed to become available would increase, thereby creating additional 'bed blockers' in hospital beds.

While such an approach may clearly be of use to bed planners at the hospital and regional level, the difficulty of incorporating patient destination into performance benchmarking nevertheless remains.

The work that we have reported here has been ongoing for the last decade. During that time, it has involved, and is still involving, many people in different parts of the world. We hope that through this article we have given an insight both into the work that we are doing and to the opportunities that it creates. Further information about the methodology can be obtained from Prof. Millard by E-mail (p.millard@sghms.ac.uk) or from the internet site (http://www.sghms.ac.uk/depts/gm/index.htm).

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