A simulation study of the winter bed crisis.

Christos Vasilakis
Elia El-Darzi

Harrow School of Computer Science

This is an author-produced electronic version of an article accepted for publication in Health Care Management Science, 4 (1). pp. 31-36, February 2001. The original publication is available at www.springerlink.com :

http://www.springerlink.com/content/mw527728q155v221/

A Simulation Study of the Winter Bed Crisis

C. Vasilakis and E. El-Darzi

University of Westminster, London

Short running title: Simulating the winter bed crisis

Corresponding Author:

Mr. C. Vasilakis,
University of Westminster,
School of Computer Science,
Watford Rd, Northwick Park,
Harrow HA1 3TP,
United Kingdom,
Tel: ++44 - 171 – 9115000 x. 4480
E-mail: coiec@westminster.ac.uk

A Simulation Study of the Winter Bed Crisis

Short running title: Simulating the winter bed crisis

Keywords: Simulation, Geriatric Medicine, Queuing systems, Bed Occupancy

Abstract:

The winter bed crisis is a cyclical phenomenon which appears in British hospitals every year, two or three weeks after Christmas. The crisis is usually attributed to factors such as the bad weather, influenza, older people, geriatricians, lack of cash or nurse shortages. However, a possible alternative explanation could be that beds within the hospital are blocked because of lack of social services for discharge of hospital patients during the Christmas period. Adopting this explanation of why the bed crisis occurs, the problem was considered as a queuing system and discrete event simulation was employed to evaluate the model numerically. The model shows that stopping discharges of rehabilitating patients for 21 days accompanied by a cessation of planned patients for 14 days precipitate a bed crisis when the planned admissions recommence. The extensive 'what-if' capabilities of such models could be proved to be crucial to the designing and implementation of possible solutions to the problem.

1. INTRODUCTION

1.1 General Discussion

Every year, without fail, the United Kingdom National Health Service hospitals face a post-Christmas bed crisis. Why should this be? Conventional wisdom places the responsibility on older people for needing to be admitted, on influenza epidemics or on bad weather. Yet the number of admissions in the post-Christmas period are not exceptional, indeed it has been reported that equivalent numbers of acute admissions can occur in summer months [1]. Woodman [2] has reported that the numbers of influenza cases last winter were far short of an epidemic and yet many intensive care facilities were stretched to the limit and many hospitals were forced to postpone elective surgery. Why then, should the crisis occur?

In supermarkets and in banks queues form when there are insufficient server units to meet the demand for service. Similarly, in hospitals, the queues form when there are insufficient beds available to admit ill people. As is the case when queues form in other circumstances a problem becomes a crisis. In supermarkets and in banks customers can go elsewhere. But sick people have no alternative options: they just have to wait. When the crisis occurs patients wait on trolleys to be admitted.

In this paper we propose a viable alternative explanation for the crisis. The movement of patients through hospitals can be seen to occur in streams. Words such as acute, rehabilitation and long stay contain dimensions of time as well as dimensions of performance. On any day the availability of hospital beds for admission depends on patients leaving the system. Here we hypothesise and demonstrate using simulation models that the cause of the crisis is a breakdown in the discharge of dependent patients from the medium stay (or rehabilitative) stream [3]. During the Christmas and New Year period surgeons are not operating on routine cases. The service changes from elective mode to emergency mode and therefore beds are available for medical patients to use. After Christmas, when the surgeons return, the surgical beds are occupied by medical patients. As the surgeons commence their work there are insufficient beds for medical emergencies and therefore, queues form.

1.2 Graphical analysis of the problem

Figure 1 provides a clearer explanation on why the winter bed crisis occurs. The data comes from St. George's Hospital and it involves patient activity for the period from 1st April 1995 to 31st March 1997. A seven-day moving average has been used to smooth out the weekly fluctuation in the admissions and discharges of the general and geriatric medical departments. The moving average was only used to make the graph more presentable and to point out the post-Christmas fluctuations.

[Insert Figure 1 near here]

It can be clearly seen that the reason behind the crisis is not the rise in the admissions but the delays in hospital discharge during and in the period immediately after Christmas. During this period the general and geriatric medical departments admitted roughly 70 more patients than they discharged. Consequently bed shortages occurred.

Figure 2 sheds light on the same problem from a different angle. To create the strata of bed occupancy the length of stay from admission to discharge of the individual patients was calculated. Then the individual lengths of stay were grouped into bands representing the inpatients who stayed 0 days, 1 to 6 days, 7 to 20 days, 21 to 41 days, 42 to 97 days and 98 plus days. These bands are based on clinical judgement and experience. The 0 days band represents the day cases., 1-6 days represents the week cases and in this instance the majority of acute patients. It is believed that about 50% of older people with complex illness stay between 7 and 21 days. The 21 to 41 and 42 to 97 bands represent the remaining 50%. Finally, the patients in the band of 98+ stay in the system until they die and these are the long stay patients.

The two-year dataset was then censused every 28 days to show the strata that would be generated by the inpatients present on the chosen census day. A 28-day interval was defined in order to census the data on the same day of the week. A Wednesday was chosen to avoid the fluctuations that occur during the week. This technique is believed to give a better indication of the characteristics of the inpatient workload than traditional methods such as waiting lists and average length of stay.

[Insert Figure 2 near here]

It can be observed that the layers of patients who stayed for 0 days, 1-6, and 98 and over remained basically unchanged. The peaks immediately after the Christmas periods appeared because the number of medium stay patients (7-20 days, 21-41 and 42-97 days) showed a high increase. These groups of patients are mainly those who are both in need of rehabilitation and of social services for discharge.

1.3 Background to the methods

El-Darzi et al [4] have used simulation models to evaluate the flow of patients within the acute, rehabilitative and long-term compartments of a hospital department of geriatric medicine and between the hospital and the community [5]. Simulation modelling has advantages because it demonstrates the fluctuations that can occur in occupancy and emptiness due to random variations in the number of people being serviced. It also highlights the findings of previous work which suggested that the key to the smooth running of the system is the emptiness in the long stay compartment [6]. Simulation also shows that decisions concerning the management of patients in any compartment have a domino effect on the system which will eventually influence the way the whole system is running.

Key concepts of the simulation model are that patients arrive randomly and independently of each other, that length of stay in the acute (short stay), rehabilitative (medium stay) and long-stay compartments is exponentially distributed and that acute beds are blocked when no beds (server units) are available for patients identified as needing rehabilitation. Equally beds in the rehabilitation compartment are blocked when there are no available beds in the long-stay.

The basic parameters of these simulation models are obtained from a task specific software (BOMPS) which generates performance statistics based upon the fit between a mixed exponential curve and bed census data [7,8]. This software package implements the concept of flow modelling [9]. Flow modelling is based on a behavioural theory of flow [10] which is based on the concept that staff interact with patients and resources to establish specialty specific, locally determined streams of flow. It is a different approach to the measurement and planning of health care resources where traditional methods (length of stay averages and waiting lists) have either failed or inaccurately described the process of care in departments such as the geriatric, psychiatric, surgical, etc. [11].

2. THE MODELS

2.1 The unconstrained model

The model comprises two compartments (see figure 3), the short stay (SS) and the medium stay (MS) which can also be referred to as the acute and rehabilitation compartments. These compartments have been set according to the description of the flow model and the parameters of the system (length of stay, conversion rate between the compartments and the admission rate) were set according to the results obtained by an analysis which was conducted on data from a hospital in Adelaide [1]. Although this data set concerns a surgical hospital it was preferred to the St. George's data set used in section 1 as the proportion of the planned patients is known. Because of the nature of the surgical department, patients do not stay for very long and accordingly, we constructed the model with only two compartments, short and medium stay.

[Insert Figure 3 near here]

The arrival rate (or admission rate) according to the flow model is 17.8 patients per day and it was assumed that their interarrival times can be considered to be independent, identically distributed variables (IID).

All patients enter the short stay compartment where they stay for 4.8 days on average. The vast majority of these patients (90.7%) will leave the system (either by death or discharge). However, 9.3% will be converted into medium stay patients where they will remain, on average, for a further 20.4 days before eventually leaving the system.

This first model has no queues or bed constraints and it was mainly used to confirm that the flow model and the simulation model under development are compatible methods of analysis, to estimate the point in time where the steady state of the system occurs, and to provide the next model with bed estimates. Indeed, the results showed that on average, 71.5% of the total patients in the system are in the short stay compartment and the rest (28.5%) are in the medium stay one. They occupy on average 85 and 34 beds respectively. The flow model analysis yielded almost the same figures. Such a conclusion was expected as shown in previous papers [4,5].

2.2 Setting up the constrained model

Having analysed the unconstrained model we will consider the problem as a queuing system, we will also introduce bed constraints and the shutting down of the discharges for certain periods in time.

A queuing system consists of one or more servers that provide service of some kind to arriving customers [12]. In this model, beds are the server units and patients are the customers. If a customer arrives and finds all servers busy, generally, he or she would join one or more queues. Similarly, patients waiting in queues within the hospital system create bed blockage in the short stay beds. The queue in the medium stay compartment represents bed blockage between the short and the medium stay compartments meaning that patients within the queue are still occupying beds in the first compartment (see figure 4, Queue 1). An occupied bed will be available again once a queued patient is allocated a bed in the second compartment.

[Insert Figure 4 near here]

To simulate the basic trigger of the winter bed crisis a second queue (Queue 2) and a third task (Delay task) were added to the system (see figure 4). When the "tap is turned off" in the medium stay compartment patients cannot leave the system. Instead they join the second queue where they remain for a further 21 days until the social services are running again. In reality these patients are still occupying the beds in the medium stay compartment. As discharge services for this group of patients and new patients cannot be provided immediately after the "tap is turned back on" we have assumed that they will spend a further 10 days on average in the system before being discharged. This assumption will be the starting point of the sensitivity analysis. At the same time as the tap of discharges is turned off, admissions are reduced by the planned proportion to take account of the non-use surgical and medical beds for planned care (32.2% in this example).

The number of beds in each compartment was calculated from the simulation results of the unconstrained model. The mean number of occupied beds of the unconstrained model was used and an assumption was made that the hospital operates under different levels of emptiness in each compartment. These levels were chosen as follows: 20% for the short stay and 10% for the medium stay and the number of beds were consequently set at 107 and 38 respectively. These levels of emptiness were based on clinical judgement.

Due to the relatively short length of stay in the two compartments the model reaches steady state within 200 days. A simulation model is considered to be in a steady state behaviour if its current behaviour is independent of the starting conditions [13]. There are two implications of the short warm up period. The technical one is that statistical results can be quickly obtained, the managerial implication being that any change in the parameters of the model (and hence in the real life system) will have an almost immediate effect.

The model was run using the batch means method which is based on a single long run [14]. This method seeks to obtain independent observations in order to be able to define the means and their confidence intervals by dividing the output data from that single run into a few large batches. The means of these batches are then treated as independent and the random seed has to be defined only once at the beginning of the run. In this example the output was divided into 10 batches of 2000 steady state days.

The models were built using the MicroSaint simulation package. MicroSaint is an icon-based, network simulation software package that lets the user build models to simulate real-life processes. The computer used was an IBM PC compatible with a 450 MHz Pentium III processor and 128 MB of RAM. The operating system was Windows NT 4.0 . The average running time was approximately 10 minutes for a single long run.

2.3 The results from the basic model

One of the basic advantages of flow modelling and consequently of these simulation models is that they bring out the interaction of the different compartments. In figure 5 the output of a test run around what it is assumed to be the Christmas holiday period has been plotted. The fluctuations in the occupancy levels can be clearly seen in the black line which represents the number of available beds in the short stay compartment. Some bed blockage exists within the system as there are no available short stay beds in one case and a very few in two other cases. When the medium stay patients are stopped from being discharged, it takes roughly two weeks after that for the crisis to occur. It then takes approximately three weeks for the system to start running smoothly again although there are still patients waiting to be discharged and thus occupying beds.

[Insert Figure 5 near here]

Table 1 provides us with a general view of the system. The first column shows the percentage of patients rejected from the system over the total admissions. In reality these rejected patients are either treated by other specialties or wait on trolleys for admission. In this model, we assume that they are treated by other specialties. The average percentage of emptiness shows the proportion of available beds in the short stay compartment over the total number of beds. The third column shows the average number of patients waiting in the queue (and thus creating bed blockage) and the fourth shows the average time spent in the queue by all the medium stay patients. For each parameter the mean, standard deviation and 95% *t* confidence intervals of the mean [14] are given.

[Insert Table 1 near here]

It can be seen that the introduction of the assumptions of the winter bed crisis has resulted in a system with lower levels of emptiness. The emptiness in the short stay is roughly 18% and in the medium stay 9% although they were given 20% and 10% of emptiness respectively. These figures were the result of the presence of bed blockage in the model as on average 4 patients were blocking beds in the short stay compartment and all the patients who were transferred to the medium stay compartment had to wait for an estimate of 2.5 days.

In Table 2 the focus is on the crisis period. The first column contains the average number of available beds in the short stay the month just before the crisis, the second column represents the average number of available beds in the month starting 10 days after the crisis and the third contains the difference of the first two columns. The same information is repeated for the medium stay compartment. It can be seen that for a whole month the hospital has to operate with approximately 8 beds fewer than normal average.

[Insert Table 2 near here]

2.4 Sensitivity Analysis

After running the models with the initial set up there is a need to explore how sensitive the system is to changes in its parameters. It has been shown that this type of model is extremely sensitive to even minor changes in the conversion rates [4] and it was confirmed with this model. However, as the focus of this paper is on the Christmas effect we have focused our sensitivity analysis on the number of days the patients have to spend in the hospital after the social services are running normally again. This value was set at 10 days of exponential average in the basic model. The behaviour of the system was examined with the values of the parameter ranging from 0 to 20 with an increment of 2. The results are summarized in Table 3.

[Insert Table 3 near here]

The columns contain the same information as in Table 2. For each simulation run the first row shows the mean number of available beds and the second the standard deviation. The p-values were obtained by a one way analysis of variance (ANOVA) which was performed on the simulated results. Clearly the number of days the patients have to wait before discharge is a significant factor for the number of available short stay beds in the post-Christmas period (column 2), for the difference in the short stay compartment (column 3) and the number of available medium stay beds during the crisis (column 5). It was proved not to be a significant factor for the period before Christmas in both compartments (columns 1 and 4) and also in the difference in the medium stay (column 6). The reason behind this phenomenon is that the number of available medium stay beds is very close to 0 even with no delays in the discharge process.

3. DISCUSSION AND CONCLUSIONS

In this paper we used simulation modelling, queuing systems and flow modelling to model the winter bed crisis. Simulation models have been proved to be valuable tools in allocating resources and in decision making in general. However, the models which were described here have been proved to be equally important in the process of understanding the interactions between the different parameters and components of the system. The key explanation for the admission problems may not be the emptiness in the short stay compartment (acute care) but the effective management of the longer stay patients [4].

The dataset provided by St. George's Hospital showed graphically the significant effect of patient management during the Christmas crisis (i.e. higher number of patients are waiting to be discharged in the period immediately after Christmas). Unfortunately this data set could not be used to feed the simulation model with input parameters. An alternative data set was used and the obtained simulation results confirmed our hypothesis that discharges rather than admissions could be the main cause of the crisis. Furthermore, taking into account the severity of the year 2000 post-Christmas bed crisis in the UK, our results would suggest that the crisis was possibly due to staff leave and public holidays rather than to influenza.

Already the Commons health committee has made a recommendation to the government to fully integrate the health and social services in the United Kingdom to end the confusion over the continuing care for elderly people [15]. In this report, it is claimed that the artificial barriers which exist between the two services lead to uncoordinated hospital discharges and that an estimate of 6000 people over 75 are being kept in hospitals although they are ready to be discharged. The Department of Health has recently pointed out the need of integrated and coherent services which will provide better co-ordination of services across health and social care boundaries [16]. The findings of this paper justified the above recommendations and showed that if discharges run smoothly then an extreme bed crisis could be avoided.

Acknowledgments

Thanks to Andrew Dillon for granting access to the St. George’s data and Wendy McCarthy for her assistance. Also thanks to Mark Mackay who authorised the use of the data from Adelaide.

REFERENCES

Reference List

[1] Millard, P. H., Mackay, M., Vasilakis, C., and Christodoulou, G., Measuring and modelling surgical bed usage, Annals of the Royal College of Surgeons of England 82 (1999) 75 - 82.

[2] Woodman, R., What caused the winter crisis in the NHS ?, British Medical Journal 318 (1999) 145.

[3] Melton L., How planning can beat the winter bed crisis, Hospital Doctor (14-10-1999) 42-46.

[4] El-Darzi, E., Vasilakis, C., Chaussalet, T., and Millard, P. H., A Simulation Modelling Approach to Evaluating Length of Stay, Occupancy, Emptiness and Bed Blocking in a Hospital Geriatric Department, Health Care Management Science 1 (1998) 143 - 149.

[5] El-Darzi, E., Vasilakis, C., Chaussalet, T., and Millard, P. H., A simulation approach to modelling the flow of patients between and within a hospital geriatric department and the community, in: Recent Developments and Applications in Decision Making , ed. Despotis, D. K. and Zopounidis, C. (New Technology Publications, Athens, 1999) 674 - 677.

[6] Harrison, G. W., Compartmental models of hospital patient occupancy patterns, in: Modelling hospital resource use: a different approach to the planning and control of health care systems, ed. Millard, P. H. and McClean, S. I. (Royal Society of Medicine, London, 1994) 53-61.

[7] McClean, S. I. and Millard, P. H., A decision support system for bed-occupancy management and planning hospitals, IMA Journal of Mathematics Applied in Medicine and Biology 12 (1995) 225 - 234.

[8] Wyatt, S., The occupancy management and planning system (BOMPS), The Lancet 345 (1995) 243 - 244.

[9] Harrison, G. W. and Millard, P. H., Balancing acute and long term care: the mathematics of throughput in departments of geriatric medicine, Methods of Information in Medicine 30 (1991) 221 - 228.

[10] Feldstein, M. S., Operational research and efficiency in the Health Service, The Lancet i (1963) 491 - 493.

[11] Millard, P. H., Current measures and their defects, in: Modelling hospital resource use: a different approach to the planning and control of health care systems, ed. Millard, P. H. and McClean, S. I. (Royal Society of Medicine, London, 1994) 29 – 37.

[12] Law, M. A. and Kelton, W. D., Simulation Modelling & Analysis (McGraw-Hill, Singapore, 1991).

[13] Pidd, M., Computer simulation in management science (Wiley, England, 1992).

[14] Banks, J., Carson, J. S. II, and Nelson, B. L., Discrete-event system simulation (Prentice-Hall, New Jersey, 1996).

[15] Warden, J., Health secretary reports on winter crisis, British Medical Journal 318 (16-1-1999) 145.

[16] Department of Health, Shaping the Future NHS: Long Term Planning for Hospitals and Related Services, (2000)

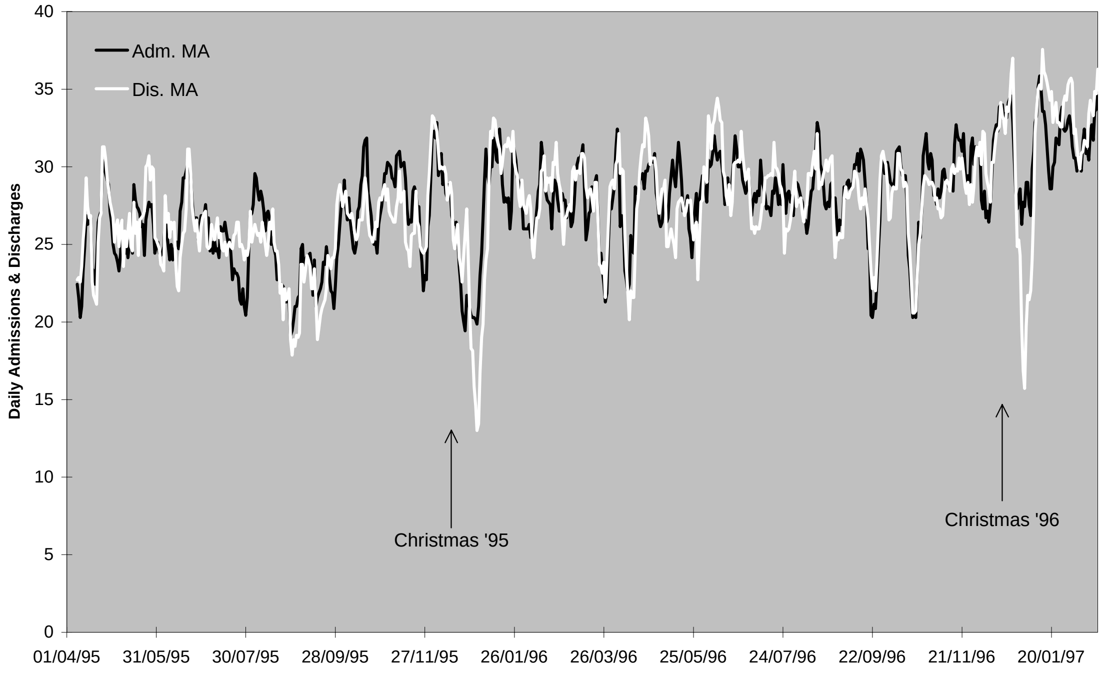

Figure 1. St. George's Hospital - General & geriatric medicine daily admissions & discharges - 7 Day moving average

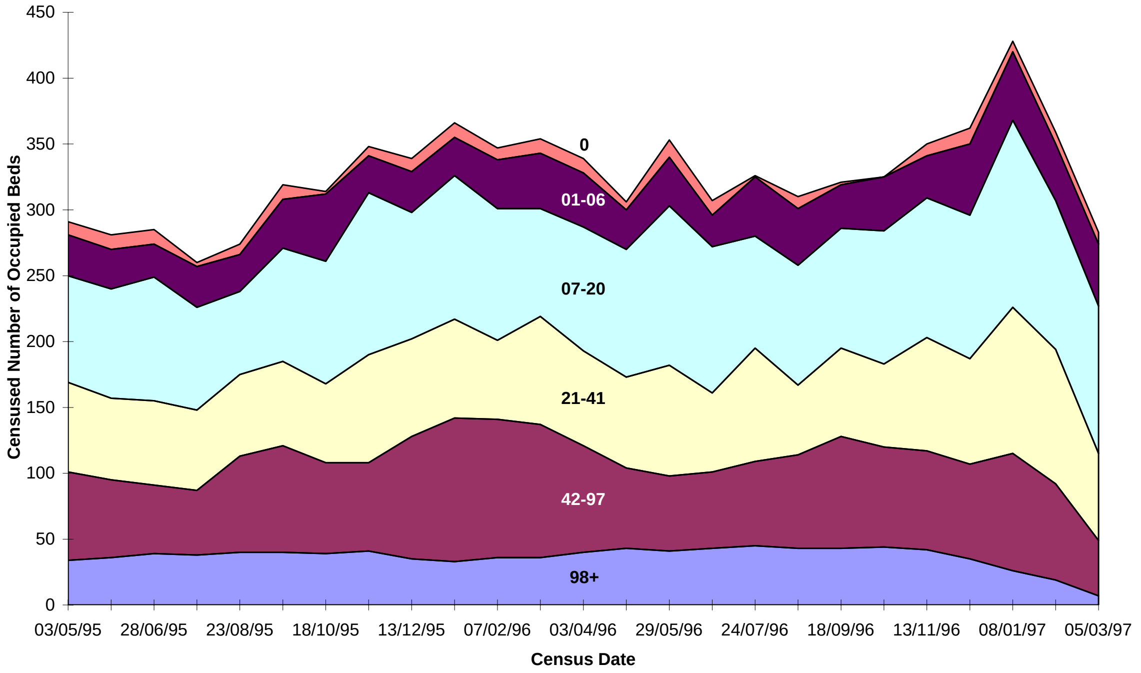

Figure 2. St. George's Hospital - Overall strata of duration of stay - 28 day censuses

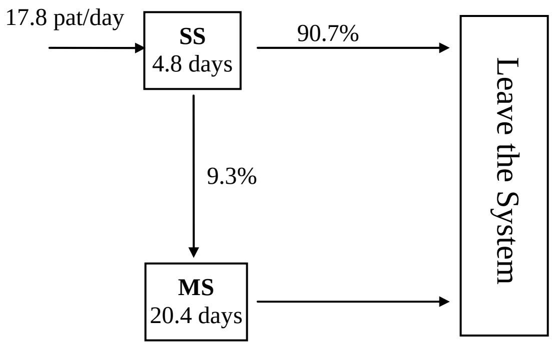

Figure 3. Graphical representation of the unconstrained model for the surgical department

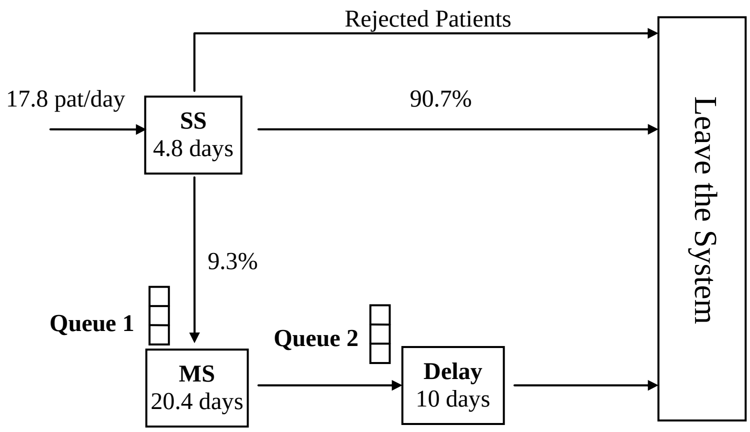

Figure 4. Graphical representation of the basic model for the surgical department

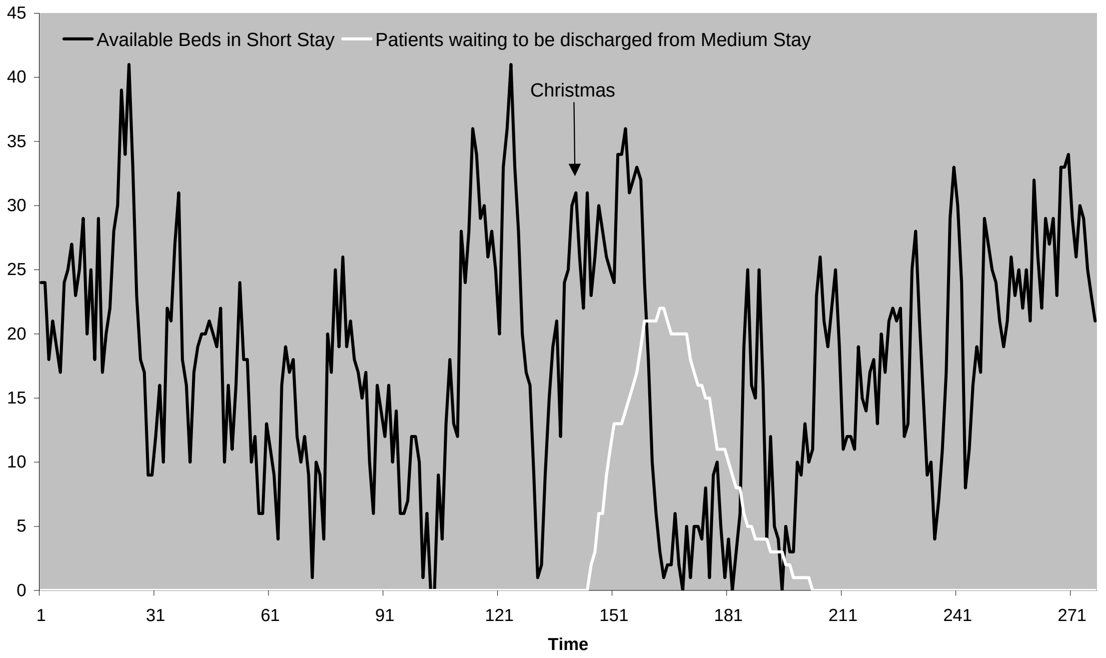

Figure 5. Output from the simulation model – Basic model for the surgical department – One single test run

Table 1. Results from simulation – Basic model for the surgical department

	Short Stay		Medium Stay		
	% of patients refused admission	*Avg % of emptiness*	*Avg # of patients in the queue*	*Avg. time spent in the queue*	*Avg % of emptiness*
Mean	*1.1%*	*18%*	*4.1*	*2.5*	*9%*
SD	*0.5%*	*1.1%*	*1.3*	*0.8*	*1.7%*
95% CL -	*0.8%*	*17.5%*	*3.1*	*1.9*	*7.7%*
95% CL +	*1.4%*	*19.1%*	*5.0*	*3.1*	*10.2%*

Table 2. Results on the crisis from simulation – Basic model for the surgical department - Number of available beds

	Short Stay			*Medium Stay*		
	Before the crisis	*During the crisis*	*Differ.*	*Before the crisis*	*During the crisis*	*Differ.*
Mean	*18.9*	*15.3*	*3.6*	*4.3*	*0.2*	*4.2*
SD	*4.1*	*5.1*	*4.3*	*3.8*	*0.7*	*3.6*
95% CL -	*17.0*	*12.9*	*1.6*	*2.5*	*-0.1*	*2.5*
95% CL +	*20.8*	*17.7*	*5.6*	*6.1*	*0.5*	*5.9*

Table 3. Sensitivity analysis on the number of days before discharge after the re-start of the social services

Days	Short Stay			Medium Stay		
	Before the crisis	*During the crisis**	*Differ. **	*Before the crisis*	*During the crisis**	*Differ.*
0	*20.7*	*21.7*	*-1.0*	*4.6*	*1.9*	*2.7*
	6.3	*6.4*	*7.6*	*3.1*	*2.4*	*4.0*
2	*20.2*	*20.4*	*-0.2*	*4.4*	*1.5*	*2.9*
	6.8	*7.6*	*9.1*	*3.2*	*1.9*	*2.6*
4	*20.8*	*18.2*	*2.6*	*4.0*	*0.7*	*3.2*
	5.9	*7.1*	*7.5*	*3.1*	*1.2*	*2.7*
6	*18.6*	*16.3*	*2.4*	*3.6*	*0.3*	*3.3*
	5.2	*8.5*	*8.4*	*3.5*	*0.6*	*3.3*
8	*19.1*	*14.6*	*4.5*	*3.8*	*0.3*	*3.4*
	6.4	*6.5*	*7.0*	*3.7*	*0.8*	*3.2*
10	*18.9*	*15.3*	*3.6*	*4.3*	*0.2*	*4.2*
	4.1	*5.1*	*4.3*	*3.8*	*0.7*	*3.6*
12	*17.7*	*13.3*	*4.4*	*3.6*	*0.1*	*3.5*
	5.7	*6.3*	*6.7*	*3.7*	*0.4*	*3.8*
14	*19.7*	*13.8*	*5.9*	*4.7*	*0.2*	*4.5*
	4.5	*6.7*	*7.1*	*3.9*	*0.5*	*3.9*
16	*19.5*	*11.8*	*7.6*	*3.5*	*0.0*	*3.5*
	5.1	*5.1*	*5.9*	*3.6*	*0.1*	*3.6*
18	*18.7*	*12.5*	*6.2*	*4.5*	*0.0*	*4.5*
	5.3	*4.1*	*5.7*	*4.2*	*0.1*	*4.2*
20	*18.3*	*11.2*	*7.1*	*2.7*	*0.0*	*2.7*
	4.3	*5.1*	*5.0*	*2.9*	*0.1*	*2.9*

* $p < 0.05$