ORIGINAL ARTICLE

BED OCCUPANCY RATE AND THROUGHPUT OF PATIENTS IN CARDIAC SURGERY DEPARTMENTS USING SIMULATION MODELS

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Background – **In the interest of efficiently using limited resources, it is important to optimize the throughput of cardiac surgery patients. Accordingly, the present study was performed to estimate the bed occupancy rate and throughput of patients in cardiac surgery departments using simulation models.**

Methods – **In this paper, the typical Heart Surgery Department of Freeman Hospital in Newcastle upon Tyne, England was considered, where there were some beds in the ward, theater, and intensive care unit (ICU). For a set of data, a computer program for Monte-Carlo simulation of the department using Fortran-77 software (Fortran Company, USA) was developed in order to observe the behavior of the department as a queuing system. Different number of beds in the ward and ICU were simulated in order to observe the bed occupancy rate in the ward and ICU and also the throughput of patients in the system.**

Results – **Bed occupancy rates in the ward and ICU for the case of 2 beds in the ICU and 11 in the ward were 78% and 81%, respectively. In this case, the throughput of 500 patients in the system could take 513 days. For 3 beds in ICU and 16 in the ward the mean bed occupancy rate was 84% in the ward and 79% in ICU. The throughput of 500 patients in the system with 9 beds in ICU and 39 in the ward could take 130 days.**

Conclusion – **To prevent disinvestment prior to building a hospital or a new ward, especially in developing countries, it is suggested to perform simulation studies to observe the behavior of system in advance.**

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Keywords • bed occupancy rate • cardiac surgery • hospital • simulation

Introduction

It is of importance to improve the performance and throughput of patients in a heart surgery department, especially when the resources are limited. A typical heart surgery department is a ward where patients enter before going to the operation theater. Following operation and before returning to the ward for final discharge, they stay in the intensive care unit (ICU) for a period of time. It is probable that some patients die within the system.

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It is of interest to observe the behavior of the system with varying numbers of beds in the ward and ICU in order to maximize the throughput of patients in the system. The running of the department can be viewed as a complex queuing system. To achieve the mentioned goals for the system, an analytical solution would be very difficult to obtain and possibly not feasible. So, using Monte-Carlo simulation[1] is essential to investigate such a system.

The application of simulation processes to hospitals has received attention in recent years. O'Keefe investigated the operation of an outpatient department using a qualitative approach.[2] Cox et al used a simulation study in order to optimize the running of an ear, nose, and throat outpatient clinic.[3] Brahimi and Worthington applied simulation models for an outpatient clinic department.[4] Hashimoto and Bell[5] investigated the behavior of an outpatient clinic to improve the performance of the clinic. Bagust et al[6] used a stochastic simulation model to dynamics of bed use in accommodating emergency admissions. Mui[7] applied a computer simulation model to simulate individuals' coronary heart disease history over time for a sampled Australian population, characterized by major coronary risk factors. Goldman et al[8] used a computer simulation model to estimate the effects of actual investments, made to change coronary risk.

The objective of this study was to calculate the bed occupancy rate in the ward and ICU with different numbers of beds in each of them and use the results to maximize the throughput of patients in the system. Since the behavior of the ward is a complex queuing system, an analytical solution would be very difficult to obtain and perhaps not possible. So, using Monte-Carlo simulation[1] is essential to investigate the system.

Monte-Carlo simulation is a simulation technique using random numbers and probability distributions. For example, time taken for an operation has a specific probability distribution, say exponential distribution. So, simulating such a system is known as Monte-Carlo simulation.

Patients and Methods

A set of data was given to us by Mounsey et al [9] consisting of the throughput and associated data of 431 patients who had coronary artery bypass surgery during a 9-month period. They underwent coronary artery bypass grafting prospectively at the Freeman Hospital in Newcastle upon Tyne, England. Data were collected from a review of patients' records and included baseline demographic characteristics, details of cardiovascular risk factors, angina grade and treadmill exercise tolerance, and the presence of serious coexistent pathology. Coronary angiographic data were also obtained from the patients' records. The patients who spent some days in the department for other types of surgical operations were excluded from this study. The coronary surgery patients normally occupy ICU beds for 24 hours or less though some spend longer. Patients spending 24 hours or less in ICU are considered as fast track patients while those spending less than 24 hours are deemed slow track patients. If a patient stays in the intensive care unit for 24 hours or less, then, for the next routine operating day, there will be a free bed in the unit allowing for a new operation.

Assume that there are M beds in the ward, N beds in the ICU, K operating theaters, and an infinite supply of patients. At any time there are m free beds in the ward and n in the intensive care unit.

Patients enter the ward from a waiting list, then go to the theater for operation, to the ICU for special postoperative cares, and finally back to the ward again for discharge. There is also the probability of death occurring in the theater, the ICU or in the ward after operation. Each patient spends one day in the ward. If there is a bed available in the ICU, she/he then undergoes surgery after which she/he enters the ICU for at least a day. The patient is then supposed to spend varying number of days in the ward, depending on her/his clinical conditions. Beds in the ward are allocated to the ICU patients and those on the waiting list with the ICU patients considered prior to the latter group, however, if there are sufficient free beds in the ward, some patients may wait in the ward for an operation.

The following are the possible events that may occur in the system:

1. patient enters the ward from the waiting list;
2. patient transfers from the ward to the operating theater and then to the ICU;
3. patient returns from the ICU back to the ward;
4. patient exits the ward after completion of treatment; and
5. patient dies in the system.

The death of a patient during operation is allowed for by having the postoperative ward stay time set to zero, nevertheless, the time spent in the ICU has to be allocated for that patient before the operation. Without a more complex stochastic formulation in the simulated system, death is not predictable. Therefore, it would not be possible to perform another operation in order to utilize the bed in the ICU, left by the deceased patient.

The sequence of the events that occurs, as system runs, is controlled by a time index with a unit of time equal to one day. Each patient in the system has to be allocated various lengths of time to spend in the system. The simulation program works by discrete time; for each day, the various events of patients' movements are ascertained and then placed in order of priority. Beds in the ward are allocated with priority to patients in the ICU

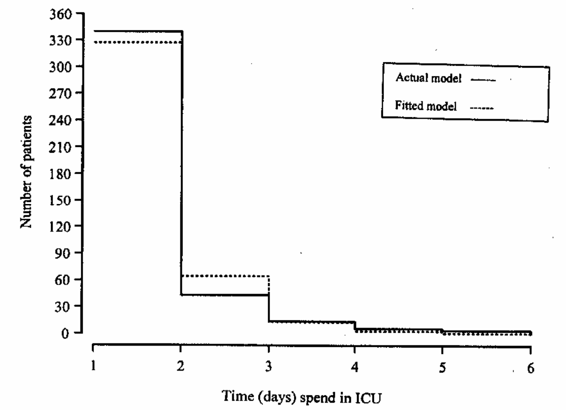

Figure 1. Time (days) spent in the ICU based on actual model and the fitted model.

over those on the waiting list. The ward beds can not be totally occupied by new patients waiting for surgery because, in that case, no beds would be left for the patients returning from the ICU, and so the whole system would be blocked.

Some assumptions follow:

1. the time spent in the ward after the operation was presumed to start when the patient returned to the ward from the ICU;
2. at each time there are some patients in the waiting list;
3. if some patients are waiting in the ward for an operation, the rule is first come-first served;
4. operations, one per theater, are only performed from Monday to Friday;
5. patients may be admitted from Sunday to Thursday;
6. no patient can be discharged on Sunday;
7. admission and discharge are at 9.00 am; and
8. priority in the system is for a discharged patient, then for a patient who is coming back from the ICU into the ward, followed by a patient coming from the ward to the ICU, and finally for the admission of a new patient.

The simulation work was carried out using a

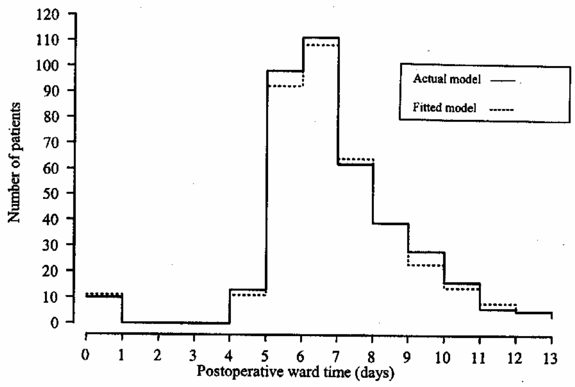

Figure 2. Time (days) spent in the ward after operation based on actual model and the fitted model.

Fortran-77 program, supporting mark 16A NAG library subroutines, on a Sun-Solaris machine.

For simulating the system, the distribution functions of time, taken in the ward and ICU, are necessary. It is rare for a patient to spend more than one day in the ward before operation. Hence, for every patient the preoperative ward time is given the value of one unit. Figures 1 and 2 show periods of times for which patients stay in the ICU and the ward after operation. As the Figure 1 shows, most patients usually spend a day in the ICU though there are some who may spend from two to more than seven days. So, a geometric distribution was fitted to the data. As Figure 2 shows, it is not possible to fit a unique distribution for the time spent in the ward after operation. Therefore, a mixture of geometric and uniform distributions was fitted to the data using maximum likelihood for parameter estimation.

The parameters for the times spent in the ICU, in the ward before operation, in the ward after operation and also the number of the beds in the ICU and that of the ward were fed into the system, and the system was simulated 40 times.[6]

Results

Table 1 shows the average bed occupancy rates in the ward and ICU for the case of 2 beds in the ICU and varying numbers of beds in the ward. When there were 5 beds in the ward, the bed occupancy rates in the ward and ICU were 90% and 46%, respectively. The bed occupancy rate in the ward was 81% and that of the ICU was 78% while having 11 beds in the ward.

Table 2 shows the mean and standard deviation of bed occupancy rate in the ward and ICU when there were 3 beds in the ICU, for different numbers of beds in the ward. When there were only 5 beds in the ward, the average occupancy rate was 96% and 37% in the ward and ICU, respectively. The mean occupancy rate in the ward decreased as the

Table 1. Bed occupancy rate in the ward and the ICU when there are two beds in the ICU.

	No. of beds in the ICU = 2			
No. of beds in the ward	Bed occupancy in the ward		Bed occupancy in the ICU	
	Mean	SD	Mean	SD
5	90%	5%	46%	8%
6	90%	5%	53%	8%
7	89%	5%	58%	8%
8	88%	5%	63%	8%
9	84%	6%	68%	7%
10	84%	6%	75%	7%
11	81%	6%	78%	6%

SD = standard deviation.

Table 2. Bed occupancy rate in the ward and the ICU when there are three beds in the ICU.

No. of beds in the ward	No. of beds in the ICU = 3			
	Bed occupancy in the ward		Bed occupancy in the ICU	
	Mean	SD	Mean	SD
5	96%	3%	37%	8%
6	96%	3%	41%	8%
7	94%	4%	45%	8%
8	93%	4%	49%	8%
9	93%	4%	53%	8%
10	91%	5%	57%	8%
11	90%	5%	63%	8%
12	89%	5%	63%	8%
13	88%	5%	69%	7%
14	87%	5%	73%	7%
15	85%	6%	76%	7%
16	84%	6%	79%	6%

number of the beds in the ward increased. As the mean occupancy rate in the ICU increased, the number of beds in the ward also increased so that the mean occupancy rate in the ICU was 79% when there were 16 beds in the ward.

Table 3 shows an instance of 9 beds in the ICU and 11 in the ward while the mean occupancy rate was 99% in the ward and 31% in the ICU. Overall, the mean occupancy rate in the ward decreased as the number of the beds in the ward increased. The maximum occupancy rate in the ICU was about 72% while having 38 beds or more in the ward.

Table 3. Bed occupancy rate in the ward and the ICU when there are nine beds in the ICU.

No. of beds in the ward	No. of beds in the ICU = 9			
	Bed occupancy in the ward		Bed occupancy in the ICU	
	Mean	SD	Mean	SD
11	99%	1%	31%	7%
12	99%	1%	31%	7%
13	99%	1%	34%	7%
14	99%	1%	36%	8%
15	99%	1%	39%	8%
16	99%	1%	39%	8%
17	98%	2%	39%	8%
18	98%	2%	40%	8%
19	98%	2%	43%	8%
20	97%	3%	44%	8%
21	97%	3%	45%	8%
22	97%	3%	47%	8%
23	96%	3%	48%	8%
24	96%	3%	50%	8%
25	96%	3%	53%	8%
26	96%	3%	55%	8%
27	95%	3%	55%	8%
28	95%	3%	57%	8%
29	94%	4%	59%	8%
30	94%	4%	60%	8%
31	94%	4%	62%	8%
32	93%	4%	63%	8%
33	92%	4%	65%	7%
34	92%	4%	67%	7%
35	91%	5%	67%	7%
36	91%	5%	69%	7%
37	91%	5%	71%	7%
38	91%	5%	72%	7%
39	90%	5%	72%	7%
40	90%	5%	72%	7%

Table 4. The mean and standard deviation of the required time (days) for throughput of 500 patients for different number of beds in the ICU.

No. of beds in the ward	No. of beds in the ICU = 2		No. of beds in the ICU = 3	
	Mean	SD	Mean	SD
5	911	15	853	9
6	778	10	718	4
7	684	6	630	7
8	624	7	560	5
9	577	7	505	7
10	537	6	465	8
11	513	5	431	7
12	487	7	410	6
13	479	7	385	4
14	467	7	370	5
15	459	6	357	6
16	452	5	342	4
17	441	5	335	4
18	434	6	325	4

Tables 4 and 5 show the mean required time for the throughput of 500 patients in the department while having varying numbers of beds in the ward and 2, 3, or 9 beds in the ICU; when there were only 2 beds in the ICU and 5 in the ward, the mean required time for the throughput of 500 patients was 911 days which declined to 853 days with 3 ICU beds and the same number of ward beds. The mean decreased when the number of beds in the ward increased; for instance, with 18 beds in the ward and 2 ICU beds, the required time for the throughput of 500 patients in the department was 434 days. The mean decreased to 325 days for 3 beds in the ICU and 18 in the ward. The mean declined when the number of beds in the ward and ICU increased. For 2 or 3 beds in the ICU, increasing the number of ward beds to above 18 did not lower the mean. The mean required time for the throughput of 500 patients in the department was 219 days when there were 9 beds in the ICU and 20 in the ward. The mean was only 130 days with the same number of beds in the ICU and 39 beds in the ward.

Table 5. The mean and standard deviation of the required time (days) for throughput of 500 patients for nine beds in the ICU.

No. of beds in the ward	No. of beds in the ICU=9		No. of beds in the ward	No. of beds in the ICU=3	
	Mean	SD		Mean	SD
20	219	4	30	157	2
21	207	4	31	151	3
22	200	5	32	149	2
23	191	2	33	147	3
24	185	3	34	142	2
25	177	3	35	141	4
26	174	2	36	138	4
27	170	4	37	135	2
28	164	2	38	133	3
29	159	2	39	130	3

Discussion

Overall, the study showed that the mean occupancy rate in the ward decreases as the number of beds in the ward increases. As the mean occupancy rate in the ICU increases, the number of the beds in the ward rises too. Nevertheless, the throughput of patients in the system does not differ markedly with a large number of beds in the ward compared to that in the ICU.

Cox et al[3] studied percentage of busy time for audiometricians in an ear, nose and throat outpatient clinic and the results. In this study, bed occupancy rate in a heart surgery department was studied. To project the incidence rates of coronary heart disease, the number of hospitalized incident coronary heart disease cases and the hospital costs associated with the first hospital admission in Australia, a research work was carried out by Mui.[7] A computer simulation model using a simulation technique was developed to simulate individuals' coronary heart disease history over time for a sampled Australian population, characterized by major coronary risk factors.[7] Brahimi and Worthington[4] used a simulation model where a doctor played the role of the server, whereas in the present study the servers were the beds in the ward and ICU. Hashimoto and Bell[5] found that by consideration of appointment time and also increasing the number of doctors in the clinic, the average patients' time in the clinic decreases significantly. In the present paper it was shown that the throughput of patients in the system usually rises as the number of beds in the ward and ICU increases. Ridderstolpe et al[10] described the implementation of a model for process analysis and activity-based costing management at a heart center in Sweden as a tool for administrative cost information, strategic decision-making, quality improvement, and cost reduction. A commercial software package (QPR Company, USA) containing two interrelated parts, "Process Guide and Cost Control", was used. All processes at the heart center were mapped and graphically outlined. They concluded that a process-based costing system is applicable and has the potential to be used in hospital management.

In this study, when there are a reasonable number of beds in the ward, there will be no queuing time in the ICU, waiting for a bed when a patient returns back to the ward. While having few beds in the ward compared to those in the ICU, some queuing in the ICU may ensue, especially when all of the beds in the ward are in use. When there are few beds in the ward compared to the ICU, because of queuing time in the ICU, the mean queuing time in the ICU is higher. The mean time, spent in the hospital, does not depend on the number of the beds in the ICU or ward when there are enough beds in the ward. For a fixed number of the beds in the ward, the average bed occupancy rate is higher for a big ICU. It is worth mentioning that to prevent a long stay in the ward and ICU, while the number of free beds in the ward is less than or equal to that in the ICU, the system should not let a new patient get into the ward if all of the beds in the ICU are in use. In the present paper, since death is not predictable, it is assumed that it would not be possible to perform another operation in the theater in order to utilize the bed in the ICU, left by the deceased patient. However, using a more complex stochastic model such as Markov Chain Monte-Carlo (MCMC) simulation and prior distributions may be possible. An example from dentistry is presented by Helfenstein et al[11] using MCMC simulation in order to demonstrate their application and use. MCMC methods may be of great value to dentists in allowing analysis of the data sets exhibiting a wide range of different forms of complexity.[12] Some other simulation approaches in medical fields were performed by different authors. A research work was carried out by Glance and Osler[13] for assessing the validity of using the standardized mortality ratio, based on the New York State Cardiac Surgery Reporting System Prediction Model, to compare coronary artery bypass grafting outcomes among hospitals, using computer simulation. Also, Goldman et al[8] used the Coronary Hearth Disease (CHD) Policy Model, a validated computer-simulation model, to estimate the effects of actual investments made to change coronary risk factors between 1981 and 1990; they also studied the impact of these changes on the incidence, prevalence, mortality, and costs of CHD during the same period and projected to 2,015. O'Keefe[2] designed an appointment system for outpatient department using a simulation model. A similar approach can be done for a heart surgery department. According to a report from the Management and Planning Organization of Iranian government, the mean bed occupancy rate in Iran's hospitals is 49%, which causes disinvestment of about 38 million dollars per year.[14]

Therefore, it can be concluded that to prevent disinvestment, a simulation study can be performed to observe the behavior of system prior to building a hospital or a new ward. Also, using simulation methods in different aspects could help researchers and managers in better understanding of the studied systems artificially. It is necessary to mention that for simulating a heart surgery department in Iran, the related data from a hospital in the country is essential. However, the current study has demonstrated the application of simulation studies in heart surgery departments.

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