ANAYSIS OF CAPACITY MANAGEMENT OF THE INTENSIVE CARE UNIT IN A HOSPITAL

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ABSTRACT

A hospital's intensive care unit (ICU) is a limited and critical resource whose efficient utilization of capacity impacts on both the welfare of patients and the hospital's cost effectiveness. Decisions made in the ICU affect the operations of other departments. Yet, decision making in an ICU tends to be mainly subjective and lacking in clear criteria upon which to base any given decision. The study reviews the capacity utilization of one particular ICU, that of a public hospital in Hong Kong, and develops a computer simulation model to improve both the unit's capacity utilization and the quality of care provided to its patients.

1. Introduction

Its intensive care unit (ICU) is the one component of a hospital that cannot afford the luxury of a bad decision, because the price exacted for that bad decision may be the life of a patient. All decisions affecting ICU patients, however, are not made within the unit itself and after the patient has gained admission to the unit. Rather, there are decisions to be made both as to *which* patients will be admitted to the unit and *when* a particular patient will be admitted. Whereas in an ideal world with infinite resources, ICU beds and staff would be available to any patient upon demand, in our less-than-ideal world hospital administrators with limited resources at hand must weigh costs against benefits, and then make decisions as to the allocation of their limited resources. The initial result is ICU units that operate under various capacity constraints, the tightest of which is commonly imposed by the fixed number of beds allotted to the unit. The subsequent result is that some patients who would otherwise qualify for immediate intensive care may, upon those occasions when all beds are occupied, have to join a queue and suffer any consequences of untimely delays in being admitted to the ICU, while others never even get to join the queue.

This paper presents the results of a theoretical analysis and computer simulation that models the admissions and discharges of a specific ICU. The two-fold ultimate purpose of the model is to help the hospital's administration explore alternative policies for improving the unit's performance on any number of dimensions, and to enable us to draw some broader inferences as to how the operating performance of ICUs in general might be improved.

2. The ICU Admission and Discharge Processes

Virtually all patients come to the ICU that is the focus of this study from four different sources: (1) Ward; (2) Accidents and Emergency; (3) Operation Theatre - Emergency; and (4) Operation Theatre - Elective.

A patient referred to the ICU by his or her physician goes through a review process that might take anywhere from a few hours to a few days.

The ICU's admission decision takes two factors into consideration: the patient's "attributes" and the "state" of the ICU. The patient's attributes include such factors as the severity of illness, age, expected length of stay, and the probable outcome. The state of the ICU refers to bed availability and the possibility of an expedited discharge of any current patients whose recovery has perhaps been more rapid than had been foreseen.

3. The Underlying Data

The present analysis is done with data that were collected from the hospital over the continuous six-month period from March to August, 1995.

A Poisson distribution has the property that the mean of the distribution is equal to the variance. We therefore computed the mean arrival rate and variance for admissions from each of the four principal sources of arrivals to the ICU. These are denoted λ and σ_a^2, respectively, and are given in Table 2A. In three of the four cases, with OT-electives being an exception in which the computed variance is about 40% larger than the computed mean, the two statistics are quite similar. We also carried out a Chi-square test of the hypothesis (Table 2B) that arrivals from each of these sources are Poisson distributed, and with that single exception could not reject the hypothesis at the $\alpha = 0.05$ level of statistical significance.

Table 2A: Arrival rate for each patient group.

Where	Mean (λ)	Variance (σ_a^2)
1. Ward	2.120/day	2.638
2. A&E	1.054	1.149
3. OT-emergency	0.489	0.489
4. OT-electives	1.130	1.537

Table 2B: Results of Chi-square goodness of fit test for arrivals.

Source Dept.	df	Critical value, χ^2	Test stat, χ^2	H_o
Ward	5	11.07	8.91	accepted
A&E	4	9.49	3.96	accepted
OT-emer	2	5.99	2.19	accepted
OT-elec	4	9.49	27.21	rejected

Note: All are one-tailed tests with α=0.05.
For detailed procedure, see, e.g., Snedecor and Cochran [8], p.75.

The next salient issue, then, is whether the service times in the ICU -- that is, the length of time that a patient spends in the ICU before being discharged -- are exponentially distributed by patient source. Once again, we test for this by first looking at the actual means, denoted μ, and variances, denoted σ_s^2, of the length of stay in the ICU for each of the four patient groups, and then conducting a Chi-square test.

Table 5A: ICU Service times (length of stay).

Where	Mean (μ)	Variance(σ_s^2)
1. Ward	63.73 hrs	4976.21 hrs
2. A&E	48.48	2952.58
3. OT-emergency	77.47	5353.98
4. OT-electives	48.72	4326.47

Table 5B: Results of Chi-square goodness of fit test for service times.

Source Dept.	df	Critical value, χ^2	Test stat, χ^2	H_o
Ward	11	19.68	18.73	accepted
A&E	7	14.07	13.70	accepted
OT-emer	10	18.31	11.24	accepted
OT-elec	8	15.51	58.44	rejected

Note: All are one-tailed tests with α=0.05.
For detailed procedure, see, e.g., Snedecor and Cochran [8], p.75.

4. Queueing Analysis

The typical queuing model with parallel multiple servers assumes that each server has the same mean service rate. We also make that assumption here, treating each of the ICU's beds as one of the parallel servers.

The subject ICU has a total of 14 beds. We exclude from our analysis any data outliers such as long-stayers and transfers from other hospitals. These outliers account for 5.89% of the total number of patients. To allow for this exclusion in our model, we carry out our analysis as if there were only 13 beds in the ICU, which reduces the available capacity by 7.14%. Thus our approach is a conservative one.

We assume that each one of those 13 beds maintains the same one of the three overall service rates and that the service system is one with s = 13 identical and multiple servers (beds) operating in parallel, with patients entering the ICU through a common queue. As a precursor to our simulation experiment, we therefore explore the steady-state operating characteristics of this classic M/M/s multiserver system.

The actual computation was carried out by using the Quantitative Systems for Business (QSB) software [4], and the results are presented in Table 8.

Table 8: Operating characteristics of the ICU in a steady state.

Performance measures	Service rate/bed/day (lowest) $\upsilon_{cm} = 0.310$	(simple avg) $\upsilon_{cs} = 0.376$	(wgt avg) $\upsilon_{cw} = 0.382$
Bed Utilization (ρ)	0.9364	0.7721	0.7600
Avg no.pat in sys(L)	23.2568	11.0232	10.7255
Avg no.pat in queue(L_q)	11.0826	0.9859	0.8459
Avg time in sys(W)	6.1624 days	2.9208	2.8419
Avg time in queue (W_q)	2.9366 days	0.2612	0.2241
Prob all beds empty(P_o)	2.304E-06	3.935E-05	4.674E-05
Prob arvg pat waits(P_w)	0.7518	0.2910	0.2672

Note: The system consists of a queue and the ICU.

5. The Simulation Model

For our simulation experiment, we build a model using XCELL+ [5], a simulation software with graphical animation. The model's basic parameters are the inter-arrival and service times, which are taken from Tables 6 and 7, respectively.

The experiment was allowed to take place over a ten-year time span. This equates to 87,600 simulated hours, after discarding the first year to remove the effect of the start-up period during which the system is empty and idle. Table 9 presents the results.

Table 9: Simulation results.

Performance measures	Results
Bed Utilization (ρ)	0.7749
Avg no. pat in queue.(L_q)	1.063
Avg time in sys(W)	3.014 days (wghtd)
Ward	72.951 hrs
A&E	57.041
OT-emer	87.960
OT-elec	74.326
Avg time in queue (W_q)	0.289 days (wghtd)
Ward	7.505 hrs
A&E	6.742
OT-emer	7.008
OT-elec	6.590
No. pat treated/yr	1,352.3 pat/yr
Ward	380.0
A&E	259.7
OT-emer	169.2
OT-elec	543.4
Max no. pat in queue	31

Note: The system consists of a queue and the ICU.

6. Conclusions

In actual fact, as shown in Table 10, except for elective surgery a very small number of patients who would otherwise have qualified for admission to the ICU during our six-month sample period were denied admission because all 14 beds were occupied. About half of the 15 non-elective surgery patients who were denied admission, did not survive. Whether these patients would have survived had they been admitted to the ICU is not known and is at best questionable. In the case of elective surgery, where almost 1/4 of the referrals have been denied admission due to a full ICU, the operation was canceled and presumably rescheduled.

Table 10: Percentage and number of patients rejected due to a full ICU during the 6 months.

Where	Percent	Number	Survival
1. Ward	3.33%	13	6
2. A&E	1.03	2	1
3. OT-emergency	0.0	0	0
4. OT-electives	23.56	49	Op. canceled

Taken in conjunction with the OT-elective arrival-rate data of Table 2A and the OT-elective service-time data of Table 5A, each of which offers the only serious deviation among the four sources of ICU patients from the classic Poisson arrivals and exponential service times distributions, both the sample data and the theoretical results suggest that insofar as there are serious issues relating to the managerial aspects of the ICU, these emanate solely from elective surgery. The further suggestion, then, is that insofar as it is possible to deal with these issues, they must be dealt with through better coordination between the ICU and the referring surgeons in scheduling elective surgery in the first place. Thus, for example, rather than have surgeons initiate the conversation by requesting information as to the possible availability of an ICU bed, if needed, "on Friday," as is ordinarily the case, the ICU's administrator might issue a blanket advisory to all surgeons who rely on the ICU on the probability that no beds will be available "on Friday", that one bed will be available, and so forth. The further analysis that we intend to undertake in this study will permit the generation of such data.

At this point our analysis suggests that the current ICU capacity of 14 beds is sufficient to handle patients at the current arrival rates. Any perceived or real imbalance in timing between when there are vacancies in the ICU and when patients are referred to the ICU, would seem to be correctable through better communication between surgeons and the unit's administration.

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