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SIMULATION OF A HOSPITAL'S SURGICAL SUITE AND CRITICAL CARE AREA

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ABSTRACT

A GPSS/H model was developed to simulate the flow of patients through a hospital's critical care units, including the operating room, post anesthesia recovery unit, surgical intensive care unit, intermediate surgical care unit, coronary care unit, intermediate coronary care unit, telemetry unit, medical intensive care unit, and ventilator unit. The primary objective of developing the model was to assist hospital clinical and administrative staff in determining critical care bed requirements. This paper describes previous research on the development of bed-sizing models, the design of the critical care simulation model, validation and use of the model, and a critique of the model's application, with implications for future research.

1 INTRODUCTION

The objective of this study was to design and implement a simulation model of a large, tertiary care community hospital's surgical suite and critical care area, for the purpose of assisting hospital management in determining critical care bed requirements. The high cost of building, equipping, and staffing critical care beds requires increased attention to the bed planning process. Simulation is an especially attractive methodology for use in this area, because of the complex nature of patient flows through the critical care area. Specifically, both random and scheduled arrivals of different types of patients (case types) to multiple units with limited capacities must be modeled.

The objective of any hospital bed planning model is to help determine the number of beds required to meet a given level of demand *in the most cost effective manner*. That is, a bed level must be determined which can accommodate projected demand without incurring the unnecessary costs associated with excess capacity. Unfortunately, the highly variable nature of the daily census in critical care units (due to the random nature of arrivals to the critical care area) means that planning for a bed level which meets demand during periods of peak utilization will result in unused beds a large portion of the time (i.e., low average occupancy). Therefore, a good bed planning model must factor in the variable nature of critical care demand, and provide information on the tradeoff between maintaining a high average occupancy and incurring adverse occurrences, such as turnaways, due to lack of available beds.

In the past, simple frequency distributions (Blumberg, 1961; Dufour, 1974; Newell, 1962; Pike, Proctor, and Wyllie, 1963) and less simple mathematical models (including queuing models and Markov chains; e.g., Bithell, 1969; Cooper and Corcoran, 1974; Esogbue and Singh, 1976; Kao, 1972 and 1974; Navarro (1970); Shonick and Jackson, 1973; Staff and Vagholkar, 1971; Thomas, 1968; Weiss, Cohen, and Hershey, 1982) have been used to help determine hospital bed requirements. While these models do consider the issue of census variability in bed planning, they are all constrained by one or more of three major simplifying assumptions, which significantly diminishes their utility in today's complex health care environment.

The first major problem with most previous models is the inclusion of only one unit (bed section)--i.e., the relationship between multiple units is not considered. Not only should the *progressive* movement of patients among units be considered (i.e., the movement of patients due to the progression of their treatment), but the movement of patients *across* units should also be modeled (i.e., movement due to limited bed availability). Consideration of this latter type of movement is especially important for making the best use of limited, costly critical care resources. Rather than plan for a bed level that accommodates workload during peak periods, a more cost-effective use of critical care beds is to consider the capacity in other, similar units as a source of alternative beds during peak times. Thus, a bed planning model should consider patient movement across critical care units during periods of especially heavy demand.

The second major problem with previous models, which is related to the first problem, is their failure to realistically model hospital policies in the event that a patient arrives to find all beds full in the desired unit. Most models consider only the option of turning patients away. However, few hospitals are willing to incur turnaways, due to the implications for quality care, as well as the potential loss of clients and revenues. In actuality, most hospitals follow a complex set of decision rules for locating a bed, before resorting to sending patients to another facility. These rules are necessary for efficient resource utilization; and a bed planning model which includes these rules can be used to investigate their effects on bed utilization.

Finally, it is very difficult to model the effects of different types of patients using previously developed mathematical models. As hospitals become increasingly specialized and routinely face decisions regarding the addition, expansion, or elimination of particular clinical programs, the ability to model the unique workload contributions of particular patient types increases in importance. Different patient types are not only admitted to a hospital at different rates, but are also admitted through different mechanisms (i.e., emergency versus scheduled arrivals), and follow different flow patterns through hospital units.

Simulation models can readily incorporate each of the above three requirements (i.e., multiple units, bed location policies, and case types). A number of simulation models have been developed for the surgical suite and critical care areas (Clipson and Wehrer, 1973; Cohen, Hershey, and Weiss, 1980; Fetter and Thompson, 1969; Kwak, Kuzdrall, and Schmitz, 1975; Williams, 1983; Zilm and Hollis, 1983). However, none of them appears to satisfactorily address the complex relationships in today's critical care environment. Previous simulation models of the surgical suite and critical care area have one or more of the following limitations:

(1) Limited number of units (generally only two);
(2) Limited number of patient flow patterns through the units;
(3) Limited number of bed location policies (generally only one;
(4) Limited arrival processes (e.g., either random or through a simplified scheduling system); or
(5) Simplified or no modeling of different case-types.

The study described herein was an attempt to improve upon previous simulation models by building a model that addresseses the above limitations, and, hence, is more representative of the complex critical care environment which exists in most hospitals today, including the study hospital. The remainder of this paper describes the model design, findings from use of the model, and conclusion, including a brief description of subsequent research. The focus of the discussion is on those aspects of the model that represent improvements over previous studies of the critical care area. The model was written in GPSS/H (Henriksen and Crain, 1989).

2 MODEL DESIGN

The simulation model is designed to represent the arrival of patients to, and their flows through, nine different units in the study hospital: (1) surgical suite (OR); (2) post anesthesia recovery unit (PARU); (3) surgical intensive care unit (SICU); (4) intermediate surgical care unit (ISCU); (5) coronary care unit (CCU); (6) intermediate coronary care unit; (7) telemetry unit; (8) medical intensive care unit (MICU); and (9) ventilator unit. All of these units, with the exception of the OR, are considered part of the critical care area. The OR was included in the model because it is a major source of admissions to the SICU.

The major components of modeling patient flows through the above units include the OR scheduling system, delineation of patient flow patterns, definition of input distributions, and designation of case types. The inclusion of all of these components meets the objective of designing a comprehensive critical care model.

2.1 OR Scheduling System

The simulation model includes both random and scheduled arrivals. While the majority of arrivals to the critical care area occurs randomly, arrivals to the surgical intensive care unit are primarily scheduled through the OR. Thus, the OR becomes an important component of any critical care planning model. Because of the complex organization of most ORs, some time will be spent addressing the manner in which the study hospital's OR was modeled relatively easily using GPSS/H.

The surgical scheduling system employed at the study hospital is a block scheduling system, in which an operating room(s) is reserved for a certain time period (e.g., morning, afternoon, entire day), on certain days of the week, for a given surgical specialty or surgeon. A simulation of a block scheduling system must generate cases from a particular specialty (or surgeon) on the appropriate day of the week, at the appropriate time, and in the appropriate operating rooms. In addition, the model must stop generating cases when the block time has ended.

GPSS/H "matrices" and "transactions" can be used to define the block schedule. The block start and stop times can be identified for each specialty in a GPSS/H matrix of days of the week and operating rooms. The GPSS/H transaction is the unit of traffic that moves along the paths, or "blocks," of the simulation model. The OR module uses transactions to initiate each day's block schedule. The OR component of the model is repeated every seven days, at which time a transaction is sent to initiate the following steps:

(1) Generate one transaction for each day of the week. Each transaction "waits" until midnight arrives for its day of the week.
(2) At the start of the day, the individual transaction splits off into as many transactions as there are specialties.
(3) Each specialty transaction splits off into as many transactions as there are operating rooms. Note that all transactions thus far generated in the OR module can be characterized by day of the week, specialty, and operating room (this information is stored with each transaction).
(4) Each operating room transaction uses its information on day of the week and operating room number to obtain data from the corresponding matrix on start times for the specialty. The transaction then waits till the block start time for its specialty, day of the week, and operating room.
(5) Upon arrival of the start time, the case type, case time, and flow pattern of the specialty's first case is determined (see next section), and the transaction is sent through the OR. (Note the transaction has now become a patient that will move through the model.)
(6) After the patient's case time has passed, the transaction uses its information on day of the week and operating room number to obtain data from the corresponding matrix on block stop times for the specialty. If the time of day when the patient leaves the operating room does not exceed the block stop time for the specialty, the patient splits off another transaction, which becomes the next patient through the room. Otherwise, the patient is the last patient through the room for the day (unless an emergency arrives).

2.2 Delineation of Patient Flow Patterns

Depending on a patient's case type (described below), he/she has a certain probability of following any one of a number of possible flow patterns through the above units as his/her treatment progresses. These flow patterns, which are presented in Table 1, were defined from interviews with clinical personnel in the study hospital. Surgery patients from the OR are assigned a flow pattern as they leave the OR, based on a pre-determined distribution of flow pattterns for each surgical specialty (see discussion of case types below). The flow patterns of other patients are determined as they leave each critical care unit, based on the historical percentage of patients discharged from one given unit to another.

In addition to these *appropriate* flow patterns, patients may follow *alternative* flow patterns in the event that a bed is not available in the desired unit. These alternative flow patterns were defined by clinical staff members, and consist of either "accommodations" (i.e., entering another critical care unit) or "bumping" (i.e., finding a patient in the desired unit who is sufficiently stable to be transferred to the next lower level of care, to free up a bed for the incoming patient). The steps followed in locating a bed depend on the type of critical care bed required. For some units, the availability of a bed in another unit (an accommodation) is checked before bumping is considered; in others, bumping is considered first; and in some, only accommodations are tried. In the event a patient is accommodated on an alternative unit, the model continues to check for bed availability in the originally desired unit, and will transfer the patient to that unit if a bed becomes available.

The concept of bumping requires the establishment of criteria for determining whether or not a patient is sufficiently "stable" for transfer to the next lower level of care, to free up a bed for an incoming patient. These criteria are defined as a proportion of a patient's "desired" length of stay. (In actuality, of course, the criteria for making such a determination are clinical; but since clinical criteria could not be incorporated into the model, length of stay was used as an alternative.) The "desired" length of stay refers to the time the patient would likely spend in the unit if there was no need for the bed by another, incoming patient, and is determined by sampling from a historical distribution of length of stay.

Interviews with physicians determined that as a general rule, patients who have reached 80 percent of their "desired" length of stay in a critical care unit are probably sufficiently stable for transfer. Thus, in the event that a bed in a given unit is needed for an incoming patient, and the steps for "bumping" are initiated, the model checks to see if there are any patients in the unit who have reached or exceeded 80 percent of their desired length of stay. If so, one of those patients is transferred to his/her next level of care (if a bed is available), and the incoming patient is admitted to the vacated bed. If no patients are eligible for bumping, the model proceeds to the next step for finding an available bed, or turns the patient away.

2.3 Definition of Input Distributions

The two major types of input distributions included in the model are:

(1) Length of stay distributions (one for each critical care unit, by flow pattern); and

(2) Interarrival time distributions of direct admissions (one for each critical care unit and for emergency admissions to the OR).

These distributions were all defined using historical data from the study hospital, collected from manual logs maintained in the critical care units. Many hospitals maintain the necessary data in their admission/discharge/transfer systems, or in a PC-based information system in the critical care area, making data collection much easier. Subsequent analyses of similar data from other hospitals have shown the length of stay distributions to closely follow the lognormal distribution, and the interarrival time distributions to follow the exponential distribution (Lowery, 1991). The use of theoretical distributions can ease model design and data collection.

2.4 Designation of Case Types

The study hospital was especially interested in investigating the effects of increases in surgery workload, by various case types. Consequently, case type categories were identified for all surgical procedures requiring a critical care bed following surgery. The department heads of the surgical specialties were asked to identify groups of surgical procedures in which the cases are clinically similar, as well as homgeneous with respect to their case time in the OR and their use of post-operative resources (i.e., flow patterns and length of stay in each critical care unit). Using these general criteria, the surgeons had little difficulty forming categories, as most surgeons already tend to think of their cases in terms of general case types.

After the categories of cases were identified by the surgeons, they were asked to assign each case type to one of the patient flow patterns presented in Table 1. In the event that different patients within a given case type could follow different flow patterns, depending on the severity of the case, the surgeons were asked to estimate the percentage distribution of patients by flow pattern.

Finally the surgeons were shown a list of all of the procedures (defined by the ICD-9-CM classification scheme) performed in their respective specialties during a recent time period, and they were asked to map each procedure to the appropriate case type. Table 2 presents an excerpt from the list of case types and corresponding flow patterns and procedures for Neurosurgery, as an example of the result of the surgeons' efforts.

The hospital's actual frequency of procedures performed during a recent time period was used as the basis for determining each specialty's percentage distribution of case types and, in turn, distribution of flow patterns. The simulation model samples from this distribution to determine the flow pattern of each case sent through the OR for a given specialty. To simplify data collection, average case times for a given specialty were used to determine case time in the OR. However, the case type definitions and historical data on individual case times could have been used to identify an average case time per case type, if desired.

3 FINDINGS

The model inputs of interest to hospital management were critical care workload (consisting of both scheduled and random arrivals) and the number of beds in each critical care unit. To help determine bed requirements for the future, the values for workload were increased (by decreasing the interarrival times of the random arrivals, and increasing the hours of OR time for the scheduled arrivals), and the bed levels in each of the critical care units were varied. The effect of these changes on the outputs of interest were then analyzed. The outputs, or performance measures, of primary interest were the utilization rates of each of the critical care units, the number of emergency turnaways due to lack of available beds, number of patients bumped from units to accommodate incoming patients, and number of patients accommodated on alternative units.

The model was validated by comparing model predictions against actual hospital performance. The only performance measures for which actual hospital data were readily available were utilization rates and turnaways; hence, the validation included only these data. Hospital data on utilization rates, by critical care unit, and turnaways for a six month period were compared against model data from six months of simulation, following a three month warmup period. A two-sample t-test was used for comparing the mean of the monthly hospital data with the mean of the monthly model data. For all of the comparisons, the means of the two sample populations were not significantly different at $p >= .30$. That is, the hypothesis that the means of the two populations are the same could not be rejected for the performance measures tested. The

Table 1: Patient Flow Patterns

Surgery Patients: From the OR	Surgery Patients: Direct Admits	Cardiology Patients	Medical Patients
1) OR->PARU->Floor	1) ->ISCU->Floor	1) ->CCU->ICCU->Floor	1) ->MICU->Floor
2) OR->PARU->ISCU->Floor	2) ->SICU->ISCU->Floor	2) ->CCU->Telem->Floor	2) ->MICU->Vent->Floor
3) OR->SICU->ISCU->Floor	3) ->SICU->Floor	3) ->CCU->Floor	
4) OR->SICU->Floor		4) ->ICCU->Floor	
		5) ->Telem->Floor	

Unit Abbreviations

OR:	Operating Room
PARU:	Post Anesthesia Recovery Unit
ISCU:	Intermediate Surgical Care Unit
SICU:	Surgical Intensive Care Unit
CCU:	Coronary Care Unit
ICCU:	Intermediate Coronary Care Unit
Telem:	Telemetry Unit
MICU:	Medical Intensive Care Unit
Vent:	Ventilator Unit

statistical tests provided no evidence of model inadequacy.

As mentioned above, the study hospital was interested in investigating the effects of workload projections on the performance measures of interest, under different bed levels in the various units. Specifically, the hospital identified the following approximate, projected increases (over 1989 workload), based on planned increases in clinical staff and implementation of new clinical programs:

	1991	1995
CCU	4.0 %	12.5 %
ICCU	6.5 %	15.5 %
MICU	8.0 %	18.5 %
SICU: Thoracic	6.5 %	15.0 %
SICU: Neuro	12.5 %	31.5 %
SICU: Periph Vasc	21.0 %	47.0 %

They were also interested in seeing the effects of a change in the flow pattern of carotid endarterectomy patients (Neurosurgery) from OR --> SICU to OR --> PARU --> ISCU.

The above increases in workload were investigated under a number of different bed level configurations, including additional beds in the SICU, MICU, and ISCU, as well as the construction of a 4 bed Ventilator Unit (in an effort to move long-staying ventilator-dependent patients out of the MICU). Data on predicted hospital performance were obtained from six-month simulation runs, following a three-month warmup period for each run. Hospital staff reviewed model predictions for the average occupancy of each unit and the number of turnaways under alternative bed level configurations. The objective of the reviews was to identify which configuration(s) resulted in an acceptable tradeoff between maintaining a high average occupancy and incurring turnaways.

Unfortunately, it was difficult for the hospital staff to reach a conclusion, because an acceptable level of turnaways was never explicitly stated. Nevertheless, the output did provide information which helped hospital staff better understand the occupancy-turnaway tradeoff, which, in turn, could help them make an informed decision regarding critical care bed requirements. At the completion of the funding period, a final decision on the number and types of beds to add had not been made.

4 CONCLUSION

The simulation model described herein represents a more complex and, hence, more realistic, critical care environment than previous models of the critical care area. While features of the model's design can be used elsewhere by individuals interested in modeling the critical care area of a hospital, the application of the model suffers from limitations in the following three areas: (1) validation of predictions; (2) analysis of model output; and (3) general applicability of the model. As with many studies, this one was limited in duration and resources, thus leaving room for improvement. Subsequent research studies have addressed, or are in the process of addressing, each of the three limitations, as described briefly below.

4.1 Model Validation

Table 2: Definition of Neurosurgery Case Types and Patient Flow Patterns

Case Type	Flow Patterns	Distribution of Flow Patterns	Procedures	ICD-9-CM Codes
1. Lumbar Laminectomy	PACU->Floor	1.00	Removal FB spinal canal	3.01
			Spinal canal explor NEC	3.09
			Excis spinal cord lesion	3.40
			IV disc excis/ destruct	80.50
			Spin canal struct op NEC	3.90
2. Craniotomy	SICU->ISCU->Floor	.20	Other craniotomy	1.24
	SICU->Floor	.80	Other craniectomy	1.25
			Incise cerebral meninges	1.31
			Other brain incision	1.39
			Ex cereb meningeal lesion	1.51
			Other brain excision	1.59
			Elevate skull FX fragment	2.02
			Ventriculostomy	2.20
			Trigeminal nerv division	4.02
			Loc exc bone lesion NEC	77.69
			Cranial puncture NEC	1.09
			Cranial osteoplasty NEC	2.06
			Decompress trigem root	4.41
			Part excis pituitary NOS	7.63
3. Aneurysm	SICU->ISCU->Floor	.45	Intracran vessel excis	38.61
	SICU-->Floor	.55	Head/neck vessel excis	38.62
			Clipping of aneurysm	39.51
4. Endarterectomy	SICU->ISCU->Floor	.05	Endarterectomy NOS	38.10
	SICU->Floor	.95	Head neck endarter NEC	38.12

The statistical validation of the critical care simulation model, as described in the previous section, actually represents an improvement over much published work on simulation in health care, in which formal validations are rarely conducted, or, if they are, the specific results of the statistical analyses are rarely presented. Nevertheless, the validation in this study can be criticized for its limited comparison between actual and model of the variability in the census, by only comparing the average *monthly* occupancies, rather than the average *daily* occupancies. In addition, the limited simulation run length of six months might pose a problem if it is not a representative sample of months.

Subsequent research on a similar, albeit simpler, critical care simulation model included the validation of the model in four different hospitals, comparing the hospitals' average *daily* census (ADC) figures with those predicted by the model (Lowery, 1991). The validation consisted of comparing the hospitals' ADC for a three month period with that predicted by the model over a two-year simulation run (after a three-month warmup). Every third daily observation was used, to adjust for autocorrelation in the data. Actual and model ADC in three critical care units (CCU, MICU, and SICU), across four hospitals, were compared. For all of the comparisons, the *P*-value was > .20, suggesting the ADCs of the two sample populations were not significantly different.

4.2 Analysis of Model Output

The analysis of the model's output for the study hospital could best be characterized as "informal," in that an experimental design was not employed to try to determine which bed level configuration, out of a number of different alternatives, resulted in the most desirable predictions of hospital performance. The lack of an experimental design was primarily due to hospital staff's uncertainty regarding the range of bed level configurations and of the values of the demand variables which they wished to consider. Without a limited number of alternatives, the design becomes extremely complicated, and/or the number of simulation runs (and the analysis of the output) becomes unwieldy. Instead, the hospital staff were satisfied to review output for a few different demand and bed levels, adjust the input values based on the results or other new information, and review the new output.

More systematic and rigorous analyses of model output employ formal experimental designs. The 1991 study discussed earlier in which a critical care model was validated in four hospitals used a formal experimental design. One of the objectives of the latter study was to identify those input variables that have the greatest effect on the performance measures of interest. To achieve this objective, a fractional factorial experimental design was used to determine the number of model replications, and the values of the input variables for each replication. The output from 486 replications of the simulation model was analyzed using multiple regression, with the input variables as independent variables, and the performance measures as dependent variables.

4.3 General Applicability of the Model

The design of the critical care simulation model, including the numbers and types of units and the patient flow patterns, is unique to the study hospital. While other hospitals have similar units and similar patient flow patterns, the critical care environments across hospitals are sufficiently different that the results from applying the model described herein cannot be generalized to other hospitals. Research is ongoing to design a comprehensive critical care simulation model whose validity can be demonstrated for multiple hospitals (Lowery and Martin, 1991).

The research includes identifying common components of the patient flow patterns among multiple critical care units in different hospitals. These common components will be coded as separate "modules," such that a user can build his/her own critical care simulation model by stringing together as many modules as necessary, in the appropriate order, to represent a given hospital. The objective is to enable a person without knowledge of a simulation language to build a unique model. In this manner, the technique of simulation can become an easy-to-use planning tool for the critical care area in multiple hospitals.

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