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Estimating Emergency Service Treatment Bed Needs

Frank Zilm, DArch, FAIA, FACHA

Abstract: Estimating the required number of emergency service treatment beds must be sensitive to utilization patterns and strategic operational assumptions. This article describes key issues and illustrates techniques for the analysis of arrival and service times. Seasonal arrival patterns, time of day of arrivals, and common statistical distributions for length of stay are discussed. Alternative modeling approaches to estimate future bed needs are described, including visits/year per treatment space, simple queuing modeling, and detailed computer simulation. Sample estimates of treatment rooms needs are provided for typical arrival rates and lengths of stay. A generalized regression model based on the simulation trials is suggested for cases that fall outside of the illustrated simulation case studies. **Key words:** *emergency, facilities, simulation, treatment beds*

EMERGENCIES are the front door to American hospitals, supporting more than 100 million visits and frequently more than half of all admissions. Variability in arrival patterns, treatment times, and other factors make the estimation of beds a planning challenge that can be addressed through careful analysis and decision making. Determining the appropriate treatment spaces is critical to minimize the risk of delays to patients, prevent unnecessary throughput waits, and improve patient and family satisfaction. This article describes an approach to the analysis of needs and provides tools to develop estimates based on limited information.

Estimating bed needs first starts with an understanding of arrival patterns, patient mix, and the components of the length of stay. Key to the analysis of arrivals is the concept of randomness, meaning the arrival of patients is independent—the appearance of one patient cannot be used to predict the next. Although this concept holds for a given period of time, there are nonrandom seasonal, day-of-week, and time-of-day patterns that predict peak periods of activity. Treatment space utilization should be made based on these peak periods of activity.

In most regions of the United States, seasonality in emergency volume is predictable and significant, ranging from 5% to 30% variation. At least 5 years of historical monthly data should be studied to identify peak demand. Indexing the monthly visits is important to minimizing the effect of overall growth in activity. The basic indexing calculation is done by dividing each month's total visits into the average monthly visits for a year (total visits divided by 12). This results in a scale that averages 1.0. If a given month's visits are higher than the average, the index will be above 1.0, with a lower monthly visit represented by a value less than 1.0. By averaging each month's indexed value, an overall pattern of demand can be calculated and easily graphed, as illustrated in Figure 1.

Notice the radial variation in the pattern among the 4 hospitals. Two of the institutions are located in areas that experience very high levels of in-migration tourists at various

From Frank Zilm & Associates, Inc, Kansas City, Mo.

Corresponding author: Frank Zilm, DArch, FAIA, FACHA, Frank Zilm & Associates, Inc, 1401 W 50th Terr, Kansas City, MO 64112 (e-mail: Frank@zilm.com).

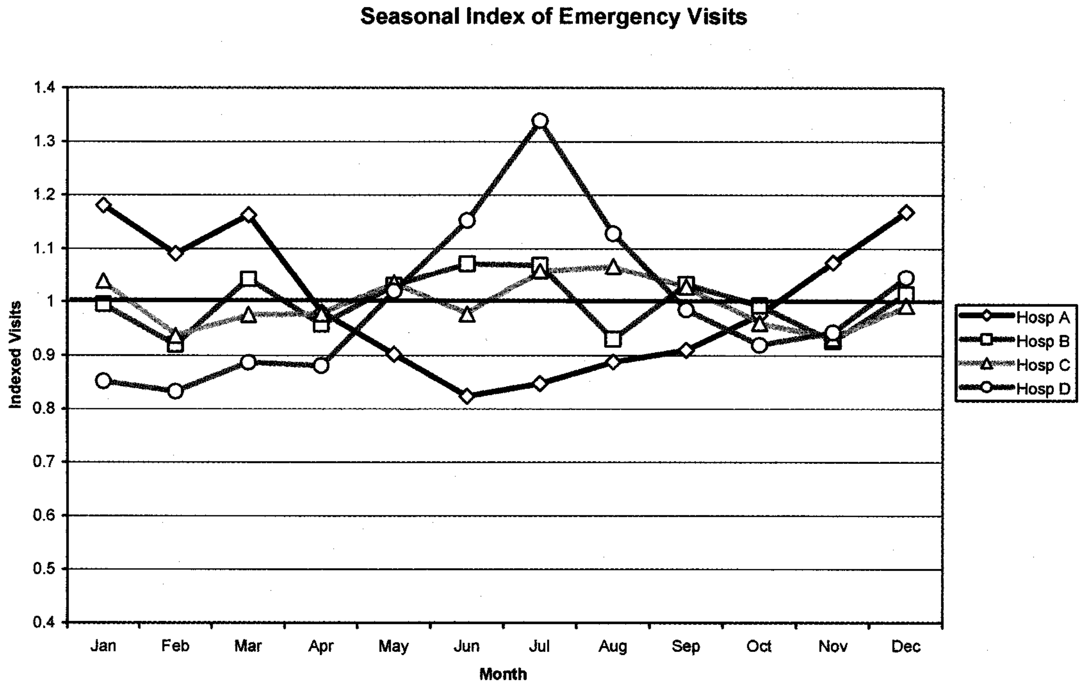

Figure 1. Seasonal index of ER visits.

times of the year—Hospital A is in Arizona and Hospital D is in Alaska. Hospitals B and C are located in Ohio and Florida in areas that do not experience the same tourist impact.

Once the peak month in activity is identified, patterns of visits by day of week and time of day should be studied for peak demand patterns. Total visits by day of week should be analyzed based on yearly dates to target the busiest day, typically Saturday, Sunday, or Monday. The last component of the arrival pattern is the time of day. Arrivals by hour frequently result in a pattern similar to Figure 2. This pattern is surprisingly consistent throughout the country. Note the difference in arrival patterns between adult and pediatric patient populations. Adult arrivals peak at 11 AM and slowly decline through the afternoon. Pediatric patients, on the other hand, peak in late evening.

Future workload forecasts should use these patterns to estimate the interarrival rate for patients during the peak period of activity. The interarrival rate is the average time between patient arrivals, an important calculation in the analysis of bed needs. Table 1 illustrates the calculation of the interarrival rate for a hypothetical emergency room (ER) with 100,000 annual visits.

The second critical task in bed needs calculation is the analysis of current length-of-stay patterns. An ideal data set should contain the following major components of the patient visit for each major patient group:

- Arrival to triage
- Triage/registration duration
- Triage to treatment space
- Treatment arrival to first provider contact
- Provider contact time
- Diagnostic times (radiology, laboratory, etc)
- Discharge disposition
- Time from admission decision to leaving the department
- Time from decision to discharge

It can be particularly valuable to analyze the utilization of imaging and laboratory services, which will typically be a part of approximately 80% of patient encounters. The time from order entry to implementation and the time from results reporting to physician review can account for significant components

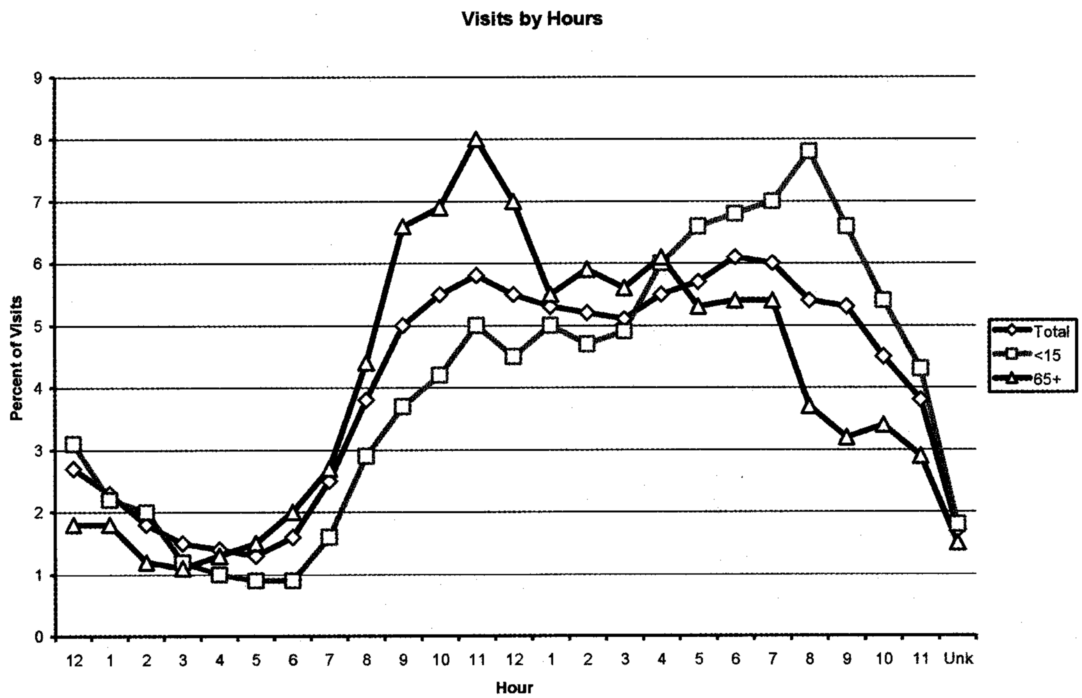

Figure 2. Percentage distribution of visits by hour. From CDC, advanced data no. 335.

of the patient stay and areas that can be reduced through digital medical records and patient tracking systems.

Delays in admissions have emerged in the past decade as a major factor in long emergency department (ED) length of stays. Nationally, admitted patients currently account for 12% of all emergency service visits. Downsizing of hospital beds and a critical shortage in nursing personnel have resulted in extended stays that can create critical logjams in emergency service availability. Forecasts of continued manpower shortage will force many emergency services to develop creative ways to respond to this problem.

Table 1. Sample calculation of interarrival times

		Interarrival time, min	
		Peak	Nonpeak
Total annual visits	100,000		
Peak month	1.10		
Peak month visits	9167		
Peak day of week	1.10		
Peak day	325		
Peak hours	10		
Percentage of total	60%		
Peak interarrival time	3.07		
Mix of Patients			
Emergent	10%	31	65
Urgent	50%	6	13
Nonurgent	40%	8	16

One of the resulting effects of the delay in admission is an increase in the average length of stay in emergency services. Frequently the distribution of length of stay follows a bimodal geometry, with admitted patients pushing the average significantly past the modal value as illustrated in Figure 3. The percentage of patients admitted from the emergency service, inpatient hospital occupancy level, and the development of an emergency service observation/clinical decision unit can increase the proportion of long-length-of-stay patients and increase the overall length of stay.

If it is not possible to collect all this information in a timely manner, the minimum data set is illustrated in Table 2.

The final piece of the puzzle is establishing assumptions regarding future patterns. In

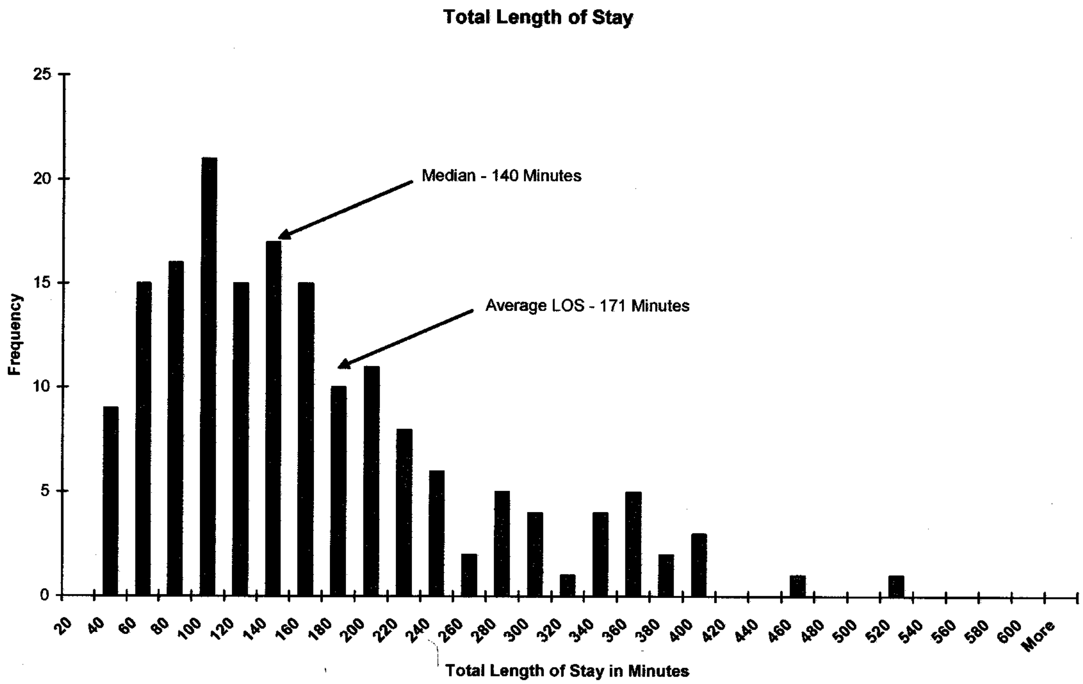

Figure 3. Sample ER patient length of stay.

most situations it is safe to assume that historical arrival patterns and seasonality will continue. Forecasting total visits has proven a daunting task, with most organizations underestimating the continued increase in the rate of visits per thousand over the past decade. Careful review of the emergency service's historical service area, the projected age-specific forecast, emergency service utilization rates, and market share should be part of the base analysis. Time series regression analyses of historical visits should be used with great caution.

A useful planning technique for establishing forecasts is to develop alternative scenarios that reflect plausible patterns of future development. These scenarios could include assumptions regarding growth, closure of competing hospitals, development of detached urgent care services, or the growth resulting from new hospital clinical initiatives. The goal of scenario analysis is not to pick

Table 2. Minimum data set for patient length of stay

		Mix/length-of-stay assumptions			
		Admitted		Discharged	
Treatment room type	Percentage of all visits	Percentage of room use	Length of stay	Percentage of room use	Length of stay
Trauma/resuscitation					
General exam					
Behavioral					
Urgent care					
Observation/holding					
Pediatric					
Total					

the most likely future but to understand the implications of the alternative futures on the needs of the emergency services. If all scenarios lead to the same estimate of need, then planning should proceed with a high level of confidence. This is seldom the case. As the analysis of bed needs develops, each scenario typically reveals variations in estimated bed needs that will require evaluation and judgment decisions regarding the beds that will be used as the base estimate of need and the potential growth target.

TRANSLATING DEMAND INTO BEDS

Three methods are commonly used to estimate bed needs for a target demand. The first is to estimate the capacity of each treatment space in terms of total annual visits per bed. This ratio has continued to drop as patient length of stay in emergency services increase, dropping from targets of 2000 visits per bed to current recommendations in the range of 1400 visits. Institutional variations in patient length of stay, seasonal peaks in activity, and patient mix make the application of suggested ratios arbitrary and high risk. This methodology provides no information on estimated delays in access to treatment areas or the potential effect of changes in throughput times.

A second approach is to estimate bed needs on the basis of target utilization goals. An example of this approach is illustrated in Table 3, which shows the treatment rooms required for a peak workload day and a maximum achievable utilization level for each type of room. The achieved utilization level will vary depending on assumptions regarding the acceptable wait for access to a bed. For high-acuity functions, such as trauma and resuscitation, there should be no wait under any circumstances. On the other hand, at peak periods a wait for access to a fast track room will occasionally occur.

Although this approach is simple to use, there are serious shortcomings, including the inability to estimate the probability of reaching bed capacity and the resulting total wait time for access to a room.

SIMULATION MODELING

Simulation modeling has emerged in the past decade as a powerful tool for estimating

Table 3. Estimating treatment rooms on the basis of utilization targets*

	Key input data				Calculations	
Space components	**Total visits**	**Length of stay, min**	**Existing treatment rooms**	**Existing utilization, %**	**Desired utilization, %**	**Estimated number of treatment rooms**
Treatment rooms						
Trauma/resuscitation	10	178	3	41	40	4
OB/gyn examination room	20	178	3	82	65	4
ENT	5	178	2	31	65	1
Psychiatric/secured holding	8	240	2	67	60	3
General	10	240	4	42	60	3
Fast track	23	115	6	61	60	7
Fast track hours of operation		12 hours per day				
Total treatment	88		20			22

*OB indicates obstetrics; gyn, gynecology; and ENT, ear, nose, and throat.

performance of emergency services (see Zilm et al., 2003).

There are 3 unique characteristics of contemporary simulation modeling:

a. Process/flow—the ability to represent the actual flow of patients through an ambulatory care system over simulated time, monitoring resource utilization, waiting times, and other characteristics.
b. Probabilistic events—Simulation modeling tools can represent the statistical probabilities associated with arrival patterns, service times, and patient characteristics.
c. Animation—the ability to illustrate activities in the model through graphic icons and even floor plans of the service.

Simulation modeling provides the most sophisticated tool for analyzing existing and future emergency service needs, without the cost of building a new department and observing actual performance. A unique capability of this tool is the ability to test the sensitivity of the performance of an emergency service on interdependent variables—for example, staffing patterns, access time to diagnostic services, and travel distances.

This robust characteristic of simulation presents one of the most time-consuming challenges in using this tool—gathering data. Few institutions regularly maintain detailed data to build a sophisticated simulation. Hopefully these data gaps will close as electronic medical charting is implemented. Until then, planners must face either extended observation data collection or utilization of surrogate data.

A SIMPLIFIED ESTIMATING APPROACH

The data requirements, time, and costs associated with developing a complex computer simulation can make this tool inaccessible. I have developed a model of a simple queuing system in an emergency service and run the model through a range of interarrival times and length-of-stay assumptions. The logic of the model assumes unconstrained services—that is, a treatment bed is always available upon demand. It also assumes a log normal distribution on patient length of stays. Given these assumptions, total demand for beds over a 200-hour simulation period was tracked and the resulting demand was graphed, as illustrated in Figure 4. Each of the 4 lines in this graph documents the simulation result for a length-of-stay distribution with a given average length of stay ranging from 90 minutes to 240 minutes. The vertical scale shows the cumulative demand for beds. For example, 80% of the time there was a need for 12 or fewer beds when the average length of stay was 90 minutes.

After running these unconstrained models, additional simulations were developed capping the beds available in the emergency service area on the basis of 80%, 90%, 95%, and 99% estimated need. The results of these simulations are summarized in Table 4.

Two generalized approaches are suggested for using these results. While less precise than a custom simulation developed for a specific circumstance, these techniques nevertheless provide a richer tool than the previously described utilization estimate. The following steps are suggested to using this approach to estimate treatment room needs:

1. Estimate interarrival times for the patient population using the peak period analysis previously described.
2. Estimate length of stay for treatment room utilization (not for total ER length of stay).
3. Use the table to look up the average length of stay and interarrival rate.
4. Determine the desired protection level for the patient population. For high-acuity trauma and emergency patients, a 99% protection level should be used. This should result in a less than 1% probability that a treatment room will be in use. For nonemergency populations, a lower protection level during peak periods is common. Few institutions can afford to build all of the treatment rooms required to assure no waiting in the peak period of the peak month. A protection level in the 80% to 90% during peak period translates into a 95% to 99% protection level over the 24-hour day.

In the arrival calculations illustrated in Table 1, if we estimate the urgent care

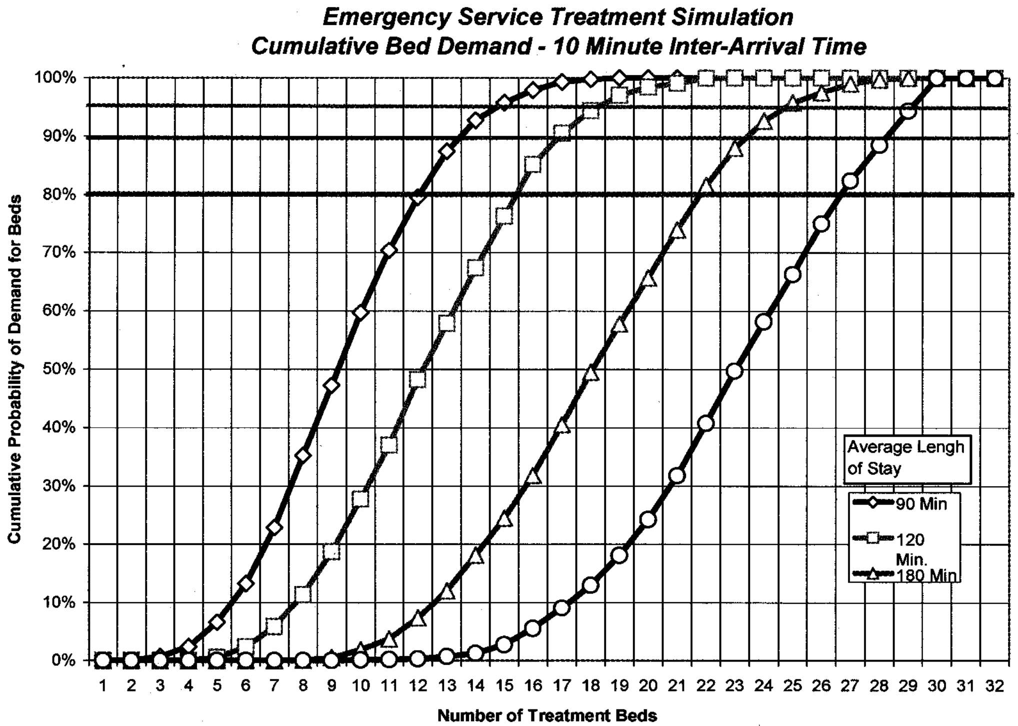

Figure 4. Example of estimating demand for treatment space.

arrivals with a 5-minute interarrival time, the number of treatment rooms needed would be 22 if the average length of stay is 90 minutes. During the peak period, approximately 1 in 4 urgent care patients would experience a delay in access to a treatment room. The average wait for all urgent patients would be 4 minutes and the average wait for the 28% that experienced a delay is estimated at 14 minutes. By adding 2 treatment beds (90% protection level), the percentage experiencing a delay is estimated at 13%, with the average delay less than 1 minute.

If the length-of-stay distribution is highly skewed, then this approach should be used with caution.

A second approach for using these results is to generalize the patterns into a predictive model. A regression analysis of this output using the interarrival time as the independent variable and the log of the estimated treatment spaces resulted in a good fit to the output, with R^2 values in the 0.92 to 0.96 range. A generalized model to estimate treatment rooms can be established using the following formula:

$$\text{Treatment rooms} = 10^{(\text{Intercept}+\text{slope}\times\text{IAT})}$$

where IAT is the interarrival time. The intercept and slope values for an 80% and 90% protection level are illustrated in the Table 5.

For example, the estimated treatment spaces for a 7-minute interarrival time, using a 90% protection level and an average length of stay of 120 minutes, can be established using the following formula:

$$\text{Treatment Beds} = 10^{(1.606586+(-0.031812\times 7))}$$
$$= 24 \text{ rooms}$$

If the patient length-of-stay distribution varies significantly from the log normal distribution or the arrival patterns do not follow a random process, then this estimating method should not be used.

MAXIMIZING FLEXIBILITY IN TREATMENT SPACES

Adaptability to accommodate as many patient disease and treatment needs clearly provides the best opportunity to maximize

Table 4. Simulation results for selected LOS and IAT patterns*,†

		Average length of stay, min															
		90				120				180				240			
			Wait				Wait				Wait				Wait		
Average interarrival time, min	Protection level, %	Beds	% w/ wait	All	With wait	Beds	% w/ wait	All	With wait	Beds	% w/ wait	All	With wait	Beds	% w/ wait	All	With wait
5	99	29	1	0	7	37	1	0	3	50	2	0	6	65	1	0	8
	95	26	5	0	8	33	4	0	9	47	6	1	10	61	5	1	11
	90	24	13	1	10	31	13	1	10	44	16	2	15	59	9	2	12
	80	22	28	4	14	29	27	4	14	42	27	5	20	55	24	5	20
10	99	17	1	0	5	21	1	0	5	27	1	0	14	33	3	0	14
	95	15	4	1	8	19	3	0	11	25	5	1	16	31	8	1	16
	90	14	8	1	12	17	1	1	14	24	9	2	18	30	13	3	18
	80	12	25	4	16	16	27	3	16	22	24	6	23	28	29	9	31
15	99	13	1	0	3	16	1	0	7	21	1	0	8	27	1	0	6
	95	11	4	1	9	14	4	0	9	19	4	1	15	24	4	1	20
	90	10	9	1	14	13	8	1	13	17	12	3	21	22	10	3	26
	80	9	18	3	17	11	24	5	23	16	20	5	25	20	24	9	35
20	99	10	1	0	14	13	1	0	3	18	1	0	6	21	1	0	14
	95	9	4	1	14	11	5	1	12	16	3	1	12	19	4	1	24
	90	8	11	2	16	10	10	2	18	14	10	2	23	17	12	4	32
	80	7	21	5	23	9	19	5	25	12	27	10	37	16	20	8	38

*LOS indicates length of stay; IAT, interarrival time; % w/wait, the percentage of all patients who experienced any wait for access to treatment bed; all, the average waiting time (minutes) for all patients seen; with wait, the average wait time for patients who experienced any wait; protection level, the estimated number of beds needed to provide no waiting for a designated percentage of all patients based on "unconstrained" system

†Simulations of each combination of LOS and IAT were run for 220 consecutive hours, after a 2-hour warm-up period.

Table 5. Regression intercepts and slope for selection simulation results

Length of stay, min	Protection level, %	Intercept	Slope
90	90	1.476154	−0.028481
	80	1.459464	−0.032338
120	90	1.606586	−0.031812
	80	1.587337	−0.033744
180	90	1.760494	−0.033361
	80	1.75487	−0.03541
240	90	1.894188	−0.035118
	80	1.861882	−0.035097

utilization of treatment rooms. A fundamental initial decision is the mix of open bay cubicles and individual rooms. Although open bay treatment spaces offer efficiency of space and potential staff coverage of multiple patients, the desire for achieving patient privacy, managing infectious contamination, and providing family support has led recent ED designs to move primarily to private patient rooms. One area that may be an exception to this approach is a large clinical decision unit, where selected patients are observed for extended periods of time by a limited staff.

The concept of "universal" rooms focuses on establishing a common room size and characteristic to manage nonurgent, fast track, and selected emergent patients. Depending upon the overall organizational concept of the service, the area of the room should be between 140 and 160 net square feet (nsf) (see article by Saba and Bardwell in this issue).

Facility planning should also consider the potential "surge" impact of a catastrophic event, including natural disasters, epidemics, and terrorism. The ability to convert a single occupancy area into a double patient holding space may be justified for emergency services that are in high-risk environments. This would mandate a room of at least 160 nsf.

As the risk of contamination from pandemic outbreaks or bioterrorism increases, plans for emergency services are also attempting to expand the number of rooms that can be used to isolate patients and staff. Two strategies frequently considered within the ED are (1) providing isolation capability in all treatment rooms or (2) the ability to create a cluster of rooms that can be isolated. The emergency service should have a dedicated, separate heating/ventilation/air conditioning (HVAC) system from the rest of the hospital to prevent potential contamination from the ED.

SUMMARY

Estimating required treatment beds is a critical step in the planning and design of emergency services. The task is complicated by variations in visits by season, day of week, and time of day. Predicting the arrival pattern flow and statistical distribution of length of stay are critical in estimating the peak demand for beds. The most sophisticated tools for estimating bed needs utilize computer simulation of existing and future conditions. However, the data requirements for this method are significant. A general approach based on generic models is suggested in this article.

Any planning for future needs must recognize that estimating workload service patterns over an extended planning horizon will include some assumptions that will turn out to be wrong. Designing for maximum flexibility in utilization of rooms, allowing for efficient expansion of a facility, and having the ability to balance staff to the flow of demand are critical considerations. Design for flexibility—no model will give you the perfect answer.

REFERENCE

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