Optimizing cardiology capacity to reduce emergency department boarding: A systems engineering approach

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Background Patient safety and emergency department (ED) functionality are compromised when inefficient coordination between hospital departments impedes ED patients' access to inpatient cardiac care. The objective of this study was to determine how bed demand from competing cardiology admission sources affects ED patients' access to inpatient cardiac care.

Methods A stochastic discrete event simulation of hospital patient flow predicted ED patient boarding time, defined as the time interval between cardiology admission request to inpatient bed placement, as the primary outcome measure. The simulation was built and tested from 1 year of patient flow data and was used to examine prospective strategies to reduce cardiology patient boarding time.

Results Boarding time for the 1,591 ED patients who were admitted to the cardiac telemetry unit averaged 5.3 hours (median 3.1, interquartile range 1.5-6.9). Demographic and clinical patient characteristics were not significant predictors of boarding time. Measurements of bed demand from competing admission sources significantly predicted boarding time, with catheterization laboratory demand levels being the most influential. Hospital policy required that a telemetry bed be held for each electively scheduled catheterization patient, yet the analysis revealed that 70.4% (95% CI 51.2-92.5) of these patients did not transfer to a telemetry bed and were discharged home each day. Results of simulation-based analyses showed that moving one afternoon scheduled elective catheterization case to before noon resulted in a 20-minute reduction in average boarding time compared to a 9-minute reduction achieved by increasing capacity by one additional telemetry bed.

Conclusions Scheduling and bed management practices based on measured patient transfer patterns can reduce inpatient bed blocking, optimize hospital capacity, and improve ED patient access. (Am Heart J 2008;0:1-8.)

Patients with acute cardiovascular diagnoses such as acute coronary syndrome and congestive heart failure require a timely transition in care from the emergency department (ED) to an inpatient cardiology unit. Patient safety and quality of care can be compromised when coordination between the ED and cardiology services is not cohesively managed. Inefficient transitions create a barrier that exposes cardiac patients to increased risk. For example, inefficient inpatient bed management can lead to "boarding" (ie, holding admitted patients in the ED until an inpatient bed becomes available), thereby potentially impeding timely or definitive therapy. Excess inpatient demand, limited capacity, and external economic pressures have created an epidemic of ED boarding across all inpatient service specialties.[1] A Government Accounting Office study found that 90% of hospitals boarded patients at least 2 hours and 20% of these hospitals averaged an 8-hour boarding time.[2] Boarding is the most significant cause of ED crowding, and cardiology departments are substantial contributors.[1-7]

Prolonged boarding can reduce quality of care for admitted cardiac patients and simultaneously threatens the ED's ability to function safely. A secondary analysis of data from an observational registry showed that boarding cardiac inpatients increased ED length-of-stay and is associated with decreased use of recommended therapies and higher risk of recurrent myocardial infarction.[8] This is consistent with recent studies suggesting that critically ill patients are more effectively treated in specialized

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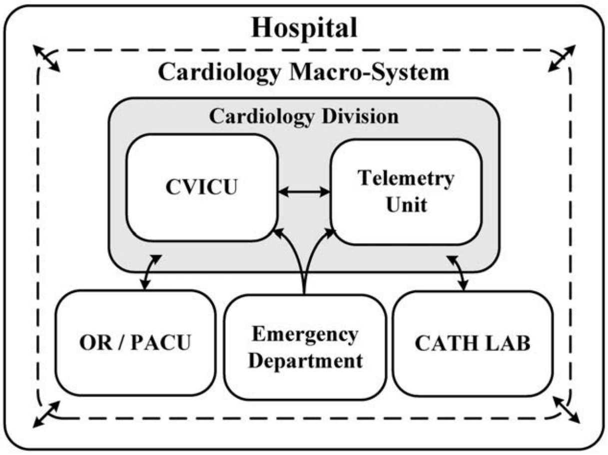
Figure 1



Cardiology macrosystem patient flow.

inpatient settings as opposed to the ED.[9-11] In addition, boarded patients require more intense care, consuming ED resources intended for evaluating and stabilizing incoming cardiac patients.[1] In a patient population presenting with acute coronary syndrome, the number of boarding patients was positively associated with 30-day rehospitalization rate.[12] Boarding also compromises out-of-hospital care for emergency chest pain patients by creating ambulance diversion and transport delays.[13-15] Hospital EDs and cardiology divisions are tightly coupled such that inefficiency at their junction can adversely affect quality of care.

Boarding patients violates the Institute of Medicine's charge to deliver safe, timely, efficient, and patient centered care, which is why it has mandated that, "Hospitals should end the practices of boarding patients in the ED and ambulance diversion, except in the most extreme cases."[1,16] The National Academy of Engineering and Institute of Medicine (both in Washington, DC) have directed the health care community to the field of systems engineering for solutions.[17] Systems engineering includes computer modeling techniques that can generate hypothesis about potential system improvements. Thus, the purpose of this study was to create a discrete event simulation to model how bed demand from competing cardiology admission sources affects ED patients' access to inpatient cardiac care. The simulation was used to examine cardiology macrosystem (Figure 1) patient flow and prospectively analyze strategies to reduce cardiac patient boarding.[18]

Methods

Study design

This was a retrospective cohort study that included all patients who interacted with the cardiology macrosystem with a focus on ED patients admitted by cardiology to a telemetry bed. Demographic, clinical, and operational information was collected from multiple information systems over a 1-year period (ie, weekdays and weekends) from May 1, 2006, to May 1, 2007. Information from each source was merged to construct patient flow times and patterns for each patient in the study cohort.

Cardiology macrosystem

The study was performed at an urban, academic, tertiary care hospital with a 45-bed ED and a 73-bed cardiology inpatient unit consisting of 47 telemetry beds and 26 cardiovascular intensive care unit (CVICU) beds. The hospital houses a cardiac catheterization laboratory (CATH LAB) composed of 4 CATH LAB bays, 2 electrophysiology bays, 1 hybrid operating room, and 16 holding area beds. The division of cardiology (telemetry and CVICU) functions within the cardiology macrosystem (Figure 1). Patients flow between the telemetry unit, CVICU, CATH LAB, ED, operating rooms (ORs), post anesthesia care unit (PACU), other hospital units, and home.

Predicting ED boarding time

Survival analysis was used to construct a Cox proportional hazard regression model to predict expected boarding time for patients admitted to a telemetry bed.[19] Boarding time, that is, "survival" in the model, was defined as the time interval between hospital admission order and the time the patient moved to an inpatient telemetry bed. The covariate selection procedure considered operational, demographic, and clinical variables based upon the hypothesis that each could effect boarding time. Covariates designed to measure the level of demand from competing telemetry admission sources were collected at the exact time an ED physician placed the admission request. The demand measurements were extracted from clinical information systems for each ED patient admitted to a cardiology location. Emergency department operational measures such as ED occupancy and number of boarded patients were also considered. Independent variables measuring hospital demand were scaled to one. Individual patient characteristics such as patient demographics (age and sex), medical history, ED-based cardiovascular disease therapies, and Thrombolysis in Myocardial Infarction risk score were considered as model covariates.[20] Medical history included prior myocardial infarction, cardiomyopathy, coronary artery disease, congestive heart failure, hypertension, hyperlipidemia, diabetes mellitus, smoking status, and family history of coronary artery disease. Emergency department–based cardiovascular disease therapies included nitroglycerin, aspirin, clopidogrel, β-blockers, heparin, glycoprotein 2b/3a inhibitors, enoxaparin, and angiotensin-converting enzyme inhibitors. A series of regression diagnostics were performed to assess the validity of the model; bootstrapping and cross-validation methods were used to assess any bias within the model.[21]

Discrete event simulation using hazard models

The simulation of patient flow through the cardiology macrosystem was created using the MATLAB (Mathworks, Natick, MA) technical computing environment and MedModel (Promodel Corporation, Orem, UT) simulation software.

Cox proportional hazard models were used within the simulation to predict ED boarding time to cardiology units.

Table I. Telemetry hazard model

Time interval	Variables	Coefficient	*P*	95% CI
0-3 h	OR × CATH LAB	−3.79	<.001	−4.47 to −3.10
	TELEMETRY	−1.99	<.001	−2.79 to −1.18
	OTHER	−1.62	.089	−3.48 to −0.24
	CVICU	−1.18	<.001	−1.78 to −0.57
3-28 h	HOSP	−3.56	<.001	−4.85 to −2.26
	TELEMETRY	−3.04	<.001	−3.80 to −2.27
	CVICU	−1.85	<.001	−2.57 to −1.12

The OR × CATH LAB variable was a weighted combination (see equation below) of both variables because of high collinearity ($r = 0.76$). The weights, WO = 5.9% for OR and WC = 29.2% for CATH LAB, were equivalent to the corresponding patient inflow fractions to telemetry. *Other*, Other hospital units.

$$\text{OR} \times \text{CATH LAB} = \left(\frac{\text{WO} \times \text{OR}}{\text{WC} + \text{WO}}\right) + \left(\frac{\text{WC} \times \text{CATH LAB}}{\text{WC} + \text{WO}}\right)$$

Patient flow between the cardiology macrosystem units (Figure 1) was modeled using basic queuing principles that classified each location. Telemetry and CVICU units were modeled as reactive, that is, these units reacted to time-dependent fluctuations in demand coming from all inflow sources. The ORs, PACU, and the CATH LAB were modeled as proactive, that is, these units directed patient flow with highest priority to and from other locations in the model. Most proactive unit patients were electively scheduled. The ED was modeled purely as an input source in relation to all other locations. The remainder of inpatient hospital beds was modeled as a single input/output source to represent the cross-service sharing of beds that existed within the hospital.

Input probability distributions generated from actual patient flow information were used to drive the timing of arrivals and departures at each simulated clinical location. Length-of-stay within the simulation was defined as the time interval from when a patient entered a unit from any location to when the patient exited that unit to any other location or home. Mann-Whitney *U* tests were used to assess differences between input and output probability distributions for the simulated versus real system. Correlation coefficients were used to compare the simulated versus real weekly temporal pattern in minute-by-minute census for each location modeled.

Patients were directed to various locations within the model based on transfer probabilities generated from real system data. These transfer probabilities were dependent on patients' previous locations. For example, a common surgical patient's pathway through the system was to (1) arrive in the OR; (2) move to the CVICU postoperatively; (3) move to the telemetry unit; and (4) be discharged home. By guiding location transfer probabilities based on previous locations, common patient flow pathways, as such, were preserved. Boarding time to telemetry, location census distributions, and temporal patterns were the major output variables validated against the real system.

Results

Modeling ED boarding time

During the 1-year study period, the cardiac telemetry units received 7,901 separate visits with 1,591 (20.1%) of these visits coming from the ED. Emergency department patients compete for telemetry beds with patients flowing in from the OR/PACU (5.9%), the CATH LAB (29.2%), the CVICU (16.0%), other remaining hospital units (14.8%), and home (14.0%). Patients boarded for telemetry had a mean boarding time of 5.3 (median 3.1, interquartile range [IQR] 1.5-6.9) hours. Patients boarded for the CVICU had a mean boarding time of 2.7 (median 1.7, IQR 0.8-3.0) hours. In comparison, the mean ED treatment time, excluding boarding time, was 4.1 (median 1.9, [IQR] 3.2-5.3 hours). The average occupancy of the telemetry and CVICU units was 88% and 77%, respectively. The independent variables used to predict boarding time measured demand in the following units: TELEMETRY, CVICU, OTHER remaining hospital units, OR, and CATH LAB. The effect of each clinical and demographic variable on boarding time was examined. Interestingly, none of these variables were found to be significant predictors of boarding time to telemetry or the CVICU. The final model for telemetry-bound patients is seen in Table I. The TELEMETRY, CVICU, and OTHER variables measured the number of beds occupied at their respective locations. The OR and CATH LAB variables combined the number of beds occupied at each location plus the number of procedures scheduled 3 hours into the future. A 3-hour window capturing future demand in the OR and CATH LAB was used as a result of insights gained from several interviews conducted on bed management personnel.

The telemetry hazard model (Table I) was used to predict expected boarding time by creating a unique probability distribution of boarding time for each patient based on the covariates collected at the time the admission order was placed. An important assumption of Cox regression is that the covariates have the same effect on the hazard function for all values of time. Variables capturing demand within the OR and the CATH LAB were found to have a nonproportional effect on the hazard function. Thus, the strategy of creating models over 2 disjoint periods with equal sample sizes was used.[22] The reader is referred to prior published work for further details on the boarding prediction methodology.[19]

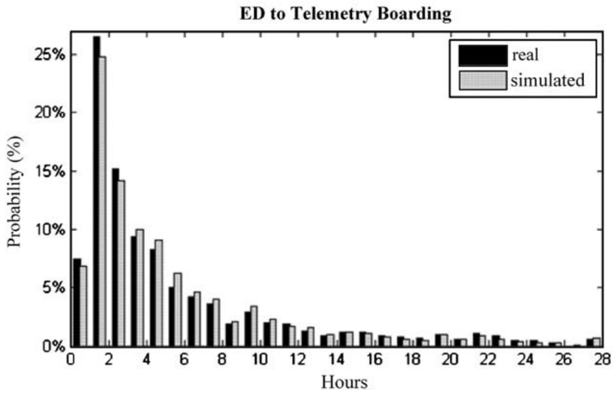
Table II. Simulation verification and validation

Location	Real system median (IQR)	Simulated system median (IQR)	Comparison measure
	Arrivals Per Week		Mann-Whitney U (*P*)
ED	882 (855-899)	883 (863-904)	.35
ED boarders	242 (226-256)	241 (232-252)	.95
Telemetry boarders	30 (23-36)	31 (24-37)	.27
CVICU boarders	6 (5-8)	7 (4-9)	.56
Telemetry unit	152 (141-161)	153 (142-161)	.53
CVICU	56 (50-64)	58 (54-62)	.25
CATH LAB	123 ((110-133)	122 (111-129)	.38
OR	298 (278-323)	297 (279-316)	.52
Cardiac surgeries	32 (24-39)	32 (25-37)	.28
	Length of stay (h)		Mann-Whitney U (*P*)
ED treatment	3.2 (1.9-5.3)	3.2 (1.9-5.3)	.96
ED boarding (all)	2.1 (0.7-5.8)	2.1 (0.8-5.9)	.19
Telemetry boarders	3.1 (1.5-6.9)	3.3 (1.7-7.0)	.33
CVICU boarders	1.7 (0.8-3.0)	1.7 (0.9-3.0)	.62
Telemetry unit	32.3 (17.2-61.4)	33.1 (18.4-61.6)	.35
CVICU	42.1 (20.3-75.2)	43.1 (21.3-74.9)	.42
CATH LAB	5.4 (3.1-7.7)	5.5 (3.1-8.1)	.34
OR	2.5, (1.5-4.0)	2.6 (1.6-4.4)	<.05
Cardiac surgeries	6.1 (3.3-8.9)	6.1 (3.4-9.0)	<.05
	Census distributions (minute-by-minute)		Correlation coefficient (*r*)
ED	32 (26-37)	32 (24-38)	0.97
ED boarding	7 (4-11)	7 (4-11)	0.96
Telemetry unit	42 (37-45)	42 (36-45)	0.78
CVICU	20 (17-22)	20 (17-23)	0.86
CATH LAB	3, (1-10)	3 (1-9)	0.94
OR	2 (0-11)	3 (1-12)	0.99
Other hospital units	731 (696-756)	731 (691-761)	0.97

Discrete event simulation verification and validation

Simulation input distributions capturing arrivals per week and length-of-stay were verified to match the real system (Table II). The simulated OR length-of-stay distribution did not meet the null hypothesis of coming from the corresponding real-system distribution. Characteristics of these distributions were compared and determined to be accurate enough for the intended application. The probability distribution of boarding time for patients telemetry bound was validated against the real system in Figure 2. Output census distributions for each location were validated against the real system (Table II). Pearson correlation coefficients ranged from 0.78 to 0.99 for weekly temporal patterns between the simulated versus real systems.

Figure 2



Boarding time probability distribution comparison.

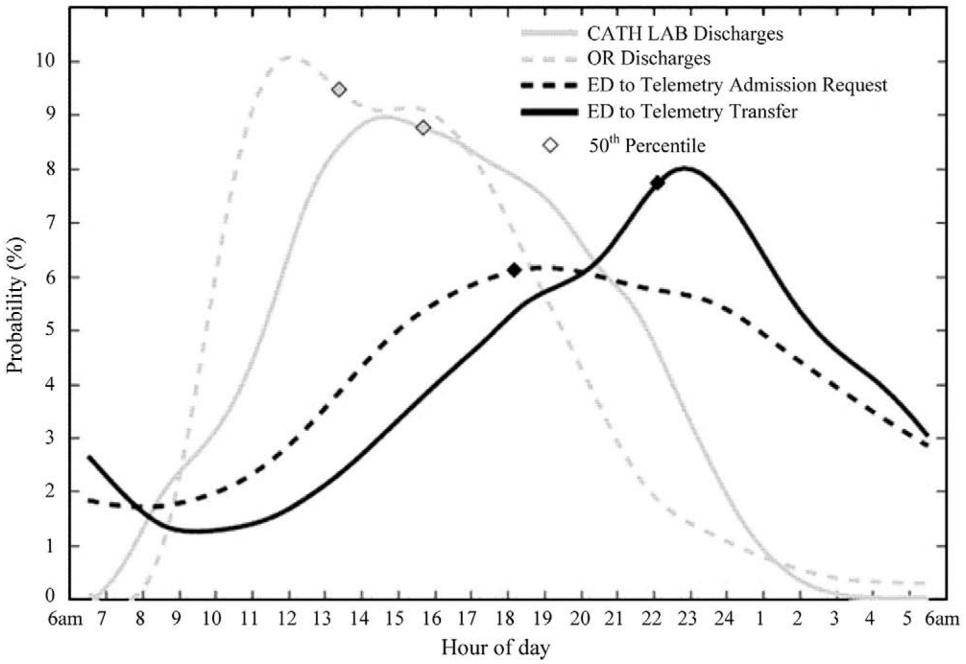
Artificial variability

Telemetry bed management is a difficult task given several sources of uncertainty. Demand uncertainty is created by variation in patient inflow coming from a multiple sources as well as variation in length-of-stay (outflow). A common misconception is that the unscheduled environment of the ED produces much of the variability in inpatient demand. The opposite was true for the system studied. Weekly variability in unscheduled patients arriving to the ED (coefficient of variation [CV] 0.03) was significantly lower than variability associated with electively scheduled surgeries (CV 0.09) and CATH LAB procedures (CV 0.10). Weekly variability in demand is being increased artificially by elective surgical and catheterization scheduling practices.[23] Demand uncertainty must be managed effectively to optimize capacity and reduce ED boarding.

Simulation model results

Results of the telemetry hazard model display that demand coming from the OR and the CATH LAB (OR × CATH LAB) was the strongest driver of boarding time. The CATH LAB is most influential because of the weighting scheme used. Electively scheduled patients coming from home represent the CATH LAB's biggest source (64.2%) of inflow. However, the outflow for these scheduled patients is quite uncertain; 50.5% were discharged home, 30.1% were directed to a telemetry bed, 8.2% went to the OR, 6.2% went to the CVICU, and 5.0% were transferred to another location within the hospital. The hospital's bed management practice required that a telemetry bed be reserved for all scheduled catheterization patients

Figure 3



Cardiology macrosystem patient flow patterns on a typical weekday (6:00 AM to 6:00 AM). Curves represent the probability of the event occurring by hour of day.

coming from home. Thus, unoccupied telemetry beds were held for these potential patients, blocking access to ED patients.

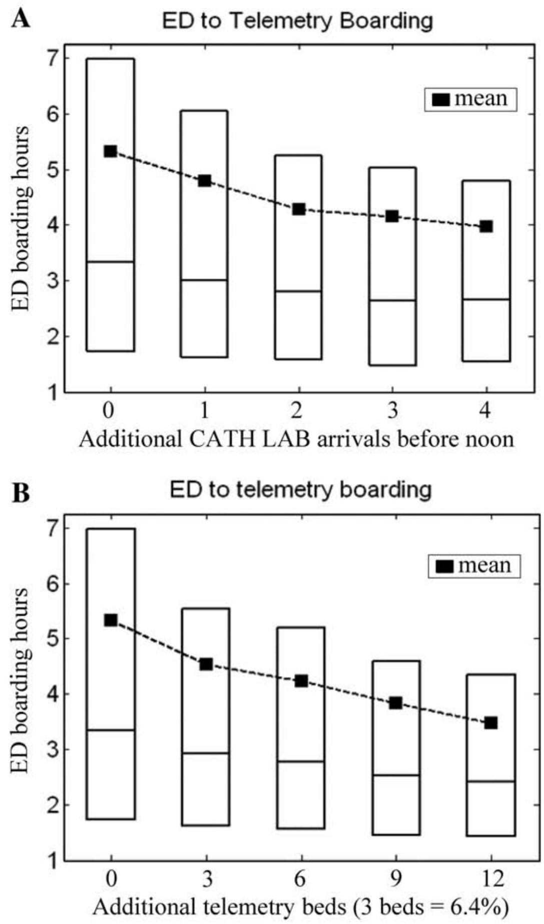
Scheduling and bed management practices drive patterns of patient flow through the cardiology macrosystem. A telemetry admission request from the ED has the highest probability of occurring at around 6:00 PM on a typical weekday (Figure 3). At this time, >40.0% of patients scheduled to undergo CATH LAB procedures that day have not yet been discharged. The CATH LAB is the largest source of telemetry demand uncertainty as late as 6:00 PM. Uncertainty does not subside to a level allowing ED patients' access until almost 11:00 PM. This is demonstrated by the peak in ED transfers to telemetry (Figure 3). The interval between the admission request peak and the telemetry transfer peak reflects patient boarding time.

Examining the repetitive weekday pattern of patient flow led to the hypothesis that reducing CATH LAB outflow during the period when ED admission requests were most likely to occur would reduce boarding time for telemetry-bound patients. Such an intervention would shift the CATH LAB discharge curve to the left (ie, earlier in the day) in Figure 3. Currently, 70.4% of CATH LAB arrivals occur before noon. The simulation demonstrates the results of having a higher percentage of patients arrive to the CATH LAB before noon on a typical weekday (Figure 4, *A*). All other inputs being constant, moving one afternoon scheduled elective catheterization case to before noon on the weekdays resulted in a 6.4% or 20-minute reduction in average boarding time. In comparison, increasing telemetry unit capacity (Figure 4, *B*) by one additional bed resulted in a 2.9% or 9-minute reduction in average boarding time. A subtle low cost scheduling solution aimed at optimizing capacity outperforms the higher cost alternative of adding capacity.

Discussion

This study demonstrates a systems engineering approach to analyze a hospital macrosystem's relationship with the ED. We developed a novel modeling technique to analyze prospective strategies aimed at reducing ED boarding time. A low-cost scheduling strategy designed to offset unscheduled arrivals (ie, ED admission requests) with elective arrivals from the CATH LAB was superior to a higher cost capacity increase. A systems approach to managing elective schedules to improve interdepartment patient flow is likely to be a more effective and feasible than expanding hospital capacity. Simulation construction and resulting analysis supported this by providing insights about how sub-optimal management practices may be rectified to increase efficiency and decrease ED boarding.

Figure 4



Alternative strategies to reduce boarding time (boxplots display median and IQR). **A**, Scheduling an additional CATH LAB patient before noon. **B**, Increasing telemetry capacity.

An interesting conclusion drawn from the hazard model was that clinical factors did not predict boarding time. We hypothesized that severity of illness would play a role in how quickly ED patients were admitted. The contrary result may be because we controlled for variability by examining patients not well enough to be discharged home and not sick enough to be admitted to the CVICU. Cardiovascular intensive care unit–bound patients were boarded, on average, half as long as telemetry-bound patients (Table II). Triaging patients based on illness severity does occur for some cardiology admitted patients but was not found in the telemetry-bound population. This steered the focus toward operational demand and management factors.

The hazard model identified CATH LAB outflow as an important driver of boarding time. CATH LAB patients were a major source (29.2%) of inflow to telemetry units and a major competitor of ED-admitted patients. Weekly catheterization patient volume is highly variable and patient transfer (outflow) pathways are uncertain. Traditional bed management practices blocked telemetry beds for all scheduled CATH LAB patients, although only 29.6% (95% CI 7.5%-48.8%) of these beds were actually needed each weekday. A large proportion of bed blocking occurred during weekday periods of frequent ED admission requests. Effectively managing CATH LAB outflow demand uncertainty and reducing bed blocking practices at key hours are likely to have the greatest effect on boarding time.

The simulation demonstrated how subtle changes in catheterization scheduling could yield significant results. Moving one afternoon scheduled elective catheterization case to before noon was equivalent to adding 2 additional telemetry beds in regard to decreases in ED boarding time for telemetry-bound patients. Increasing telemetry beds produced a relatively minor effect when capacity was not being optimized, and scheduling changes are often easier to implement than capacity increases. Coupling this change with informed bed management policies that require one telemetry bed be held for every 2 scheduled CATH LAB patients would reduce bed blocking further. This policy assumes a 50% daily outflow to telemetry, safely above the 29.6% (95% CI 7.5%-48.8%) that presently exists. Bed blocking is a necessary practice that ensures the safety of patients, but it is a large source of waste in a system with scarce resources. Hospital-based solutions should be directed toward scheduling and bed management practices that reduce bed blocking when ED patients are in need.

In the hospital's current policy, CATH LAB patients who may need a telemetry bed have higher priority than ED patients. Current hospital reimbursement structures create a lower priority to ED admissions because they typically generate the lowest margins, resulting in less revenue compared with other types of patients.[1] Thus, the ED serves as a buffer providing free excess capacity for cardiology's least profitable patient population. Economic incentives encourage cardiology services to use free capacity and bed management policies, and ED boarding practices reflect this. Unfortunately, it is the quality of the boarded patient's care and the ED system that is affected.

A limitation of the study was that it was conducted at a single academic medical center with specific operational measurements (ie, length-of-stay distributions, bed capacity, patient transfer probabilities, etc). Although the exact operational measurements are unique to this institution, operational characteristics and patient flow patterns are common across many US hospitals. Emergency department boarding and the resulting overcrowding is a nationwide epidemic.[1-7] Challenges that arise from managing artificial variability associated with electively scheduled procedures have been identified at several institutions.[24-26] In addition, financial incentives favoring inpatient bed provisions for elective admissions undergoing procedures over ED admissions are a result of nationwide reimbursement structures.[1] Each hospital is unique; however, many urban tertiary care facilities are delivering care in similar environments with similar operational characteristics resulting in similar challenges with regard to patient flow and ED overcrowding. For this reason, the notion of optimizing capacity by reducing bed-blocking practices during peak ED to hospital outflow may have wider applicability across multiple inpatient settings in many different hospitals.

In addition, the study methodology aimed at optimizing inpatient capacity may be of value to other hospitals. Simply, quantifying patient flow and characterizing sources of uncertainty in demand can lead to improved evidence-based scheduling and management practices. Developing simulation models from these measurements allows improvement hypotheses to be tested before implementation. Using a systems engineering approach to measure and understand patient demand and flow among various hospital units can provide more objective- and measurement-based insights that can result in capacity optimization strategies that decrease patient waiting and improve access.

Conclusion

Surrounded by operational uncertainty, resource scarcity, competing economic interests, and patient safety lays the boarded patient; a representative of a widening quality gap in the health care system. This gap exists at the boundary between hospital departments reinforcing the need for a systems engineering approach. In this study, systems engineering tools were used to quantify patient flow in the hospital and measure its effect on ED boarding. From this we determined that ED boarding was not solely driven by a lack of inpatient capacity. In fact, increasing capacity will have a minimal effect when the management of patient flow is suboptimal. Solutions that optimize capacity by counterbalancing unscheduled inpatient arrivals (ie, ED admission requests) with elective arrivals and creating bed management practices based on measured patient transfer patterns are likely to be more effective. The next step involves implementing these solutions and measuring their effect on the real system. Systems engineering tools are capable of continuously generating these solutions. Using them will lead to new operations management practices that remove waste, increase efficiency, and improve the quality of hospital patient care.

References

1. Institute of Medicine. Hospital-based emergency care: at the breaking point. Institute of Medicine. Washington, DC: National Academy Press; 2006.
2. US General Accounting Office. Hospital emergency departments: crowded conditions vary among hospitals and communities; 2003. Washington, DC: GAO–03-460 (document number).
3. Asplin BR, Magid DJ, Rhodes KV, et al. A conceptual model of emergency department crowding. Ann Emerg Med 2003;42: 173-80.
4. Asplin BR, Magid DJ. If you want to fix crowding, start by fixing your hospital. Ann Emerg Med 2007;49:273-4.
5. Derlet R, Richards J, Kravitz R. Frequent overcrowding in U.S. emergency departments. Acad Emerg Med 2001;8:151-5.
6. Derlet RW. Overcrowding in emergency departments: increased demand and decreased capacity. Ann Emerg Med 2002;39:430-2.
7. Schneider SM, Gallery ME, Schafermeyer R, et al. Emergency department crowding: a point in time. Ann Emerg Med 2003;42: 167-72.
8. Diercks DB, Roe MT, Chen AY, et al. Prolonged emergency department stays of non–ST-segment-elevation myocardial infarction patients are associated with worse adherence to the American College of Cardiology/American Heart Association guidelines for management and increased adverse events. Ann Emerg Med 2007; 50:489-96.
9. Cowan RM, Trzeciak S. Clinical review: emergency department overcrowding and the potential impact on the critically ill. Crit Care 2005;9:291-5.
10. Trzeciak S, Rivers EP. Emergency department overcrowding in the United States: an emerging threat to patient safety and public health. Emerg Med J 2003;20:402-5.
11. Chalfin DB, Trzeciak S, Likourezos A, et al. Impact of delayed transfer of critically ill patients from the emergency department to the intensive care unit. Crit Care Med 2007;35:1477-83.
12. Pines JM, Hollander JE. The impact of emergency department crowding on cardiac outcomes in ED patients with potential acute coronary syndromes. ACEP Research Forum 2007;50:S3.
13. Schull MJ, Morrison LJ, Vermeulen M, et al. Emergency department overcrowding and ambulance transport delays for patients with chest pain. CMAJ 2003;168:277-83.
14. Schull MJ, Lazier K, Vermeulen M, et al. Emergency department contributors to ambulance diversion: a quantitative analysis. Ann Emerg Med 2003;41:467-76.
15. Schull MJ, Morrison LJ, Vermeulen M, et al. Emergency department gridlock and out-of-hospital delays for cardiac patients. Acad Emerg Med 2003;10:709-16.
16. Institute of Medicine. Crossing the quality chiasm: a new health system for the 21st century. Washington, DC: National Academy Press; 2001.
17. Institute of Medicine, National Academy of Engineering. The tools of systems engineering. In: Reid PP, Compton DW, Grossman JH, et al, editors. Building a better delivery system: a new engineering/ health care partnership. Washington, DC: National Academy Press; 2005.
18. Nelson EC, Batalden PB, Huber TP, et al. Microsystems in health care: Part 1. Learning from high-performing front-line clinical units. Jt Comm J Qual Improv 2002;28:472-93.
19. Levin S, Han J, Aronsky D, et al. Stranded on emergency isle: modeling competition for cardiac services using survival analysis. Industrial Engineering and Engineering Management. Singapore: International Conference on Industrial Engineering and Engineering Management 2007; pp. 1772-6.
20. Antman EM, Cohen M, Bernink PJ, et al. The TIMI risk score for unstable angina/non–ST elevation MI: A method for prognostication and therapeutic decision making. JAMA 2000;284:835-42.

21. Harrell FE Jr, Lee KL, Mark DB. Multivariable prognostic models: issues in developing models, evaluating assumptions and adequacy, and measuring and reducing errors. Stat Med 1996;15:361-87.
22. Schemper M. Cox analysis of survival-data with nnonproportional hazard functions. Statistician 1992;41:455-65.
23. Litvak E, Long MC. Cost and quality under managed care: irreconcilable differences? Am J Manag Care 2000;6:305-12.
24. Litvak E, Long MC, Cooper AB, et al. Emergency department diversion: causes and solutions. Acad Emerg Med 2001;8:1108-10.
25. Litvak E, Buerhaus PI, Davidoff F, et al. Managing unnecessary variability in patient demand to reduce nursing stress and improve patient safety. Jt Comm J Qual Patient Saf 2005;31:330-8.
26. McManus ML, Long MC, Cooper A, et al. Variability in surgical caseload and access to intensive care services. Anesthesiology 2003;98:1491-6.