APPLYING SYSTEMS ENGINEERING TOOLS TO MEASURE AND IMPROVE HOSPITAL-BASED HEALTH CARE DELIVERY

By

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LIST OF ABBREVIATIONS

ACC .... American College of Cardiology
ACS .... Acute Coronary Syndrome
ADT .... Medipac Admit / Discharge / Transfer Database
AHA .... American Heart Association
AMI .... Acute Myocardial Infarction
CATH LAB .... Catheterization Laboratory
CCL .... Cardiac Catheterization Laboratory
CVICU .... Cardiovascular Intensive Care Unit
CVD .... Cardiovascular Disease
DES .... Discrete Event Simulation
ECG .... Electrocardiogram
EDWIS .... Emergency Department Electronic Whiteboard System
ED .... Emergency Department
EM .... Emergency Medicine
ICU .... Intensive Care Unit
IOM .... Institute of Medicine
IT .... Information Technology
LOS .... Length-of-Stay
NACB .... National Academy of Clinical Biochemistry
NAE .... National Academy of Engineering
NASA .... National Aeronautics and Space Administration
NHLBI .... National Heart, Blood and Lung Institute
OR .... Operating Room
PACU .... Post Anesthesia Care Unit
QI .... Quality Indicator
STEMI .... ST-Elevation Myocardial Infarction
TIMI .... Thrombolysis in Myocardial Infarction
TLX .... Task Load Index
UA .... Unstable Angina
US .... United States
VPIMS .... Vanderbilt Perioperative Information Management System
VUMC .... Vanderbilt University Medical Center

CHAPTER I

INTRODUCTION

The foundation of this doctoral research was built upon evaluating emergency department (ED) work processes at the individual provider, provider team and system levels. Prior to developing the primary goal of this dissertation, preliminary (post Master's Degree) research was aimed at studying the ED at the individual provider and provider team levels. Three peer reviewed publications and several published abstracts were produced from this work and displayed in the appendix. The titles of the publications and a brief description of their objectives are provided below:

1. Levin S, France DJ, Hemphill R, Han J, Slagle J, Aronsky D. Shifting Toward Balance: Measuring the distribution of workload among emergency physician teams. *Ann Emerg Med.* 50:419-423, 2007.

   The objective of this investigation was to determine time-dependent workload patterns for ED physicians across work shifts and to demonstrate how ED demand patterns and the timing of shift changes influence the balance of workload among a physician team.

2. Levin S, France DJ, Hemphill R, Jones I, Chen K, Rickard D, Makowski R, Aronsky D. Tracking Workload in the Emergency Department. *Hum Factors.* 48(3):526-539, 2006.

   The objective of this study was to create a methodology for measuring transient levels of physician workload in the ED.

3. France DJ, Levin S. System Complexity as a Measure of Safe Capacity for the Emergency Department. *Acad Emerg Med.* 13:1212-1219, 2006.

   System complexity is introduced as a new measure of system state for the ED. In its original form, the measure quantifies the uncertainty of demands on system resources. For application in the ED, the measure is modified to quantify both workload and uncertainty to produce a single integrated measure of system state.

The preliminary work summarized above was not the major focus of the doctoral research; however it was a necessary step in accumulating knowledge essential to this research. Studying ED physicians and nurses in their work environment was a valuable process that provided information about the challenges ED providers must overcome to deliver high quality care. It was also necessary to understand the ED information technology (IT) infrastructure and how providers and researchers may use it. Most importantly, valuable insight was gained about how the ED interacts with the rest of the hospital. The ED-centered studies were necessary in developing a focus for a research project that would improve the quality of ED patient care.

Surprisingly, the quest to apply systems engineering skills to improve the ED led to the hospital. The hospital claims a major stake in how safe and efficient the ED functions. Developing a simulation tool to study the effects of changes to hospital operations on the ED would be unique, relevant and useful. This doctoral research focused on the relationship between the ED and the Division of Cardiology. A large number of patients pass through this interface, making the relationship pertinent to both parties. In addition, cardiac patients require timely care, which raises an interesting paradigm between safety and efficiency in health care systems.

The research presented in this dissertation focuses on modeling patient flow through a hospital macro-system and determining how it affects access to ED patients. A patient flow modeling strategy was developed to quantify and prospectively analyze the relationship between the ED and Cardiology. First, the three specific aims of this research are outlined. Then background is provided on the state of emergency medicine and the promise of systems engineering tools to improve the safety and efficiency of health care. A section describing hospital data collection, merging and verification follows. Then each specific aim is explained in greater detail. Each aim is presented as a stand alone manuscript per graduate school requirements. Thus, some overlap exists between manuscripts. A conclusion section follows the three manuscripts which provides a general interpretation of all of the doctoral research, including the preliminary work. Future work is then described, followed by the appendix.

CHAPTER II

SPECIFIC AIMS

I. Stranded on Emergency Isle: Modeling Competition for Cardiac Services Using Survival Analysis

The objective of this specific aim was to use survival analysis to determine how demand from competing cardiology admission sources affects access to ED patients requiring inpatient cardiac care. The model incorporates bed management policies of the division of cardiology and demonstrates how variability in demand for cardiac services (i.e., surgical, catheterization, telemetry, intensive care) affects ED boarding time for cardiac patients.

II. Optimizing Cardiology Capacity to Reduce Emergency Department Boarding: A Systems Engineering Approach

The objective of this specific aim was to demonstrate how ED boarding can be minimized by optimizing inpatient capacity and reducing bed blocking practices during peak times of ED-to-hospital patient outflow. A discrete event simulation (DES) was developed and used to recommend outpatient scheduling changes and bed management policies that will reduce ED boarding. These low-cost changes are compared to high-cost capacity increases to demonstrate how capacity increases should not precede capacity optimization.

III. Simulating Competition for Hospital Admissions: The operating room versus the emergency room

The objective of this specific aim was to determine how projected increases in surgical patient volume will affect ED patient access to inpatient cardiac services. A secondary aim was to prospectively evaluate how strategies to increase inpatient throughput can improve ED patient access or accommodate increases in surgical volume. A DES using survival analysis regression was created to characterize patient flow and model competition for hospital admissions. The simulation demonstrates how interventions to increase throughput or add capacity will have the most significant effect on the highest priority (surgical) patients.

CHAPTER III

BACKGROUND AND SIGNIFICANCE

State of Emergency Medicine

Emergency Department Crowding Causes and Effects

Modern emergency medicine has reached a critical stage due to a variety of inter-dependent forces that threaten the EDs' ability to administer timely, safe and cost-effective patient care. Steadily increasing demand for hospital services has been met by reductions in hospital system capacity creating an imbalance that has fallen on to the shoulders of EDs nationwide.[1,2] Hospital admissions have risen 13% and ED visits have risen 26% from 90.3 million to 113.9 million annually between 1993 and 2003. Over this same period the United States (US) has lost 703 hospitals, 198,000 hospital beds and 425 hospital-based EDs.[2]

Heightening demand has been proposed to be a result of the growing US population along with other economic and legislative factors that have rendered EDs the primary source of health care for large US populations that are either uninsured or beneficiaries of Medicaid.[2] The concurrent decrease in capacity has been a result of cost reduction strategies and lower reimbursements by managed care, Medicare and other payors. The effects of inadequate capacity are being intensified by our aging, sicker population that consumes more ED resources for longer periods of time. In addition, EDs have access to a wide range of expensive medical evaluation tools, which may not be available to local providers or health care clinics. This has led to specific patients opting to seek care at local EDs and primary care physicians referring patients to EDs in order to consolidate the medical testing process.[2] The ED is not optimally designed to treat patients using the ED as a primary source of health care. These less acute patients crowd the ED and often experience long wait times because they are of lower clinical priority than more critically ill patients.

The direct consequences of the public demand and hospital system capacity disparity faced by EDs nationally are crowding, inpatient boarding and ambulance diversion.

1. *Crowding* is defined as a situation in which the identified need for emergency services outstrips the available resources in the ED.[3] Results of a national survey conducted in 2002 found crowding to be prevalent in academic, private, urban and rural EDs. 91% of EDs surveyed reported crowding as a problem, while 39% reported periods of daily crowding.[4]

2. *Boarding* refers to holding patients who have been admitted to the hospital in the ED until an inpatient bed becomes available. The ED doorways must always remain open, thereby forcing EDs to absorb the excess demand of the entire hospital system when access to inpatient care becomes blocked.[2]

3. *Ambulance diversion* is a result of crowding in which EDs are determined to be completely full or unsafe to care for additional ambulatory patients. During these time periods, ambulances are diverted away from crowded EDs and sent to other health care locations better able to manage the patient en route. However, while an ED is on diversion, patients who present by other modes of transportation must be assessed and treated.

The overlapping effects of crowding, boarding and ambulance diversion have forced EDs to operate sub-optimally. The pressures that the ED system face are filtered to health care providers that work in this environment daily and may result in decreased quality of care.[2]

The ED is notorious for being a stressful, chaotic and unpredictable environment. When the fluctuant nature of the ED is coupled with punctuations of high-risk time-critical activities there is an increased likelihood that serious consequences may result for both the providers and patients. Crowding only exacerbates these circumstances. Several studies have documented how the nature of Emergency Medicine (EM) negatively affects physicians, nurses and clerical staff.[5-14] Occupational stress and depression among emergency medicine physicians are extremely high in comparison with other medical specialists.[11] High rates of burnout and stress are known to contribute to the relatively high levels of projected attrition within the specialty.[5] In a population of pediatric emergency physicians from 37 separate departments, it was found that only 22% believed they could practice pediatric emergency medicine after the age of 50.[10]

This environment is having a similar effect on the nursing and clerical staff as well.[14] It is a clear and general consensus that the ED setting has a profoundly negative impact on its workforce.

Understanding the association between ED crowding and adverse patient outcomes has been a more complex task. However, evidence is emerging to substantiate this linkage. Several studies have demonstrated the impact of crowding on specific processes that are known to determine patient outcomes. Schull et al. measured an association between ED crowding and increased door-to-needle time for thrombolysis patients suspected of acute myocardial infarction (AMI).[15] Several independent studies linked ED crowding with poorer performance on pneumonia quality of care measures.[14,16-18] In two separate studies Hwang et al, and Pines and Hollander found that an increase in ED patient census was significantly associated with poorer pain management.[19,20] More general and contentious studies have demonstrated a direct association between ED crowding and increased mortality rates.[21,22]

A separate body of literature focuses on the human aspect of ED health care delivery. Several publications address the prevalence of human error in emergency medicine.[23-25] A highly influential report released by the Institute of Medicine (IOM) entitled *To Err is Human: Building a Safer Health System* estimated that between 44,000 and 98,000 patients die of iatrogenic injury annually. The ED has been specifically identified as a location where adverse events are highly likely to be attributable to error. Studies estimate that the proportion of ED adverse events deemed preventable are between 53 and 83 percent in comparison to the overall estimates of 27 to 51 percent for hospital-based events.[23] Despite these ominous circumstances EDs continue to be effective, which is attributable to the scores of ED staff that painstakingly do their job well.

Emergency Department Throughput

External factors which drive demand for emergency services remain beyond EDs' control. However, there are several internal tools and process design changes that have been used to manage crowding and improve ED throughput. Prior to describing these techniques it is necessary to understand patient flow through the ED. Asplin et al. created a conceptual model in Figure 1 which partitions ED crowding into three separate, but dependent components: input, throughput and output.[1] The model uses operations management concepts to identify the acute care sub-system components that contribute to or are affected by ED crowding. Following the creation of the conceptual model a group of 74 experts was convened by the American College of Emergency Physicians to develop crowding measures which are categorized by input, throughput and output.[26] Input measures capture patient demand, complexity and ED capacity. Throughput measures capture ED efficiency and ED workload. Output measures assess hospital efficiency. These measures guide data collection and provide national standards of measurement reporting that may be

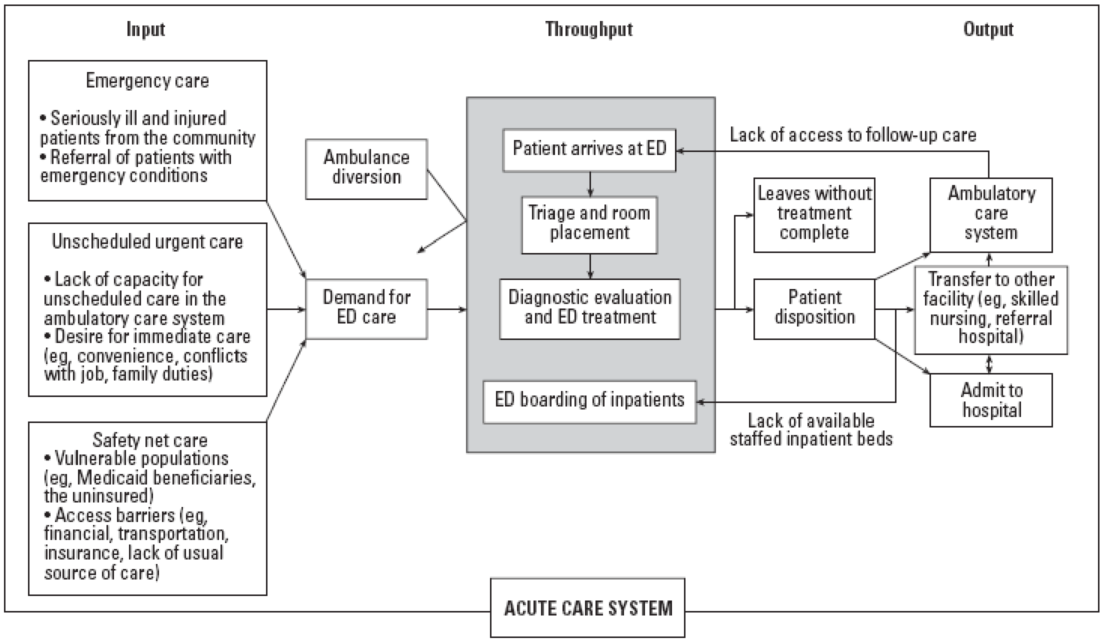

Figure 1. ED crowding conceptual model[1]

used to assess ED operations. These measures may be used within each ED to evaluate interventional strategies. They are also standardized to facilitate comparison between separate EDs.

The demand for emergency services comprises the input to the model. Demand for emergency services is an environmental factor that is beyond the ED's control. Demand (input) must be effectively managed by processes which encompass the throughput portion of the model. Throughput represents only the internal ED patient care processes. Several broad barriers to ED patient throughput have surfaced within the emergency medicine literature and were summarized in the IOM's 2006 *Hospital-Based Emergency Care: At the Breaking Point*. These barriers include, but are certainly not limited to:

1. *Ancillary service delays* – Delays in diagnostic and screening tests are strongly associated with patient length-of-stay (LOS). An Emergency Nurses Association survey reported that radiology and laboratory test turn-around times account for one half of all ED service delays.[2,27,28]

2. *Defensive medicine* – A rise in medical malpractice claims within the ED has led to a defensive approach to providing care. Physicians have access to a wide range of medical evaluation tools within a confined space, thus are more likely to be blamed for missing a diagnosis if not all resources are used. Fear of litigation may lead to ancillary service overuse and prolonged monitoring periods which hinder patient flow.[2]

3. *Inadequate physical space* – ED providers face constraints in the amount of physical space available to care for patients. Patients are often treated in hallways and other areas not specifically designed for patient care. Providers often encounter user-unfriendly spatial layouts and equipment design.[27,29-31]

EDs alone may only improve throughput and have done so using the tools and process re-designs listed below:

1. *Fast tracks* – An area designed to care for patients with minor illnesses or injuries. Fast tracks operate in about 30% of all EDs and approximately 30% of patients are routed through fast track care pathways.[28,32]

2. *Zone nursing* – A system where all of a nurse's patients are located in one area, thus eliminating the need for nurses to travel long distances during their shift.[28,32]

3. *Bedside registration* – Patients are quickly triaged and placed in a bed where they are seen by a physician. A staff member uses a mobile computer to officially register the patient.[2]

4. *Team triage* – A physician or physician assistant is located within a triage area in order to quickly treat and discharge patients with minor illnesses and injuries.

5. *Admission / Discharge Units* – Separate admission / discharge units that do not share resources with the ED effectively expand capacity and lead to better patient flow.[2]

6. *Information technology (IT)* – IT improve efficiency in a variety of ways by providing; electronic health records, patient tracking and ED system operations information, triage assessment tools, etc.

The Vanderbilt University Medical Center (VUMC) ED incorporates a fast track, zone nursing scheme, team triage and information technology solutions to increase throughput. These tools have proven to increase efficiency; however there are several obstructions to their successful implementation. Complex cost and revenue management issues as well as inter-departmental battles for resources usually hinder the implementation of these techniques.[30] Using these tools internally may alleviate some symptoms of crowding however they will not fully address the demand and capacity disparity that plagues the entire hospital system. Output barriers play a vital role in ED throughput.

Emergency Department Boarding

Output factors are noted as the most significant cause of ED crowding.[33] Many of the earliest studies that analyzed ED crowding were focused on the number of ED arrivals (input) as drivers of ED throughput and ambulance diversion. A recent study by Rathlev et al, measured the association between ED LOS and standardized input and output factors. Output factors such as hospital occupancy, the number of elective surgical admissions and the number of ED admissions were the only factors associated with ED LOS.[34,35] A related study by Litvak and Long found daily variability in surgical caseload to be the single most important contributor to ED diversion.[36] Schull et al, reported similar results when finding that the number of boarded patients was the most important determinant of ambulance diversion.[35] These studies and others have concluded that efforts to reduce crowding should be directed toward output factors involving the hospital.

The strongest output barrier is restricted access to inpatient hospital beds.[1,2,4,26,27,35,37-40] This has created a boarding epidemic across the nation. A Government Accounting Office study found that 90 percent of hospitals boarded patients at least 2 hours and 20 percent of these hospitals reported an average boarding time of 8 hours.[41] In comparison, Vanderbilt admitted ED patients are boarded an average of 4.5 hours, however the admission rate is significantly higher at 27% compared to the national average of 13%.[42] The Vanderbilt ED spends much of its resources caring for boarded patients. Over May 1, 2006 to May 1, 2007 the Vanderbilt ED spent 23% of total patient care hours tending to boarded patients. Dale et al conducted a study on Vanderbilt ED nurses and found that boarded patients constituted 32% of the patients studied and 38% of nursing workload. Nurses spent 43% of their patient care time (direct and indirect) performing tasks for boarded patients.[43] Boarding places a large burden on the EM system compromising both safety and functionality.

Boarding creates hazardous conditions for other patients present in the ED. It has been established that the most important cause of ED crowding is boarding. Therefore, boarding is responsible for most all of the previously mentioned effects of ED crowding. However, Pines et al, measured a direct relationship between boarding and patient outcomes. In an acute coronary syndrome (ACS) patient population, a positive association was measured between 30 day re-hospitalization rate and the number of boarded patients present in the ED.[44] The hypothesis was derived from the fact that boarded patients demand a lot of attention as a result of their clinical complexity and severity of illness. These patients require a constant level of on-going care, which is why they require further treatment in inpatient settings.[45-47] These patients compete for resources that are intended for evaluating and stabilizing incoming emergency patients. This relationship between human resource attention and outcomes was also discovered at the University of Pennsylvania. Fishman et al. demonstrated that ACS patients presenting during labor intensive trauma activation procedures were at increased risk of experiencing 30 day cardiovascular complications.[48] When attention is diverted from incoming patients, safety is threatened. Boarding creates this phenomenon in the ED on a daily basis. In addition, boarding jeopardizes safety for potential patients by contributing to ambulance diversion and inadequate surge capacity.[2,36]

Boarding is unsafe for the boarded patient as well. The ED is not optimally designed to care for these patients.[2] ED nurse staffing levels are particularly inadequate. ICU nurses are assigned at most 2 patients compared to ED nurses that may be assigned up to 10 patients.[49] Nurse to patient ratio has proven to be critical. In hospital care, increasing nursing patient load above 4 patients has been associated with a 7% increase in 30-day mortality rate and a 7% increase in the odds of failure-to-rescue per additional patient.[50] Other studies have shown a direct linkage between boarding and patient outcomes. A secondary analysis of data from an observational registry (Can Rapid Risk Stratification of Unstable Angina (UA) Patients Suppress Adverse Outcomes with

Early Implementation of the American College of Cardiology (ACC) / American Heart Association (AHA) Guidelines, CRUSADE) showed that boarding worsens outcomes for cardiac patients with non-ST-segment-elevation myocardial infarction. ED LOS for these patients was associated with a decreased use of ACC/AHA guideline recommended therapies and a higher risk of recurrent myocardial infarction.[51] Other literature discusses the impact of boarding critically ill patients admitted to an intensive care unit (ICU). The ED is responsible for their initial care phase which has been found to most significantly impact the progression of organ failure and mortality for these patients.[52] Boarding these patients in a non-ICU setting could cause treatment delays at a pivotal point in the hospital course, potentially resulting in poor outcomes.[45-47]

Boarding is a non-value added step in the health care process that compromises the patient's hospital experience, adds stress to ED providers and increases the likelihood of medical errors, delays in treatment and diminished quality of care.[2] This has lead to the US IOM mandate for hospitals to end the practice of boarding patients except in the most extreme circumstances.[2] Hospitals across the US must strive to minimize boarding time for all ED admitted patients.

Cardiovascular Disease in the Emergency Department

Nearly 80 million American adults have one or more types of cardiovascular disease (CVD). Approximately 1 of every 2.8 deaths is attributable to CVD.[53] AMI is the particular CVD that claims the most lives.[54]

Nearly 1.2 million Americans will suffer a new or recurrent coronary attack each year, and 335,000 individuals will die in the emergency room or before ever reaching a hospital. Chest pain prompts over 5 million ED visits and is the second highest principal reason for arrival. AMI results in more than 1 million hospitalizations annually and CVD ranks the highest in hospital discharges.[53,55,56] Cardiac patients comprise a large proportion of demand for both emergency and hospital services.

Many of these patients begin a patient care pathway that starts in the ED. Initial risk assessment and treatment in this setting is extremely time sensitive. A large number of randomized clinical trials during the 1990s concerning the management of CVD have led to numerous new diagnostic tools and treatment strategies. In light of these new data, the ACC and the AHA have developed clinical practice guidelines to provide standards for ACS diagnosis and treatment and to construct an evidence based framework for clinical decision making.[57-62] Accompanying these guidelines are several time-dependent performance measures, both for initial and re-occurring evaluation and treatment. The time sensitive nature of cardiac patient care in the ED makes this population particularly vulnerable to the threats of crowding. The aforementioned studies by both Pines et al and Dierks et al support this.[44,51] In addition, AMI risk assessment and management is one of the most complicated tasks ED physicians must undertake. The leading cause of malpractice claims in the ED result from missed myocardial infarctions , yet excluding the possibility of an AMI or other CVD requires a minimum of 6-12 hours of evaluation and diagnostic tests costing more than a thousand dollars.[2] Patient safety and ED efficiency are strongly connected on the ED cardiac care pathway.

Systems Engineering Tools to Improve the Quality of Health Care

The health care delivery system in the US is complex and vastly segmented. The entire system is comprised of a large amount of sub-systems which serve specific purposes and have their own incentives and performance measures. Patients with a wide array of medical conditions must be guided appropriately down patient care pathways that may involve contact with numerous sub-systems, interactions with dozens of health care professionals and representation in many different information and communication technological systems.

The sub-systems are often tightly coupled and governed by linear and complex interactions. Charles Perrow describes tight coupling between two components of a system in a simple manner by stating, “what happens in one directly affects what happens in the other.”[63] Linear interactions are those that are familiar and quite visible, while complex interactions are those that are unfamiliar, unplanned and either not visible or not immediately comprehensible.[63] The high degree of dependency between sub-systems and the prevalence of complex interactions in health care reinforce the need for a systems approach to quality improvement.

Before discussing specific system engineering tools used to improve quality it is important to define “quality” within the health care arena. The IOM report, *Crossing the Quality Chasm: A New Health System for the 21st Century* describes six key dimensions in which today's health care system functions at far lower levels than it can and should.[64] The six dimensions are:

1. *Safe* – avoiding injuries to patients from the care that is intended to help them;

2. *Effective* – providing services based on scientific knowledge to all who could benefit and refraining from providing services to those not likely to benefit (avoiding underuse and overuse, respectively);

3. *Patient centered* – providing care that is respectful of and responsive to individual patient preferences, needs, and values and ensuring that patient values guide all clinical decisions;

4. *Timely* – reducing waits and sometimes harmful delays for both those who receive and those who give care;

5. *Efficient* – avoiding waste, including waste of equipment, supplies, ideas, and energy;

6. *Equitable* – providing care that does not vary in quality because of personal characteristics such as gender, ethnicity, geographic location, and socioeconomic status;

System engineering techniques will be most effective if they are used to evaluate and then improve health care with respect to one or more of these dimensions.

System engineering tools have been developed to aid in the analysis, control and design of large complex systems. These tools focus on the objectives of an entire system and how each element performs and interacts with the rest of the system in order to complete the overall system goals. Many of the mathematical tools of systems engineering developed from operations research, which was a discipline that evolved in World War II to study complex operational problems. Systems engineering techniques which have been used to make great improvements in other industries are now being introduced into the health care sector. The National Academy of Engineering (NAE) and the IOM have recommended the use of systems engineering tools to improve health care with respect to the six quality aims, however little has been done to date. [65-67]

The system engineering tools that are relevant to the doctoral research including the preliminary work are listed below:

1. *Human factors engineering* – a field of study concerned with the interaction of humans with the tools, machines and systems that make up their work environment;

2. *Variability analysis* – using operations research tools to identify causes of variability in order to develop strategies to control “natural” variability and eliminate “artificial” variability;

3. *Queuing theory* – the mathematical study of wait lines;

4. *Discrete event simulation* – modeling the behavior of a system so that the behavior of the system imitated may be understood under specific conditions.

Specific components of these techniques will be discussed in further detail as appropriate. Integrating these tools to study the EDs role in the entire hospital system represents a systems approach to understanding health care processes and how they may be improved to better manage excess demand.

Human Factors Engineering

Human factors engineering encompasses a plethora of techniques aimed at studying how humans behave psychologically and physically in relation to particular environments, products or services.[68] Human factors engineering is applicable to the design or redesign of systems that include a human interface. The multi-disciplinary field draws from work conducted in cognitive psychology, engineering, computer science, sociology, anthropology, and artificial intelligence. The human factors engineering techniques used in the preliminary work involve time-in-motion task analysis and subjective workload assessment.

Time-in-motion task analysis includes any means of assessing what actions a human subject performs and why these actions are being performed. Task analysis methods involve "the structured decomposition of work activities or decisions and classification of these activities as a series of tasks, processes, or classes."[69] This method is commonly performed by direct observation. Observation requires an informed observer to "shadow" a subject and systematically record the time and duration of specific tasks as they are performed.

Subjective workload assessment techniques require a subject to rate or distinguish a level of workload required to perform a specific task. The subject may also be asked to rate his/her own workload at an instant in time. Subjective workload assessment techniques are frequently used because of their high face validity, ease of use, subject acceptability, low cost and known sensitivity to workload variation. Among the various methods of subjective workload assessment, the National Aeronautics and Space Administration (NASA) Task Load Index (TLX) is a popular and validated tool that was used within preliminary research. This workload assessment technique uses pair wise comparisons as well as a multidimensional bipolar rating scale to ultimately compile an overall workload score for an operator performing a specific task. Workload is associated with six major factors: mental demand, physical demand, temporal demand, effort, performance, and frustration level. It is well validated and extremely successful in reducing inter-rater variability.[69-71] The technique's multidimensional nature provides valuable diagnostic information about sources of workload and helps facilitate the rater's ability to assess workload.[69,70] The technique can be quickly administered as well, rendering it a potentially useful and feasible tool in medicine. Time-in-motion task analysis and subjective workload assessment via the NASA-TLX are the human factors tools used to study emergency medicine physicians within the ED.

Variability Analysis

Variability in demand challenges the ability of a service to be distributed efficiently.[39] The health care service industry is expected to be able to accommodate peaks in demand while operating efficiently and cost effectively during periods of down time. The variability that plagues a complex segmented system such as a hospital must be eliminated or effectively managed in order for the system to be efficient and safe.

Litvak and Long have separated the concept of hospital variability in to two components; natural and artificial variability.[72] Natural variability forms an umbrella for clinical variability, demand variability and professional variability. Clinical variability comprises the wide range of illnesses a patient might have. The level of severity within a specific illness also contributes to clinical variability. Patient demand variability involves the arrival rate (as in queuing theory) and LOS of patients in need of service. Professional variability recognizes the variability in professionals' ability to treat patients within and across health care settings. “The constant challenge to the health care system is to efficiently convert a naturally variable incoming group of sick patients into a homogeneous outgoing stream of well patients.”[72] The ultimate goal is to optimally manage natural variability, but an unfortunate consequence of sub-optimal management is the introduction of another form of variability.

Artificial variability is unpredictable and driven by competing interests among inter-dependent system components, sub-optimal management practices and a myriad of other poorly understood factors acting within a hospital.[72] It is unnecessary and leads to decreased efficiency and excess cost. The most cited example of artificial variability involves the variation of daily bed occupancy of inpatient wards.[39,72] Managing the demand for beds is thought to be challenging because of the natural variability of patient flow through physician offices or the ED. Unexpectedly, typically 80% of variation in demand for inpatient beds comes from operating rooms. The artificial variability created by electively scheduled daily surgical caseloads has been known to swing up to 50% on the same day of the week.[72] McManus et al. showed a higher association between scheduled caseload and ICU diversion than unscheduled patient volume and diversion.[39] High occupancy inpatient wards such as the ICU have significant downstream effects on the ED. Litvak contends that, “the single most important factor contributing to ED diversion is the daily variability in the operating room elective surgical caseload.[36] Smoothing demand for inpatient services by eliminating artificial variability has proven to improve patient flow and decrease the peak stress levels placed upon hospital sub-systems and staff.[73] It is important to understand the sources of natural and artificial variability inherent to a health care system before it may be effectively managed.

Queuing Theory

Queuing theory is a science which uses mathematical tools to understand waiting lines or queues. These tools are able to characterize queuing systems in which entities (i.e. patients, laboratory specimens, etc.) flow through a system. A simple example may involve a customer arriving for a service, then waiting for the service, eventually being processed through one or more services channels and eventually departing. Queuing models are based upon three important variables of the queuing system: the arrival rate (λ), the service time (τ), and the number of servers (c).[74,75] The arrival rate is a distribution of inter-arrival times, which in an unscheduled environment is often described by an exponential distribution.[76] Service time is a similar distribution of the time an entity spends being processed at a specific station or server. A critical measure in queuing theory involves the ratio of average arrival time to average service time for a single server. (equation 1)

$$\rho = \frac{\lambda}{\tau} \qquad (1)$$

This ratio (ρ) may be considered a measure of congestion or traffic intensity for the server being measured.[74] When (ρ) > 1, the queue for the server is growing and conversely when (ρ) < 1, the queue is decreasing and in steady-state. When

(ρ) = 0, the server is being utilized optimally (100%) while remaining in steady-state. The fundamentals of queuing theory, although simple, have the power to answer very complex questions involving flow systems such as a hospital.

Queuing methods have been applied to problems in most service industries but have yet to become commonplace in health care. On several occasions the use of queuing in health care has been demonstrated. McManus et al. and Gorunescu et al. created queuing models to characterize the effects of fundamental queuing measures on the probability of a patient being rejected admission to the ICU and geriatric medicine department respectively.[77,78] Kim et al. took this further by using queuing measures to analyze how surgical scheduling practices and bed allocation schemes may be improved to reduce the number of cancelled surgeries due to ICU bed unavailability.[79] Green et al. developed a queuing model to create a staffing schedule which would optimize the timeliness of care for ED patients.[80] The staffing model was implemented and the number of patients leaving without being seen (surrogate measure of timeliness of care) was reduced. Reinus et al. and Shreyas et al. used queuing theory to study and optimize the schedules created for computer tomography and ultrasonography resources.[81,82] Results of several of these studies have demonstrated models which are highly sensitive to input changes. Thus, small changes in fundamental queuing measure inputs may result in large changes in outcome variables (i.e. rejection rate of ICU admissions). The quantification and characterization of the independent queuing systems in health care have potential to provide valuable and highly detailed information about scheduling and capacity utilization of resources and how they may be optimized.

Discrete Event Simulation (DES) Principles

DES is a method of developing a stochastic model of the behavior of a system. The state of the system at a point in time is described by the values of model variables. Dynamic behavior of the system may be observed by tracking the model variables over time as entities (i.e., patients, staff, laboratory orders, etc.) pass through the system to and from nodes where processing events occur. The rules governing the motion of entities, and the variables that are being collected are what make up the model. Rules which describe human-machine systems must often be based on probability theory. The process of building a DES or any simulation model involves an iterative process of verification and conceptual and mathematical validation to ensure that it is an accurate representation of the real world.

The relationship between verification and validation in the real world and simulated world is linked by systems theories shown in Figure 2.[83] In a real world system, knowledge and understanding about a system or problem entity is desired. Systems theories describe the characteristics and behavior of the system. The real world system is measured to provide system data and experiments may be conducted to gather system results. Systems theories are developed by abstracting what has been observed from system data and by hypotheses generated from experimental system results.

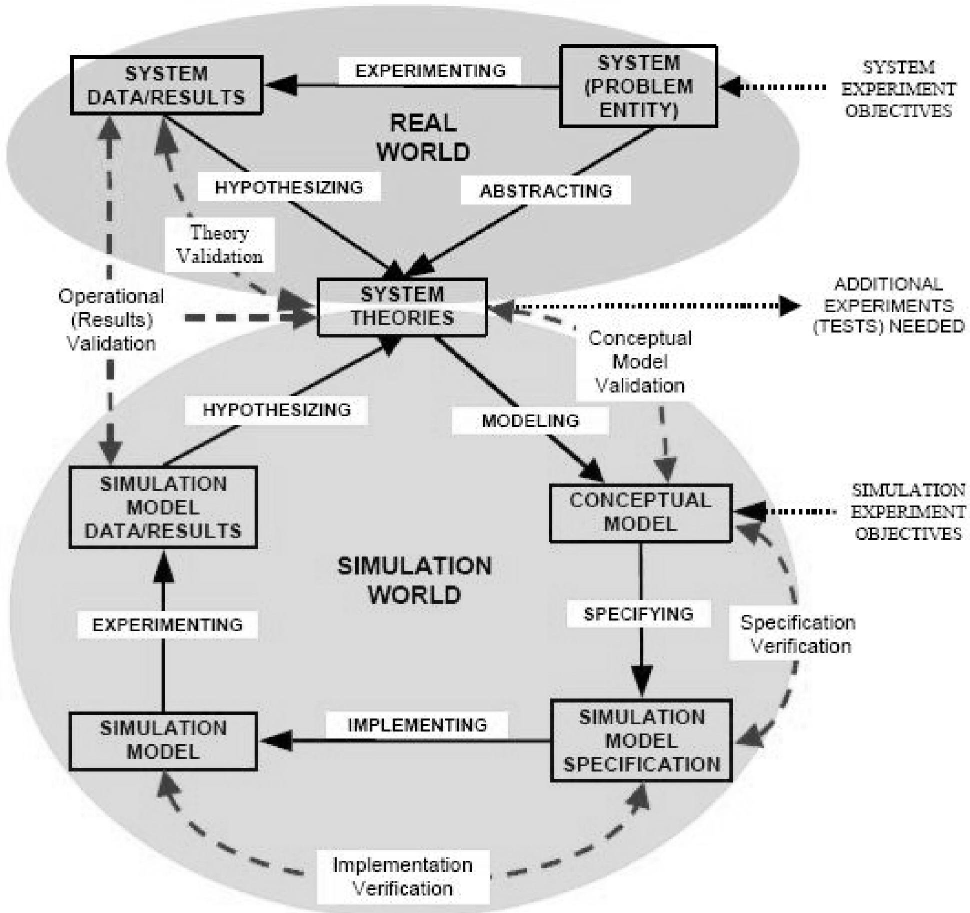

Figure 2. Real world and simulation world verification and validation relationship[83]

System theory validation involves comparing system data to system theories to determine if there is agreement. This process requires that many experiments be conducted on the real system which is impractical in a health care setting. This is where simulation is valuable.

Simulation may be used to hypothesize system theories through experimentation separate from the real world system. The first phase in the process involves creating a conceptual model of the system. The conceptual model is the mathematical and logical representation of the system in relation to the particular objectives. The following simulation model specification phase involves describing how the conceptual model will be implemented on a computer system. This includes decisions about software and programming languages. The simulation model, which is the conceptual model in operation on a computer platform, is then created using an implementation verification feedback loop. Experimentation may then be conducted to render simulation model data and results.

Verification and validation procedures are on-going throughout the development process. Implementation verification is an important step in accurately transforming the conceptual model to a representative simulation model. When a simulation language is used, implementation verification is concerned with ensuring that; (1) the simulation language is error free, (2) the simulation language has been properly implemented on the computer, and (3) that a pseudo random number generator has been properly implemented. There are two basic approaches to verifying the simulation software: static testing and dynamic testing.[83,84] Static testing is conducted by structured walk-throughs, correctness proofs and examining structural properties of the program. Dynamic testing involves observing the simulation under different conditions. Techniques such as, dynamic testing traces, degenerate tests, animation examinations, investigations of input-output relationships, internal consistency checks and component re-programming are dynamic forms of verification.

Validation may be broken into three types: input data validation, conceptual model validation and operational model validation. Data validation is not often associated with simulation model validation, however it is usually one of the most difficult, costly and time consuming steps involved in creating a simulation model. Real system data is needed for building the conceptual model and operationally validating the model. This data must be accurate and sufficient in quantity to develop system theories used to develop the model and to capture the problem entity. Real system input and output data should be checked for consistency, screened for outliers and otherwise scrutinized to ensure that it is accurate. Conceptual model validation is an iterative development procedure used to determine that the theories and assumptions underlying the conceptual model are consistent with the real world system theories. This validation process is also responsible for ensuring that the model's representation of the problem entity and the model's structure, logic and mathematical causal relationships are "reasonable" for the intended purpose.[83] Operational validity involves comparing output behavior from the simulation model and real system. Measures must be in agreement at the level of accuracy that is required for the intended purpose.

There are numerous techniques that are used for simulation model validation. These methods are listed below and may apply to one or more types of model validation.

1. *Sensitivity analysis* – Also called parameter validation, this method consists of changing input parameters to determine the effects on output behavior.

2. *Predictive validation* – Model-forecasted system behavior is compared to actual system behavior to determine if they are in agreement.

3. *Cross validation* – If sufficient historical data exists, system data are split in to training and testing sets. The training set is used to build the model and the testing set is used to determine whether the model behaves as the system does.[83,85]

4. *Internal validation* – Numerous replications (runs) of a stochastic model are made to determine the amount of internal stochastic variability. Results may be used to determine the number of replications and appropriate run lengths needed to generate consistent outputs.

5. *Extreme conditions testing* – The model must be structured so that output behavior is realistic under any extreme and unlikely combination of circumstances simulated.

6. *Face validation* – Simply asking individuals who are knowledgeable of the system whether model logic and behavior are reasonable.

7. *Turing tests* – Asking knowledgeable individuals whether they can discriminate between real and simulated outputs.[83,86]

Model verification and validation are necessary in creating a DES that accurately describes the performance of the real system with an acceptable degree of accuracy. The verification and validation techniques described are general means of assessing this accuracy.

Discrete Event Simulation (DES) in Health Care

The majority of previous DES research in health care has three major overlapping focuses: (1) conducting sensitivity or performance analysis on patient throughput, (2) researching the effects of process changes on patient throughput, and (3) determining optimal staffing schedules.[76,87-97] To our knowledge, none have focused on the relationship between two sub-systems in a hospital. Several previously conducted DES studies in health care are described below. Baeslar et al. developed a DES to predict the maximum demand that the ED is able to handle without increasing average wait time over an acceptable threshold.[87] ED simulation has been used to test the impact of different triage methods or to research the effects of implementing a new fast track lane.[89,91,94] Other studies have focused on determining appropriate staffing levels and staffing schedules that will optimize staffing resource utilization and allow the system to still perform at a predefined level.[76,90,92,96] Accurate DES is a tool that may be quite valuable in probabilistically modeling socio-technical systems in order to understand how a system performs and may respond to changes.

Systems Engineering Integration

The systems engineering tools discussed in this dissertation are useful in dissecting the inner-workings of large tightly-coupled systems such as health care. The tools may be used to understand what drives performance within these systems. Human factors engineering focuses on the assessment of performance at the human-system interface. Performance assessment involves studying how a system should be designed or re-designed to cooperate with operators, maximize their productivity and prevent accidents. Queuing theory, variability analysis and DES analyze the performance of the system at a higher level. These tools are designed to measure demand patterns and consider how health care resources process this demand. These techniques become especially effective when heightened demand challenges a system's capacity.

The system engineering tools outlined in this research have been used to create highly reliable safe and efficient systems in manufacturing, transportation, nuclear power, telecommunications and finance.[66] Success in other industries has prompted the IOM and NAE to recommend applying these methods from engineering and operations management to improve the safety and efficiency of health care.[66] The doctoral research presented is in direct response to this recommendation.

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CHAPTER IV

DATA COLLECTION AND VERIFICATION

Data used for each specific aim and the preliminary work was collected from various VUMC clinical information systems. The information systems are listed below along with a brief description.

1. The *Emergency Department Electronic Whiteboard Information System* (EDWIS) is a patient tracking system that is available for ED staff via clinical workstations and a 60 inch plasma touch sensitive screen located within the adult ED. The system tracks ED process times (registration time, time to bed, disposition decision time, discharge time) and is used to look up clinical data and update patient care information through links to StarPanel, WizOrder and Order Tracker.

2. *StarPanel* is Vanderbilt's electronic medical record system. It integrates patient data from various information systems throughout the hospital. This includes lab results, radiology reports, discharge summaries, anatomic pathology, and physician notes.

3. *WizOrder* is Vanderbilt's computerized care provider order entry system. WizOrder is used at the point of care in the ED to order laboratory studies,

radiology studies, medications, etc. The order times within the system are time stamped according to when they are entered.

4. *Order Tracker* is an information system used by ED nurses to document the status of orders. When the nurse performs the order they document it at a clinical workstation located in each emergency room. All order documentation is time stamped.

5. *Vanderbilt Perioperative Information Management System (VPIMS)* brings electronic charting and data analysis capabilities to surgical patient care at Vanderbilt. The system is designed to provide documentation and management tools to care providers involved in perioperative care. Surgery schedules and start and complete times will be collected from this system.

6. The *Medipac Admit/Discharge/Transfer (ADT) Database* records the times in which patients are admitted, discharged or transferred. Arrival times are recorded for admits and transfers and departure time is recorded for discharges. The location the patient arrives from or goes to is simultaneously reported. Cardiology patient flow is tracked through the ADT database.

7. *Bed Board* tracks the status of beds (i.e., available, occupied, needs clean) in the VUMC hospital units. Bed board is used by hospital administrators and bed management personnel to assess available capacity. The system tracks patient census over time and stores this information in a local database on an hourly basis.

Raw operational data collected from the various systems was cleaned, verified, merged and formatted into a single research table using Matlab™ software. This process may be seen in Figure 3. The first step involved downloading data from the Vanderbilt information systems to a local research

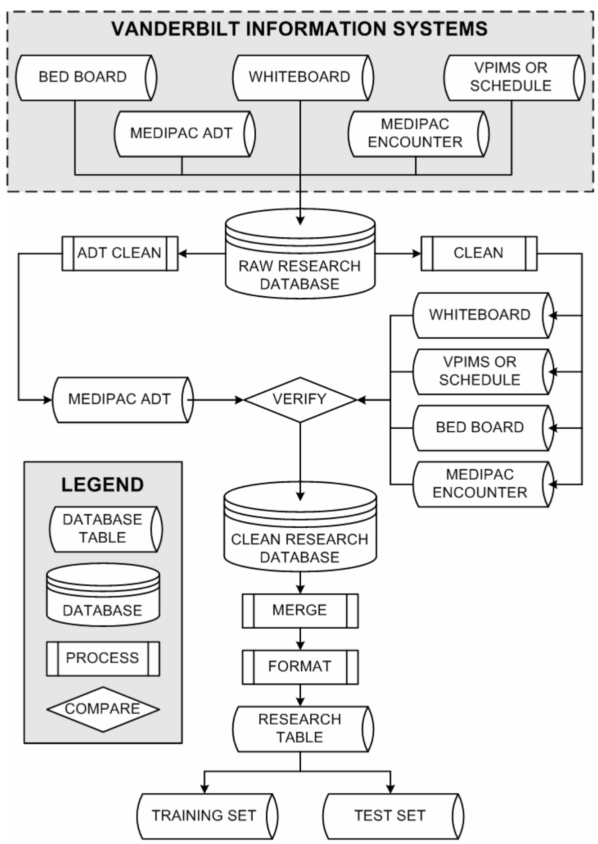

Figure 3. Vanderbilt University information system data flow

database. The data tables were cleaned using executable files. Corresponding information from each of the tables were compared to assess accuracy and reliability. This was not always a direct comparison. For example, the ADT table which captures each patient's movement through the hospital system was particularly important to verify. A program was written to clean and aggregate ADT information, then generate minute-by-minute census counts in the hospital locations modeled. The ADT censuses constructed were compared to the hourly censuses available in bed board. This process was done to assess the reliability of time stamped patient flow information coming from all systems. After the data from each table was verified, it was transferred to the clean research database. Executable files merged and formatted the data into one research table. The data was then split into training and testing sets. All operational information used within this research was pulled and processed from both training and testing research data tables.

Clinical information was extracted from, StarPanel, WizOrder and OrderTracker systems. StarPanel interacts with WizOrder and OrderTracker, thus all clinical information used within the study was collected from StarPanel.

CHAPTER V

STRANDED ON EMERGENCY ISLE: MODELING COMPETITION FOR CARDIAC SERVICES USING SURVIVAL ANALYSIS

Abstract

Patients with cardiovascular disease (CVD) consume a large proportion of inpatient, procedural and emergency services within United States health care system. These patients are major contributors to the steadily increasing demand for health care services nationwide. Unfortunately, economic and legislative factors have resulted in concurrent reductions in hospital system capacity. The resulting imbalance has fallen directly on to the shoulders of emergency departments (ED) in the form of boarding. Boarding refers to the act of holding admitted patients in the ED until an inpatient bed becomes available. Boarding is a barrier to efficient throughput, a major contributor to ED overcrowding and a threat to patient safety. Patients with CVD often use the ED as an entry point to the hospital system. These patients frequently experience long boarding times as a result of hospital wide competition for inpatient resources.

The objective of this study is to use survival analysis to determine how demand from competing cardiology admission sources affects access to ED patients requiring inpatient cardiac care. The model reflects bed management policies of the division of cardiology and demonstrates how variability in demand

for cardiac services (i.e., surgical, catheterization, telemetry, intensive care) affects ED boarding time for cardiac patients.

Introduction

CVD afflicts nearly 80 million Americans and is the leading cause of death in the United States.[1] Patients with CVD or symptoms of CVD demand a large proportion of hospital resources. Chest pain prompts over 5 million ED visits annually, and CVD ranks the highest of all disease categories in hospital discharges.[1,2]

Recent efforts and advancements in clinical medicine and medical technology have greatly improved the quality of CVD care for individuals. However, remarkably less effort has been devoted toward improving the efficiency and productivity of delivering health care to large populations.[3] Steady increases in demand for health care and the system's limited ability to adapt have created a crisis, making the efficient distribution of health care resources more important than ever. The results of these circumstances are most evident in the ED, which serves as an initial health care system entry point for many patients with CVD.

Various financial incentives and legislative factors have channeled excess hospital system demand in the direction of EDs nationwide. Excessive boarding has been a direct consequence. Boarding refers to the process of holding hospital admitted patients in the ED until an inpatient bed becomes available. Boarding patients is a major cause of ED overcrowding, which leads to ambulance diversion, inadequate disaster surge capacity, and challenges ED providers' ability to administer safe and timely care.[4-7] Boarding patients is not only sub-optimal use of ED services that are designed to treat acute injuries and illnesses but may also be detrimental to the boarded patient. This is especially relevant for critically ill patients who may be more effectively treated in specialized inpatient settings.[4] In addition, these patients tend to be highly labor intensive, creating an environment where other patients may not receive adequate care from ED staff.[7] Boarding is a non-value added step in the health care process that compromises the patient's hospital experience, adds stress to ED providers and increases the likelihood of medical errors, delays in treatment and diminished quality of care.[6] Patients with CVD are particularly vulnerable within an emergency setting because of the time-sensitive nature of health care needed.[8]

Boarded patients compete for inpatient services with a variety of other patients coming from different locations within and outside the hospital. Current reimbursement structures place the lowest priority on ED admissions because they typically generate the lowest margins, resulting in less revenue as compared to other types of patients.[6] Thus, heightened competition from other admission sources combined with low priority status strands admitted patients in the ED for long periods of time.

Numerous studies and interventions have been designed to combat ED overcrowding by increasing throughput internally. These efforts have made an impact but are limited because they fail to address the hospital system in which the ED operates. ED overcrowding is a hospital-wide dilemma, yet few studies have addressed this from a hospital systems engineering vantage point.[3,9] The purpose of this study is to develop models that determine how the cardiac sub-system influences boarding in the ED. The models will be used to determine how demand from competing cardiology admission sources affects access to ED patients requiring inpatient cardiac care. The resulting models may also be used to predict expected boarding time for cardiac patients in the form of probability density functions.

Methodology

Cardiology System

The study was performed at an urban, academic, tertiary care hospital with a 73 bed cardiology division consisting of 47 telemetry beds, which provide specialized cardiac monitoring and 26 cardiovascular intensive care unit (CVICU) beds, which are designed to care for critically ill patients with CVD. The division of cardiology operates within the hospital system as shown in Figure 4. Patients flow in to the cardiology system from the surgical center, ED, catheterization laboratory, other locations within the hospital (e.g., outpatient clinic) and from outside the hospital. Patients may also flow between the telemetry and CVICU units. The composition of patient admissions sources for both the telemetry and CVICU units is shown in Fig. 5. Patients exiting the cardiology system may enter all locations mentioned except the ED.

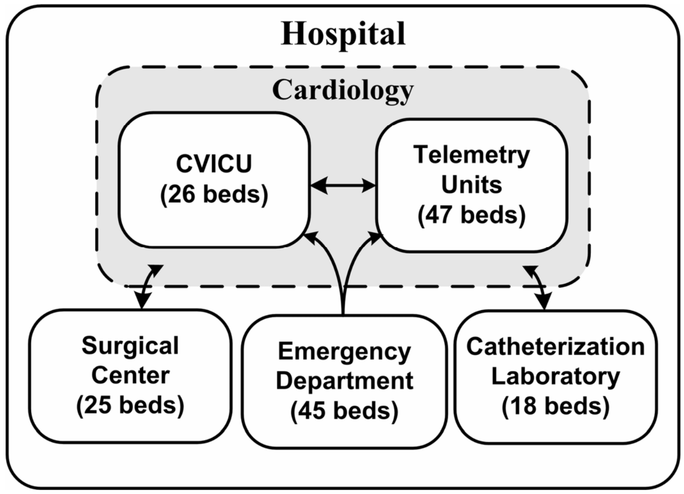

Figure 4. Cardiology system patient flow

Cox Hazard Regression Model

Survival analysis was used to construct a Cox hazard regression model to predict expected boarding time for patients admitted to a cardiology telemetry or CVICU bed. A separate model was created for each set of patients. Operational, demographic, and clinical information was collected from various hospital information systems over a one year period from May 1, 2006 to May 1, 2007. Boarding time (i.e., “survival” in the model) was defined as the time interval between hospital admission order and the time the patient moved to a telemetry or CVICU bed. Covariates designed to capture the level of demand from competing cardiology admission sources (Fig. 5) were captured at the time the ED physician requested the admission. Individual patient characteristics such as patient demographics, past history, ED-based CVD therapies and Thrombolysis in Myocardial Infarction (TIMI) Risk Score, a measure of ACS severity, were considered as model covariates.[10] ED operational measures such as ED occupancy and number of boarded patients were also considered.

The model selection procedure considered system and clinical variables that were collected based upon the hypothesis that they may have an impact on boarding time. These variables were placed into a multi-variate model paying close attention to any collinearity that existed. Model variables which captured demand from competing cardiology admission sources were deemed most important based upon the strength of their coefficients and statistical significance. These model variables formed the preliminary main effects model. Collinear variables that were determined to be important were strategically combined instead of excluding one variable. Originally excluded model variables were placed back into the model to determine if inclusion improved the log-likelihood of the model or if inclusion changed any other model variable coefficients by > 20%.[11] All demographic, ED and clinical variables were eventually excluded because they did not improve or change the model.

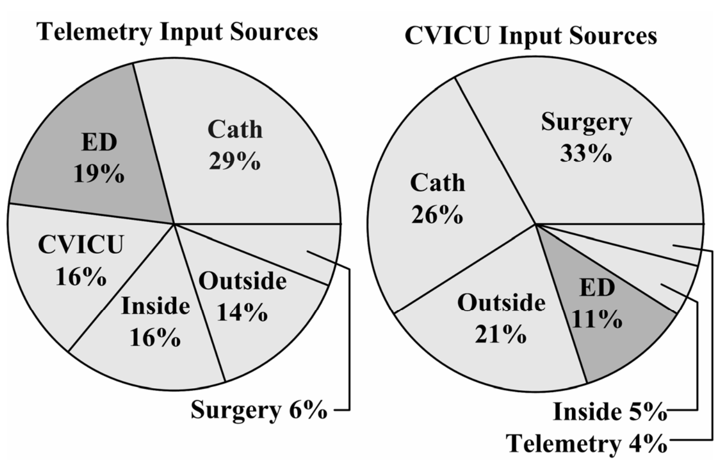

Figure 5. Cardiology admission sources

Model Validation

A series of regression diagnostics were performed to assess the validity of the model and cross-validation was performed to assess any bias within the model. An important assumption of Cox regression is that the covariates have the same effect on the hazard function for all values of time. The proportional hazard assumption was scrutinized by examining plots of scaled Schoenfeld residuals and using the test outlined by Grambsch and Therneau in 1994.[12] Variables representing surgical center and CCL operational states were found to be non-proportional. Thus the strategy of creating models over two disjoint time periods with equal sample sizes was employed.[13] The models were re-evaluated and determined to be proportional.

The Martingale residuals for each covariate were examined to determine the best functional form of a covariate.[14] No covariate transformations were determined to improve the model. Cox-Snell residuals were then examined to assess the overall fit of the model.[15] Several models were then created and compared from sampled data using a bootstrapping methodology in order to determine generalizability across all data.

Results

During the 1-year study period the division of cardiology received over 7,900 separate visits to the telemetry units and 2,980 separate visits to the CVICU. 1,591 and 332 boarded patients were admitted to the telemetry units and CVICU, respectively. Patients boarded for telemetry beds had a mean boarding time of 5.3 (min, median, max: 0.4, 3.4, 27.8) hours and patients boarded for CVICU beds had a mean boarding time of 2.7 (0.4, 1.7, 24.9) hours.

Separate Cox regression models were built to predict boarding time for telemetry and CVICU admissions. The model variables used within each model are defined in Table 1.

Table 1. Telemetry hazard model variables

Variables (min, mean, max)	**Description**
TELEMETRY (25, 42, 47)	Number of telemetry beds occupied
CVICU (12, 20, 26)	Number of CVICU beds occupied
HOSP (546, 735, 915)	Number of remaining hospital beds occupied excluding telemetry, CVICU, surgery, catheterization lab and the ED
SURG (0, 9, 45)	Number of occupied operating rooms plus the number scheduled surgeries to be performed in the next 3 hours
CATH (0 ,5 ,25)	Number of occupied catheterization laboratory beds plus the number of scheduled catheterization procedures to be performed in the next 3 hours
SURGCATH (0, 0.2, 1.0)	See Equation 2

All model variables were scaled to 1.0 by dividing each variable by the maximum variable value recorded in order to facilitate cross-variable coefficient comparisons. SURGCATH is a weighted combination of the SURG and CATH variable which had high collinearity (r = 0.76). The weights, WS for SURG and WC for CATH are equivalent to the corresponding fractions of admission source composition seen in Fig. 5. For the telemetry model, WC = 29% and WS = 6%. The calculation for the SURGCATH variable is displayed below in Equation 2.

$$SURGCATH = \left(\frac{WS \times SURG}{WC + WS}\right) + \left(\frac{WC \times CATH}{WC + WS}\right) \qquad (2)$$

Using the telemetry model, this assigns an appreciably higher weight to catheterization laboratory patients, since much more of these patients flow in to telemetry relative to surgical patients.

The final models for both the telemetry and CVICU are displayed in Table 2 and Table 3, respectively. The models are split close to the median boarding time in order to accommodate the non-proportional effect of the SURGCATH variable across all boarding times.

Table 2. Telemetry hazard model

Time Int.	Variables	Coeff.	p-value	95% CI
0 - 3 hours	SURGCATH	-3.79	<0.001	-4.47, -3.10
	TELEMETRY	-1.99	<0.001	-2.79, -1.18
	HOSP	-1.62	0.089	-3.48, -0.24
	CVICU	-1.18	<0.001	-1.78, -0.57
3 - 28 hours	HOSP	-3.56	<0.001	-4.85, -2.26
	TELEMETRY	-3.04	<0.001	-3.80, -2.27
	CVICU	-1.85	<0.001	-2.57, -1.12

Table 3. Cardiovascular intensive care unit hazard model

Time Int.	Variables	Coeff.	p-value	95% CI
0 - 2 hours	SURGCATH	-3.32	<0.001	-4.84, -1.79
	CVICU	-2.87	0.001	-4.69, -1.04
2 - 25 hours	CVICU	-4.81	<0.001	-7.47, -2.14
	SURGCATH	-1.95	<0.001	-3.07, -0.82

Both models predict expected boarding time by creating unique probability density functions for each boarded patient based upon the covariates collected at the time admission order is placed. A hazard ratio is calculated for each time section of the model for each patient. Thus, two separate but related hazard ratios are calculated for each patient. Telemetry patient hazard ratios range from 0.03 to 5.39 for the first time interval and 0.26 to 5.84 for the latter time interval. CVICU patient hazard ratios range from 0.06 to 3.48 for the first time interval and 0.13 to 5.12 for the latter time interval. The hazard ratios create a newly informed survivorship function. The derivative of the survivorship function is calculated to produce a unique probability density function for each patient. An example is demonstrated in Table 4, where survivorship functions of patients with hazard ratios (first time interval hazard ratio, second time interval hazard ratio:

Table 4. Unique patient survivorship function characteristics

Hazard Ratio	25th Percentile (hours)	50th Percentile (hours)	75th Percentile (hours)
BASE (1,1)	1.9	3.1	6.7
0.3, 0.7	3.8	6.3	11.0
0.3, 5.0	3.0	3.7	4.6

0.3, 0.7) and (0.3, 5.0) are compared to the baseline survivorship function for telemetry boarded patients. The hour values represent the point in time when there is a 25%, 50% and 75% chance that the patient will have been moved to a telemetry bed from when the admission order was placed (boarding time). Negative model coefficients create an inverse relationship between model covariate values and the hazard ratio. As model covariates increase (e.g., occupancy of the telemetry units), the hazard ratio decreases producing an altered survivorship function with a higher probability of the patient spending more time boarding. A graphical depiction of how hazard ratios alter the survivorship and probability density function is shown in Fig. 6.

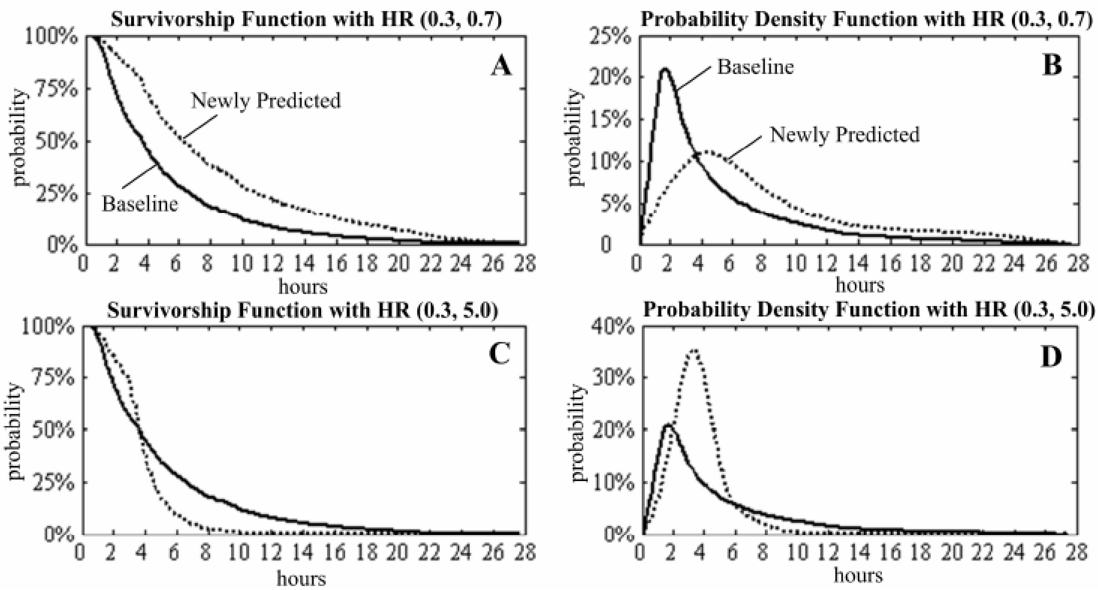

Figure 6. Boarding time prediction methodology; A) Survivorship function for patient with hazard ratio of 0.3/0.7; B) Probability density function of expected boarding time corresponding to plot A; C) Survivorship function for patient with hazard ratio of 0.3/0.5; D) Probability density function of expected boarding time corresponding to plot C.

Discussion

The Cox regression models demonstrate how changing demand from competing admission sources will alter the probability density function of a CVD patient's expected boarding time. Increasing patient demand from all cardiology admission sources, especially from the surgical center and catheterization laboratory will increase the length and uncertainty of expected boarding time. The models characterize the impact of different system components on boarding time while probabilistically addressing the uncertainty inherent in complex socio-technical systems such as a hospital.

Variability in Electively Scheduled Procedures

The models depicted in Table II and Table III display the strong effect that variability in surgical and catheterization laboratory demand has on access block to cardiac inpatient services. The majority of these procedures are electively scheduled; however, variability in demand for these services often exceeds the natural variability associated with ED arrivals.[16,17] The telemetry model displays the SURGCATH variable as being the most influential for the first 3 hours of patient boarding time. Catheterization laboratory demand strongly influences the SURGCATH variable because of the weighting scheme based upon the nature of telemetry unit input. Bed management policy requires that a telemetry bed be available for all current patients and patients scheduled in the near future who are to undergo a catheterization procedure. Thus, open beds within the telemetry units must be held (blocking access to ED patients) for "potential patients" coming from the catheterization laboratory. Increasing scheduled patients not only increases demand for services but also increases the uncertainty involved with effectively managing capacity. Many of these patients (52%) do not end up needing a bed and are discharged home. This may be a reason why the SURGCATH variable had a non-proportional or diminishing effect over time and was not included in the model after 3 hours. The effects of this bed management policy are evident in the telemetry model. A similar phenomenon occurs with surgical patients and the CVICU. CVICU model coefficients support the notion that daily variability in surgical caseload is a major contributor to intensive care unit unavailability, leading to ED overcrowding.[16]

Clinical Non-Factors

During the design phase of the study it was expected that clinical variables indicating severity of CVD would be associated with decreases in boarding time. This was not the case with either the telemetry or CVICU model. This may be because the variability in severity of illness for patients on the same care pathway (i.e., ED to telemetry) is not broad enough to produce an overall statistically measurable effect. Patients moving from the ED to telemetry are not ill enough to require intensive care unit services, but they are not well enough to be discharged home. Certain clinical circumstances may trigger a patient to move from the ED to the telemetry unit or the CVICU quicker than usual, but an overall population effect was indistinguishable. However, it should be recognized that more critically ill patients moving to the CVICU do, on average, depart earlier than telemetry bound patients.

Discrete Event Simulation (DES) Integration

DES is hypothesized to provide the flexibility that is needed to increase the usefulness of the models. A DES that integrates the Cox competition models would provide a means of determining how patient flow within a sub-system such as cardiology affects the ED. Further, a DES could be used by unit managers and hospital administrators to determine how changing bed management policies influence ED patient flow.

The telemetry and CVICU models above will be used in a DES of the cardiac system to explore how changing the scheduling of electively scheduled surgical and catheterization procedures may reduce pressure on the ED. It is the authors' hypothesis that an equal or greater amount of electively scheduled procedures, which strongly drive revenue within a hospital, can be strategically scheduled to increase ED cardiac patient throughput.

Conclusion

This study demonstrates the use of survival analysis, specifically Cox regression, as a novel method for modeling competition for hospital resources at the system level. The specific results of the competition models may not apply to other institutions, however the methods and interpretation of these models are generalizable.

A considerable amount of literature cites ED overcrowding as a hospital system problem, but few studies have developed or applied quantitative methods to determine how demand for hospital system resources effects ED operations. The competition model outlined provides a robust method of probabilistically analyzing the interdependencies of components in a complex hospital system.

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CHAPTER VI

OPTIMIZING CARDIOLOGY CAPACITY TO REDUCE EMERGENCY DEPARTMENT BOARDING: A SYSTEMS ENGINEERING APPROACH

Abstract

Background: Patient safety and emergency department (ED) functionality are compromised when inefficient coordination between hospital departments impedes ED patients' access to inpatient cardiac care.

Objective: To create a discrete event simulation model of hospital patient flow and determine how bed demand from competing cardiology admission sources affects ED patients' access to inpatient cardiac care.

Design: Retrospective cohort study of all patients who came in contact with the cardiology system over a 1-year period (May, 2006 to May, 2007).

Setting: Urban, academic, tertiary care hospital with a 45-bed emergency department and a 73-bed cardiology inpatient unit.

Patients: 1,591 ED patients admitted by cardiology to a telemetry inpatient bed.

Measurements: ED boarding times, defined as the time interval between cardiology admission request to bed placement, and intra-hospital patient transfer data were obtained from multiple clinical information systems and used to build and test a discrete event simulation. Demographic, clinical and bed demand data were collected for each ED patient admitted to a telemetry bed at the time of cardiology admission request. Cox proportional hazard regression

was applied to predict expected boarding time for each patient. The boarding prediction regression model was embedded into the discrete event simulation to examine prospective strategies to reduce cardiology patient boarding.

Results: The boarding time for ED patients who were admitted to the cardiac telemetry unit averaged 5.3 hours (median, IQR: 3.1, 1.5 to 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 (CATH LAB) 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% [51.2 to 92.5] of these patients did not move to a telemetry bed and are discharged home each day. Results of simulation-based analyses showed that scheduling 1 additional elective case before noon results in a 6.4% or 20 minute reduction in average boarding time and placing 1 additional telemetry bed results in a 2.9% or 9 minute reduction in average boarding time.

Limitations: The study is limited to a single hospital with specific operating characteristics.

Conclusions: Results demonstrate how altering outpatient schedules and creating informed bed management practices based on known patient flow patterns can reduce inpatient bed blocking, optimize hospital capacity, and improve ED patient access.

Introduction

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” (i.e., 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 percent of hospitals boarded patients at least 2 hours and 20 percent 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 EDs 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 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 re-hospitalization 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 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 macro-system (Figure 7) 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 macro-system with a focus on ED patients admitted by cardiology to a telemetry bed. Demographic, clinical and operational information was collected over a 1-year period from May 1, 2006 to May 1, 2007. Demographic and clinical information was collected from, StarPanel, the institution's electronic medical record system. Time-stamped patient flow information was collected from; (1) the ED electronic whiteboard information system used to track patient process times and clinical information in the ED, (2) the Medipac Admit / Discharge / Transfer Database which records patients movements to and from hospital units, (3) the Electronic Bed Board which tracks the status (i.e., available, occupied, needs cleaning) of all inpatient beds, and (4) the Perioperative Information Management System used to provide documentation and management tools to care providers involved in perioperative care. Information from each of the sources was merged to construct patient flow times and patterns for each patient in the study cohort.

Cardiology Macro-System

The study was performed at an urban, academic, tertiary care hospital with a 45-bed emergency department and a 73-bed cardiology inpatient unit consisting of 47 telemetry beds and 26 cardiovascular intensive care unit

(CVICU) beds. The division of cardiology (telemetry and CVICU) functions within the cardiology macro-system (Figure 7). Patients flow between the cardiology division and the; cardiac catheterization lab (CATH LAB), ED, operating rooms (OR) and post anesthesia care unit (PACU), other hospital units and home. Patients also flow within the cardiology division between the CVICU and telemetry unit.

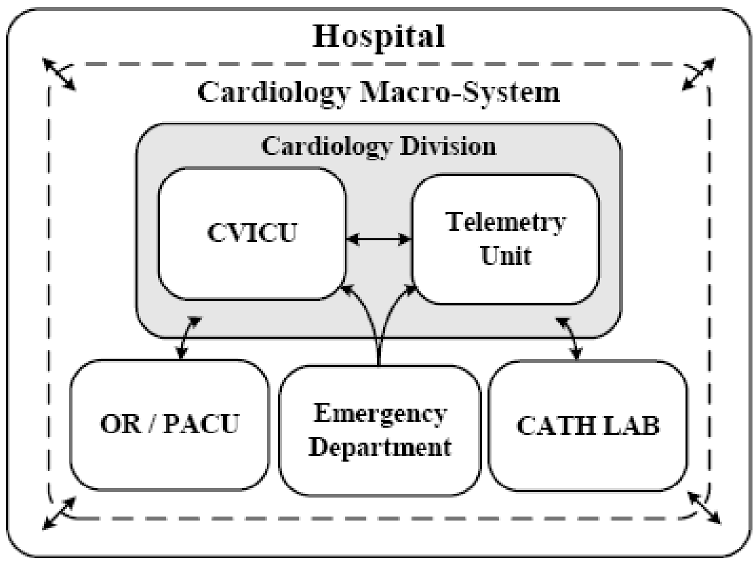

Figure 7. Cardiology macro-system patient flow
* CVICU: Cardiovascular intensive care unit
* OR/PACU: Operating rooms and post anesthesia care unit
* CATH LAB: Catheterization laboratory

Predicting Emergency Department 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, i.e., "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. Hazard regression was chosen to predict boarding because of the complexity and unpredictability inherent to the cardiology macro-system. Preliminary research had shown that ED patients were not consistently transferred to telemetry beds even though beds were available. Moreover, different types of patients received different priorities which changed over time. In addition, the system is directed by humans who introduce further variability to work practices and shift timing.[20,21] System and work process variability was probabilistically captured using hazard regression.

The covariate selection procedure considered operational, demographical 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 (Figure 7) over the one-year study period. ED operational measures such as ED occupancy and number of boarded patients were also considered. To allow reliable cross-variable comparisons, independent variables measuring hospital demand were scaled to 1.0 by dividing each variable by the maximum variable value recorded. Individual patient characteristics such as patient demographics (age and sex), past medical history, ED-based cardiovascular disease therapies, and Thrombolysis in Myocardial Infarction (TIMI) Risk Score were considered as model covariates.[22] Past 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. ED-based cardiovascular disease therapies included; nitroglycerin, aspirin, clopidogrel, beta-blockers, heparin, glycoprotein 2b/3a inhibitors, enoxaparin, and ACE inhibitors. A series of regression diagnostics were performed to assess the validity of the model; bootstrapping and cross-validation methods were employed to assess any bias within the model.[23]

Discrete Event Simulation using Hazard Models

The simulation of patient flow through the cardiology macro-system was created using the MATLAB® (Mathworks, Natick, Massachusetts) technical computing environment and MedModel™ (Promodel Corporation, Orem, Utah) simulation software. Embedded hazard models governed the relationship between the ED and cardiology units. All other macro-system locations were modeled using basic queuing principles. Logic directing patient flow in the simulation was based upon a framework which classified each location modeled. Telemetry and CVICU units were modeled as reactive, i.e., 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, i.e., these units directed patient flow with highest priority to and from other locations in the model. The majority of 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.

The simulation was probabilistically driven by actual, unaltered distributions collected from multiple clinical information systems. Input distributions provided the timing of arrivals and departures in each 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. All input distributions were verified by comparing measurements of central tendency and variability from the simulated versus real systems. Mann-Whitney U tests were used to assess differences between independent parameter distributions for the simulated versus real systems. 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 upon transfer probabilities derived 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 post-operatively; (3) Move to the telemetry unit; (4) Be discharged home. By guiding location transfer probabilities based upon previous locations, common patient flow pathways, as such, were preserved. Simulated inflow and outflow location probabilities were verified to match the real system. Boarding time to telemetry, location census distributions and temporal patterns were the major output variables validated against the real system. All output variables were cross-validated using a 6-month training set and a 6-month testing set.

Results

Modeling ED Boarding Time

During the one-year study period the cardiac telemetry units received 7,901 separate visits with 1,591 (20.1%) of these visits coming from the ED. ED 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, IQR: 3.1, 1.5 - 6.9) hours. Patients boarded for the CVICU had a mean boarding time of 2.7 (1.7, 0.8 - 3.0) hours. In comparison, the mean ED treatment time, excluding boarding time, was 4.1, (1.9, 3.2 - 5.3) hours. The average occupancy of the telemetry and CVICU units was 88% and 77%, respectively. The independent variables (Table 5) used to predict boarding time measured demand in the following units: TELEMETRY, CVICU, OTHER remaining hospital inpatient units, OR and CATH LAB. The effect of each clinical and demographical 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 5. The TELEMETRY, CVICU and OTHER variables measured the number

Table 5. Telemetry Hazard Model

Time Int.	Variables	Coeff.	p-value	95% CI
0 - 3 hours	OR x CATH LAB	-3.79	<0.001	-4.47, -3.10
	TELEMETRY	-1.99	<0.001	-2.79, -1.18
	OTHER	-1.62	0.089	-3.48, -0.24
	CVICU	-1.18	<0.001	-1.78, -0.57
3 - 28 hours	HOSP	-3.56	<0.001	-4.85, -2.26
	TELEMETRY	-3.04	<0.001	-3.80, -2.27
	CVICU	-1.85	<0.001	-2.57, -1.12

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 OR x CATH LAB (equation 3) variable was a weighted combination of the OR and CATH LAB variable which had high collinearity (r = 0.76). The weights, WO = 5.9% for OR and WC = 29.2% for CATH LAB are equivalent to the corresponding inflow fractions to telemetry.

$$OR\ x\ CATH\ LAB = \left(\frac{WO \times OR}{WC + WO}\right) + \left(\frac{WC \times CATH\ LAB}{WO + WS}\right) \tag{3}$$

The telemetry hazard model (Table 5) is used to predict expected boarding time by creating a unique probability distribution of boarding time for each patient based upon the covariates collected at the time the admission order is 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 non-proportional effect on the hazard function. Thus, the strategy of creating models over two disjoint time periods with equal sample sizes was employed.[24] The reader is referred to prior published work for further details on the boarding prediction methodology.[19]

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 6). The simulated OR length-

Table 6. Simulation Verification and Validation

Location	Real System median, (IQR)	Simulated System median, (IQR)	Comparison Measure
	Arrivals Per Week		Mann-Whitney U (p-value)
ED	882, (855 - 899)	883, (863 – 904)	0.35
ED BOARDERS	242, (226 - 256)	241, (232 – 252)	0.95
TELEMETRY BOARDERS	30, (23 – 36)	31, (24 - 37)	0.27
CVICU BOARDERS	6, (5 – 8)	7, (4 – 9)	0.56
TELEMETRY UNIT	152, (141 – 161)	153, (142 – 161)	0.53
CVICU	56, (50 – 64)	58, (54 – 62)	0.25
CATH LAB	123, (110 – 133)	122, (111 – 129)	0.38
OR	298, (278 – 323)	297, (279 – 316)	0.52
CARDIAC SURGERIES	32, (24 – 39)	32, (25 – 37)	0.28
	Length-of-Stay (hours)		Mann-Whitney U (p-value)
ED TREATMENT	3.2, (1.9 – 5.3)	3.2, (1.9 – 5.3)	0.96
ED BOARDING (ALL)	2.1, (0.7 – 5.8)	2.1, (0.8 – 5.9)	0.19
TELEMETRY BOARDERS	3.1, (1.5 – 6.9)	3.3, (1.7 – 7.0)	0.33
CVICU BOARDERS	1.7, (0.8 – 3.0)	1.7, (0.9 – 3.0)	0.62
TELEMETRY UNIT	32.3, (17.2 – 61.4)	33.1, (18.4 – 61.6)	0.35
CVICU	42.1, (20.3 – 75.2)	43.1, (21.3 – 74.9)	0.42
CATH LAB	5.4, (3.1 – 7.7)	5.5, (3.1 – 8.1)	0.34
OR	2.5, (1.5 – 4.0)	2.6, (1.6 – 4.4)	< 0.05
CARDIAC SURGERIES	6.1, (3.3 – 8.9)	6.1, (3.4 – 9.0)	< 0.05
	Census Distributions (minute-by-minute)		Correlation Coef. (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

of-stay distribution did not meet the null hypothesis of coming from the corresponding real system distribution. The simulated OR length-of-stay distribution did not meet the null hypothesis of matching the real length-of-stay probability 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 8. Output census distributions for each location were validated against the real system (Table 6). Pearson's correlation coefficients ranged from 0.78 to 0.99 for weekly temporal patterns between the simulated versus real systems.

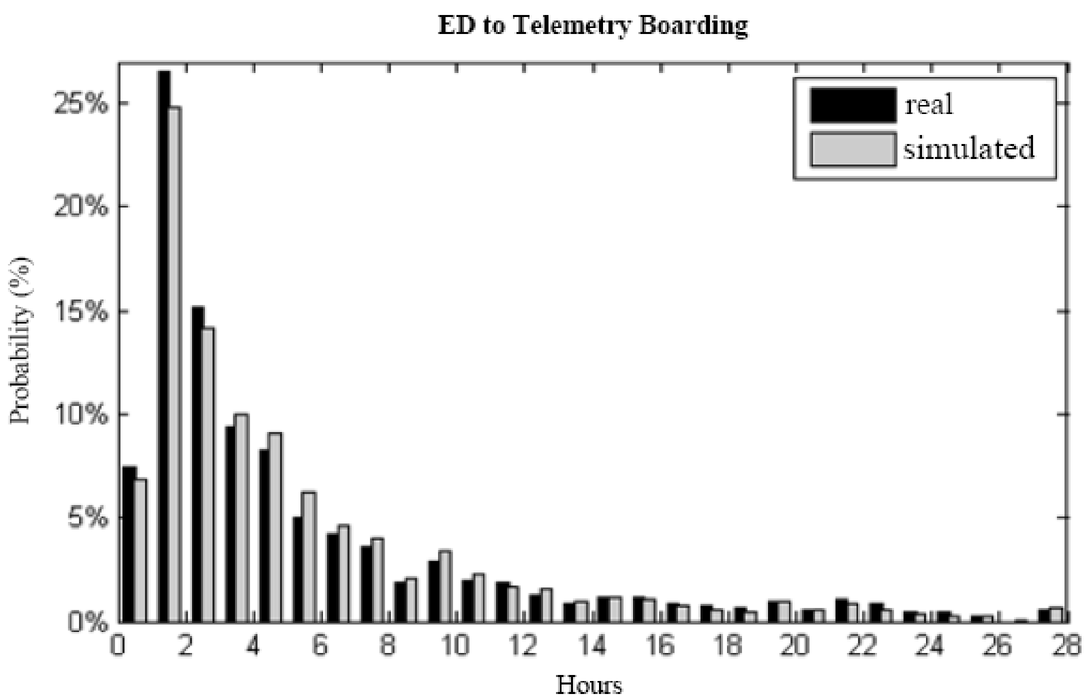

Figure 8. Boarding time probability distribution comparison

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 by 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 elective catheterization scheduling practices.[21] Demand uncertainty will need to 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 x CATH LAB) was the strongest driver of boarding time. The CATH LAB is most influential because of the weighting scheme employed. Electively scheduled patients coming from home represent the CATH LAB's biggest source (64%) of inflow. However, the outflow for these scheduled patients is quite uncertain; 51% were discharged home, 30% were directed to a telemetry bed, 8% went to the OR, 6% went to the CVICU and 5% 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 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 macro-system. A telemetry admission request from the ED has the highest probability of occurring at around 6 pm on a typical weekday (Figure 9). At this time, over 40% of patients scheduled to undergo

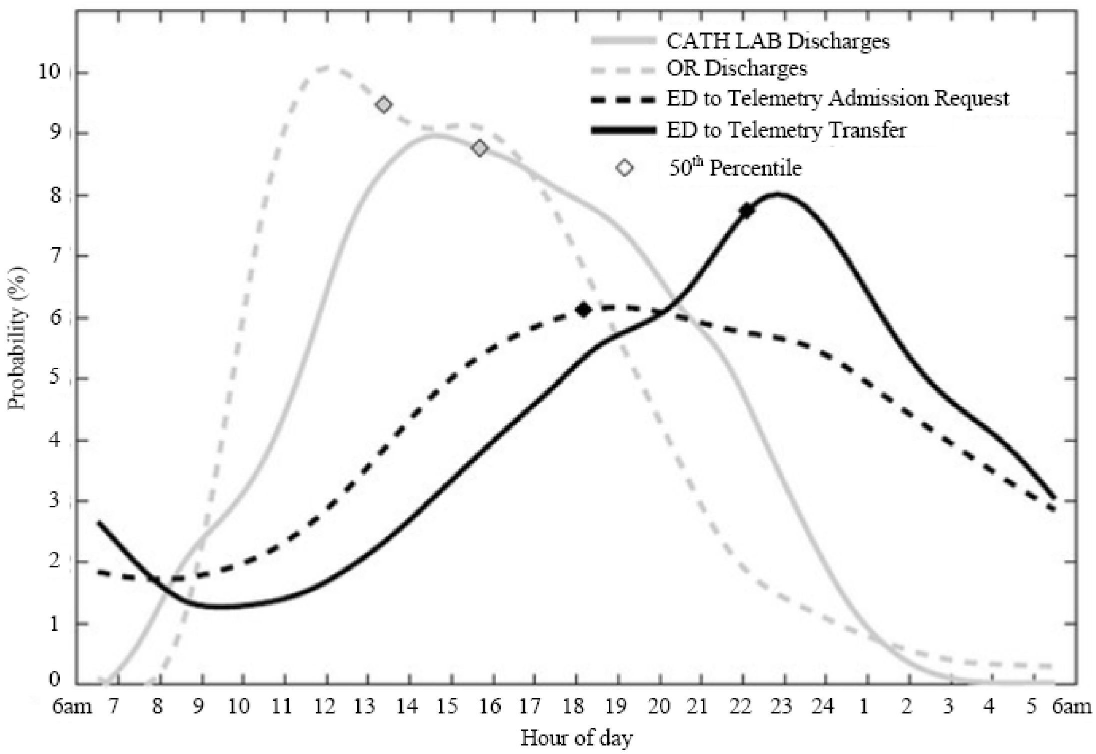

Figure 9. Cardiology macro-system patient flow patterns on a typical weekday (6am to 6am). Curves represent the probability of the event occurring by hour of day.

catheterization procedures that day, have not yet been discharged from the CATH LAB. The CATH LAB is the largest source of telemetry demand uncertainty as late as 6 pm. Uncertainty does not subside to a level allowing ED patients' access until almost 11 pm. This is demonstrated by the peak in ED transfers to telemetry (Figure 9). The interval between the admission request peak and the telemetry transfer peak approximates boarding time.

The repetitive weekday pattern of flow led to the hypothesis that reducing CATH LAB outflow during the period of time when ED admission requests were most likely would reduce boarding time for telemetry bound patients. Such an intervention would shift the CATH LAB discharge curve to the left (i.e., 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 before noon on a typical weekday (Figure 10 A). All other inputs being constant, scheduling one additional catheterization patient 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 10 B) by one additional bed resulted in a 2.9% or 9 minute reduction in average boarding time.

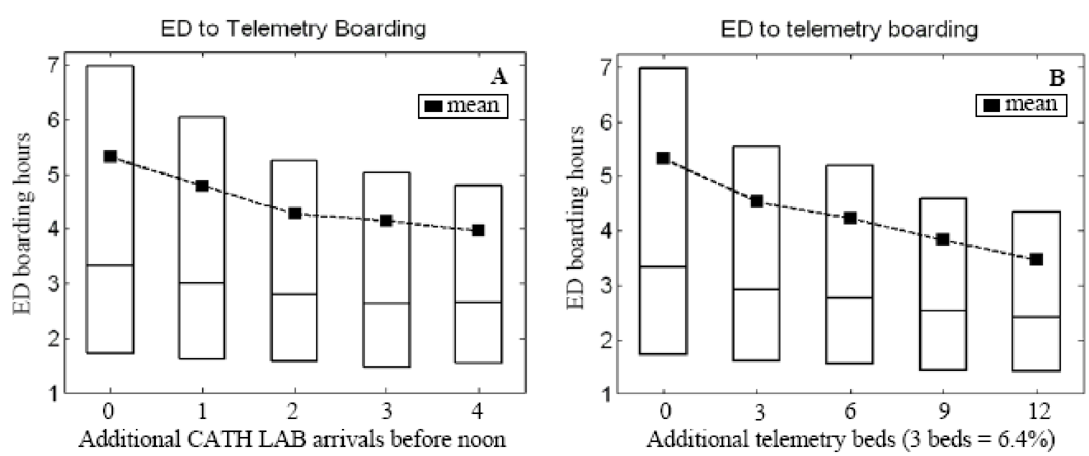

Figure 10. Alternative strategies to reduce boarding time. A) Scheduling an additional CATH LAB patient before noon B) Increasing telemetry capacity

A subtle low cost scheduling solution aimed at optimizing capacity outperforms the higher cost alternative of adding capacity.

Limitations

This study was conducted at a single academic medical center with specific operational characteristics. However, comparable hospitals may well operate with similar demand characteristics and bed management policies. In addition, the notion of optimizing capacity by reducing bed blocking practices during peak ED to hospital outflow is expected to be generalizable across all inpatient settings.

Simulation modeling has implicit limitations. The simulation is a simplified representation of the real system. Not all characteristics can be mathematically modeled. However, the simulation was built on real hospital system information, thus minimizing the need for critical assumptions or estimations. The model was verified and validated appropriately to ensure its accuracy.

Discussion

This study demonstrates a systems engineering approach to analyze a hospital macro-system's relationship with the ED. We developed a novel modeling strategy to analyze prospective strategies aimed at reducing ED boarding time. A low cost scheduling strategy was found to be superior to a higher cost capacity increase. Simulation construction and resulting analysis characterized cardiology macro-system dynamics and provided insight about how sub-optimal management practices can decrease efficiency and lead to delays in care.

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. CVICU bound patients were boarded, on average half as long as telemetry bound patients (Table 6). Triaging patients based on illness severity does occur for some cardiology admitted patients, but wasn't 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% [7.5% to 48.8%] of these beds were actually needed each weekday. A large proportion of bed blocking occured during weekday periods of frequent ED admission requests. Effectively managing CATH LAB outflow demand uncertainty and reducing bed blocking practices at key hours is likely to have the greatest effect on boarding time.

The simulation demonstrated how subtle changes in catheterization scheduling could yield significant results. Scheduling just one additional catheterization procedure before noon was equivalent to adding two additional telemetry beds in regard to decreases in ED boarding of 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. In the study hospital, 4 interventional cardiologists worked the 7am to noon shift in the CATH LAB. They are relieved by 4 cardiologists working from noon to when all their procedures are complete. By scheduling 5 cardiologists on morning shift and 3 in the afternoon, the scheduling changes needed to significantly reduce boarding time would be met, assuming that the needed CATH LAB space was available. Coupling this change with informed bed management policies that require one telemetry bed is held for every two scheduled CATH LAB patients would reduce bed blocking further. This policy assumes a 50% daily outflow to telemetry, safely above the 29.6% [7.5% to 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 of 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 fosters a lower priority to ED admissions because they typically generate the lowest margins, resulting in less revenue as compared to 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 utilize 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.

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 and amend its effect on emergency and cardiac care. This process led to solutions (i.e., CATH LAB scheduling alterations and new bed management practices) aimed at managing uncertainty in telemetry bed demand. The next step involves implementing these solutions and measuring their effect on the real ED 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.

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Chapter VII

SIMULATING COMPETITION FOR HOSPITAL ADMISSIONS: THE OPERATING ROOM VERSUS THE EMERGENCY ROOM

Abstract

Objectives: To determine how projected increases in surgical patient volume will affect emergency department (ED) access to inpatient cardiac services and to prospectively evaluate how reducing inpatient length-of-stay (LOS) and increasing inpatient capacity can improve ED patient access or accommodate increases in surgical volume.

Design: Discrete-event simulation using survival analysis regression was used to model patient competition and flow through an inpatient cardiology system. The simulation was created using data collected from a retrospective cohort of patients, who came in contact with the cardiology system over a one year period from May, 2006 to May, 2007.

Setting: A single United States, urban, academic, tertiary care hospital with a 45-bed ED and a 73-bed cardiology inpatient unit consisting of 47 telemetry and 26 cardiovascular intensive care unit (CVICU) beds.

Participants: 1,923 ED and 1,506 cardiac surgery patients admitted to a cardiology inpatient bed.

Main Outcome Measures: ED patient access and cardiac surgery throughput. ED patient access was captured by measuring ED patient boarding time (i.e., time delay from admission request to inpatient bed placement).

Results: ED patients boarded for a telemetry and CVICU bed had a mean boarding time of 5.3 (median, inter-quartile range: 3.1, 1.5 - 6.9) hours and 2.7 (1.7, 0.8 - 3.0) hours, respectively. Increasing surgical volume 10% in the simulation resulted in a 37 (12%) and 33 (20%) minute increase in mean boarding time to telemetry and the CVICU, respectively. Reducing cardiac inpatient LOS by 60 minutes or increasing capacity by 1 telemetry or CVICU bed resulted in either a 7 to 9 minute reduction in average boarding time or an 11% to 19% increase in surgical patient volume accommodated.

Conclusions: Simulating competition dynamics for hospital admissions provides prospective planning information and demonstrates how interventions to increase throughput or add capacity will have the most significant effect on highest priority (surgical) patients.

Introduction

Competition for hospital-based health care services was elevated over the last decade because of inverse trends in demand and supply. United States hospital admissions have increased 13% and emergency department (ED) visits have risen 26% between 1993 and 2003. Over this same period, financial pressures have caused the country to lose 703 hospitals, 198,000 hospital beds and 425 hospital-based EDs.[1] All patients are not economically equal in the

United States commercialized health care system. Hospitals face financial pressure to provide specific services and are often motivated to allocate resources in response to profit opportunities rather than medical need.[2] Profit centers and sinks have emerged in hospitals and management practices based upon priority structures are in place. From a financial standpoint, the operating room (OR) and the emergency room fall on opposite ends of the spectrum. Electively scheduled surgical patients typically generate the most revenue, while naturally arriving ED patients generate the least, and often cost the hospital money.[1]

The two most common routes to hospital inpatient admissions begin in the OR (e.g., 35%) and the ED (e.g., 50%).[1] ED and surgical patients are constantly competing for inpatient resources.[3,4] Financial incentives to improve surgical patient access include; (1) surgical patients paying better margins; (2) elective surgeries must be cancelled or delayed if inpatient beds are unavailable post-operatively; (3) if service is poor, elective patients can choose to be treated at other hospitals, and; (4) admitting profitable patients promotes loyalty among admitting physicians.[1] There are limited financial incentives to improve ED patient access. This has created a severe bottleneck at the ED – hospital interface reducing ED patient throughput and causing conditions of crowding.[1,5-9]

Emergency Department Boarding

When inpatient beds are unavailable, admitted patients wait (board) in the ED, occupying space and consuming resources, until a bed is available.

Boarding time is defined as the time interval from when a hospital admission request is placed to when the patient is transferred to an inpatient bed. Boarding is a common characteristic of United States hospitals. Out of 2000 hospitals surveyed, 90% boarded patients at least 2 hours and 20% averaged an 8-hour boarding time.[9] Boarding is the most significant contributor to the crowding crisis that plagues EDs nationwide.[1,5-9] Two government sanctioned reports suitably titled, “Bursting at the Seams” and “At the Breaking Point” describe the threat to quality and safety that crowding has placed on the emergency care system and how ED boarding is a major contributor.[1,8] This has lead to the Institute of Medicine’s mandate for hospitals to end the practice of boarding patients except in the most extreme circumstances.[1] Hospitals across the country must strive to minimize boarding time for all ED admitted patients despite the financial disincentives.

Objective

The hospital of study is currently constructing new operating facilities scheduled to open within 5 years. Surgical patient volume is projected to increase substantially. The purpose of this study was to create a stochastic discrete-event simulation used to determine how projected increases in surgical volume will affect ED patient access to inpatient cardiac services. The simulation focuses on patient flow through the division of cardiology. The specific goals of the simulation were to; (1) quantify the effects of increases in surgical volume on cardiac patients boarding time in the ED; (2) examine how reducing inpatient length-of-stay (LOS) can free capacity to improve ED patient access and accommodate new surgical volume, and; (3) Inform cardiology inpatient capacity expansion plans. The simulation tool was used to improve cardiology administrators' ability to plan for the upcoming increase in surgical volume.

Methods

Setting and Design

The study was performed at an urban, academic, tertiary care hospital with a 45-bed emergency department and a 73-bed cardiology division consisting of 47 telemetry beds and 26 cardiovascular intensive care unit (CVICU) beds. The division of cardiology (telemetry and CVICU) runs within the cardiology macro-system, seen on the right side of Figure 11.[10] Patients flow between the division of cardiology and the; ED, OR and post anesthesia care unit (PACU), cardiac catheterization laboratory (CATH LAB), other hospital units, and home.

The study design was a retrospective cohort study that included all patients who came in contact with the cardiology macro-system. ED and surgical patients admitted by cardiology to a telemetry or CVICU bed were the focus of the study. Demographic, clinical and operational information was collected over a one year period from May 1, 2006 to May 1, 2007. Demographic and clinical

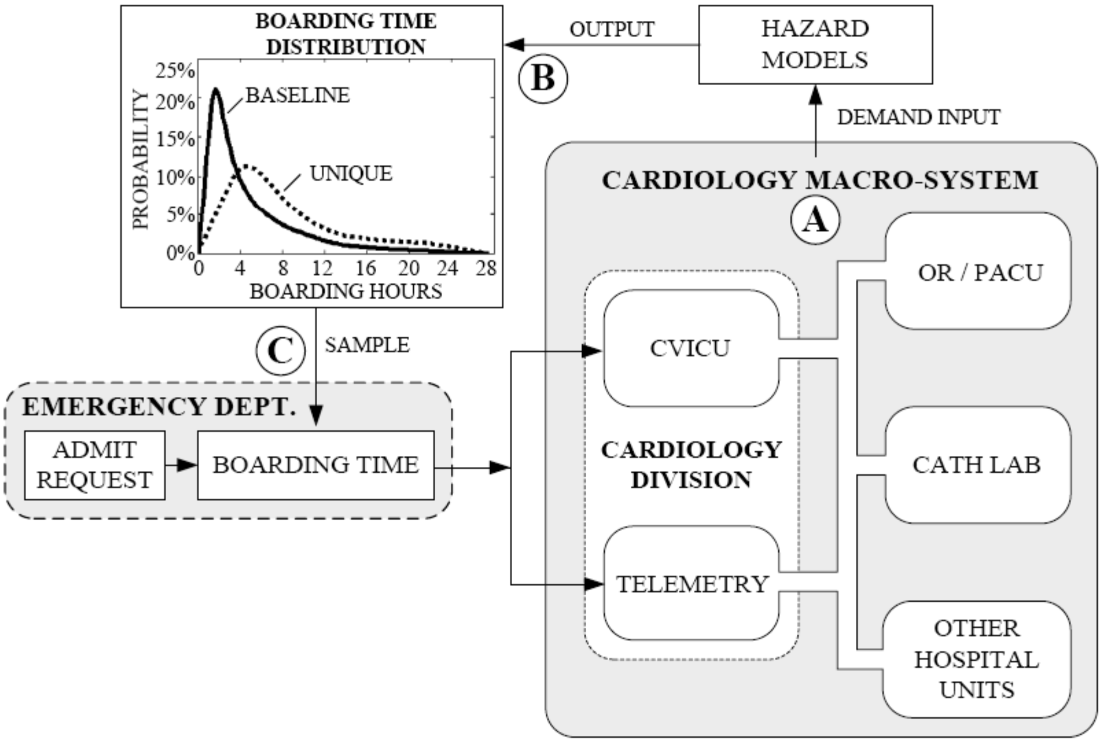

Figure 11. Discrete event simulation using survival models
CVICU: Cardiovascular intensive care unit
OR / PACU: Operating rooms and post anesthesia care unit
CATH LAB: Cardiac catheterization laboratory

A) Demand measurements collected from cardiology macro-system and input to hazard model
B) Hazard model outputs a unique probability distribution of expected boarding time
C) Time interval is sampled from distribution and assigned to patient as boarding time

data was collected from, StarPanel, the institution's electronic medical record system. Time-stamped patient flow information was collected from the; (1) ED electronic whiteboard information system used to track patient process times and clinical information in the ED, (2) Medipac Admit / Discharge / Transfer Database which records patients movements to and from hospital units, (3) electronic bed board which tracks the status (i.e., available, occupied, needs cleaning) of all inpatient beds, and (4) perioperative information management system used to provide documentation and management tools to care providers involved in perioperative care. Information from each of the sources was merged to construct patient flow times and patterns for each patient in the study cohort.

Modeling Boarding Time

Survival analysis was used to construct a Cox proportional hazard regression model to predict expected boarding time for patients admitted to a cardiac telemetry or CVICU bed.[11] Separate hazard models were created for patients boarded for the telemetry unit and CVICU. Boarding time (i.e., "survival" in the model) was defined as the time interval between hospital admission order and the time the patient moved to an inpatient bed. Hazard regression models were used to predict boarding, because of the unpredictability inherent to the cardiology macro-system. A basic queuing approach was initially used to model ED boarding time; however the ED admission decision process proved to be too complex to be described by fundamental queuing principles. Preliminary research determined that ED patients were not consistently transferred to cardiology beds even though beds were available. Patients received different priorities for admission which were subject to change over time and the system was directed by humans who introduce variability to work practices and shift timing.[12,13]

The covariate selection procedure considered operational, demographical and clinical variables based upon the hypothesis that each could effect boarding time. Covariates designed to measure the level of demand from competing telemetry and CVICU admission sources were collected at the exact time an ED physician placed the admission request. The proportion of patients admitted to cardiology from competing admission sources is seen in Figure 12. Demand

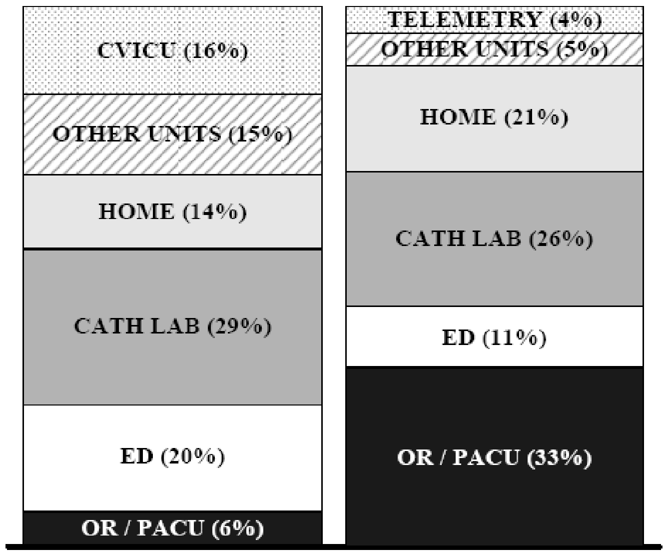

Figure 12. Competing cardiology inpatient admission sources

measurements from competing admission sources were extracted from clinical information systems for each ED patient admitted to a division of cardiology location over the one year study period. ED operational measures such as ED occupancy and number of boarded patients were also considered. To facilitate cross-variable comparisons, independent variables measuring hospital demand were scaled to 1.0 by dividing each variable by the maximum variable value recorded. Individual patient characteristics such as patient demographics (age and sex), past medical history, ED-based cardiovascular disease therapies, and Thrombolysis in Myocardial Infarction (TIMI) Risk Score were considered as model covariates.[14] Past 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. ED-based cardiovascular disease therapies included; nitroglycerin, aspirin, clopidogrel, beta-blockers, heparin, glycoprotein 2b/3a inhibitors, enoxaparin, and ace inhibitors.

Model variables which captured demand from competing cardiology admission sources were deemed most important based upon the strength of their coefficients and statistical significance. All demographic, ED and clinical variables were eventually excluded because they did not improve or significantly change the model. A series of regression diagnostics were performed to assess the validity of the model, bootstrapping and cross-validation methods were employed to assess any bias within the model.[15] Variables capturing demand within the OR and CATH LAB were found to have a non-proportional effect on the hazard function. Thus, the strategy of creating models over two disjoint time periods with equal sample sizes was employed.[16]

The independent variables used to predict boarding time measured demand in the following units: TELEMETRY, CVICU, OTHER hospital units, OR and CATH LAB. The variables are defined in Table 7. 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 OR x CATH LAB variable (equation 4) is a weighted combination of the OR and CATH LAB variables which had high collinearity (r = 0.76). The weights, WO for OR and WC for CATH LAB are equivalent to their corresponding fraction of patient inflow, seen in Figure 12. For the telemetry model, WO = 6%

Table 7. Hazard Model Variables

Variables (min, mean, max)	Description
TELEMETRY (25, 42, 47)	Number of telemetry beds occupied
CVICU (12, 20, 26)	Number of CVICU beds occupied
OTHER (546, 735, 915)	Number of remaining hospital beds occupied excluding telemetry, CVICU, surgery, catheterization lab and the ED
OR (0, 9, 45)	Number of occupied ORs plus the number scheduled surgeries to be performed in the next 3 hours
CATH LAB (0 ,5 ,25)	Number of occupied CATH LAB beds plus the number of scheduled catheterization procedures to be performed in the next 3 hours
OR x CATH LAB (0, 0.2, 1.0)	See Equation 1

and WS = 29%. The calculation for the OR x CATH LAB variable is displayed below in Equation 4.

$$OR\ x\ CATH\ LAB = \left(\frac{WSO \times OR}{WC + WO}\right) + \left(\frac{WC \times CATH\ LAB}{WC + WO}\right) \tag{4}$$

The telemetry and CVICU hazard models used to predict expected boarding time may be seen in Table 8 and Table 9. The hazard models output unique probability distributions of expected boarding time for each patient based upon the covariates collected at the time the admission order is placed. The reader is referred to “Stranded on Emergency Isle: Modeling Competition for Cardiac Services Using Survival Analysis” for further details on the boarding prediction methodology.[11]

Patient Flow Simulation Using Survival Models

The discrete event simulation of patient flow through the cardiology macro-system was created using the MATLAB® (Mathworks, Natick, Massachusetts) technical computing environment and MedModel™ (Promodel Corporation, Orem, Utah) simulation software. The hazard models used to

Table 8. Telemetry hazard model

Time Int.	Variables	Coeff.	p-value	95% CI
0 - 3 hours	OR x CATH LAB	-3.79	<0.001	-4.47, -3.10
	TELEMETRY	-1.99	<0.001	-2.79, -1.18
	OTHER	-1.62	0.089	-3.48, -0.24
	CVICU	-1.18	<0.001	-1.78, -0.57
3 - 28 hours	HOSP	-3.56	<0.001	-4.85, -2.26
	TELEMETRY	-3.04	<0.001	-3.80, -2.27
	CVICU	-1.85	<0.001	-2.57, -1.12

Table 9. CVICU hazard model

Time Int.	Variables	Coeff.	p-value	95% CI
0 - 2 hours	OR x CATH LAB	-3.32	<0.001	-4.84, -1.79
	CVICU	-2.87	<0.001	-4.69, -1.04
2 – 25 hours	CVICU	-4.81	<0.001	-7.47, -2.14
	OR x CATH LAB	-1.95	<0.001	-3.07, -0.82

predict boarding time for telemetry and CVICU patients were embedded within the model. All other macro-system locations were modeled using basic queuing principles. A conceptual model of the simulation can be seen in Figure 11. A snapshot of demand was captured from each of the simulated cardiology macro-system locations at the time point when a cardiology admission request was placed for a simulated ED patient. The demand measurements were input to the appropriate hazard model (step A). The hazard model outputted a unique probability distribution of boarding time (step B) for the corresponding patient. A random sample was drawn (step C) from the unique probability distribution which defined boarding time for that patient. This process was repeated for each ED patient admitted to cardiology.

Logic directing patient flow in the simulation was based upon a framework which classified each location modeled. Telemetry and CVICU units were modeled as reactive, i.e., these units reacted to time-dependent fluctuations in demand coming from all inflow sources. The OR and the CATH LAB were modeled as proactive, i.e., these units directed patient flow with highest priority to and from other locations in the model. The ED was modeled purely as an input source in relation to all other locations. The other hospital units were modeled as a single input / output source to represent the cross service sharing of beds that exists within the hospital.

Patients were directed to various locations within the model based upon transfer probabilities collected from the real system. These transfer probabilities were dependent on patients' previous locations. For example, a common surgical patient's pathway through the system is to; (1) Arrive at the OR; (2) Move to the CVICU post-peratively; (3) Move to a telemetry unit when intensive care services are no longer needed; (4) Be discharged home. By guiding location transfer probabilities based upon previous locations, common patient flow pathways, as such, were preserved.

The simulation was probabilistically driven by actual, unaltered distributions collected from multiple clinical information systems. Distributions capturing the number of arrivals and LOS (excluding boarding time) were simulation inputs. Inter-arrival rate distributions were aggregated by day of week and hour of day. LOS within the simulation was defined as the time interval from when a patient enters a unit from any location to when the patient exits that unit to any other location or home. The number of arrivals and LOS distributions for each location were verified by comparing measurements of central tendency and variability from the simulated versus real system as seen in Table 10. Mann-

Table 10. Simulation Verification and Validation

Location	**Real System median, (IQR)**	**Simulated System median, (IQR)**	**Comparison Measure**
	Arrivals Per Week		**Mann-Whitney U (p-value)**
ED	882, (855 - 899)	883, (863 – 904)	0.35
ED BOARDERS	242, (226 - 256)	241, (232 – 252)	0.95
TELEMETRY BOARDERS	30, (23 – 36)	31, (24 - 37)	0.27
CVICU BOARDERS	6, (5 – 8)	7, (4 – 9)	0.56
TELEMETRY UNIT	152, (141 – 161)	153, (142 – 161)	0.53
CVICU	56, (50 – 64)	58, (54 – 62)	0.25
CATH LAB	123, (110 – 133)	122, (111 – 129)	0.38
OR	298, (278 – 323)	297, (279 – 316)	0.52
CARDIAC SURGERIES	32, (24 – 39)	32, (25 – 37)	0.28
	Length-of-Stay (hours)		**Mann-Whitney U (p-value)**
ED TREATMENT	3.2, (1.9 – 5.3)	3.2, (1.9 – 5.3)	0.96
ED BOARDING (ALL)	2.1, (0.7 – 5.8)	2.1, (0.8 – 5.9)	0.19
TELEMETRY BOARDERS	3.1, (1.5 – 6.9)	3.3, (1.7 – 7.0)	0.33
CVICU BOARDERS	1.7, (0.8 – 3.0)	1.7, (0.9 – 3.0)	0.62
TELEMETRY UNIT	32.3, (17.2 – 61.4)	33.1, (18.4 – 61.6)	0.35
CVICU	42.1, (20.3 – 75.2)	43.1, (21.3 – 74.9)	0.42
CATH LAB	5.4, (3.1 – 7.7)	5.5, (3.1 – 8.1)	0.34
OR	2.5, (1.5 – 4.0)	2.6, (1.6 – 4.4)	< 0.05
CARDIAC SURGERIES	6.1, (3.3 – 8.9)	6.1, (3.4 – 9.0)	< 0.05
	Census Distributions (minute-by-minute)		**Correlation Coef. (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

Whitney U tests were used to assess differences between independent parameter distributions for the simulated versus real system. The simulated surgery LOS 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.

Boarding time to the telemetry unit and CVICU, location census distributions and temporal patterns were the major output variables validated against the real system. Boarding time validation for telemetry and the CVICU patients is displayed in the LOS section of Table 10. The real versus simulated minute-by-minute census distribution for each location modeled is seen at the bottom of Table 10. Correlation coefficients were used to compare temporal patterns of corresponding census measurements. The boarding and census output variables were cross-validated using 6-month training set and a 6-month testing set to ensure generalizability.

Results

The division of cardiology received 10,881 separate visits during the one year study period. The telemetry unit received 7,901 of those visits with 1,591 (20%) patients arriving from the ED and 510 (6%) patients arriving from the OR. The CVICU received 2,980 visits with 332 (11%) patients arriving from the ED and 996 (33%) patients arriving from the OR. Patients boarded for telemetry had a mean boarding time of 5.3 (median, inter-quartile range: 3.1, 1.5 - 6.9) hours.

Patients boarded for the CVICU had a mean boarding time of 2.7 (1.7, 0.8 - 3.0) hours. In comparison, the mean ED treatment time, excluding boarding time, was 4.1, (1.9, 3.2 - 5.3) hours. The average occupancy of the telemetry and CVICU units was 88% and 77%, respectively.

The simulation created from one year of patient flow data reached steady state after running 2 weeks; however, an 8 week warm-up period was used to be sure that all results were collected during steady state. Variability in boarding time results (major response variable) associated with random number generation was adequately attenuated after the simulation was run in steady state for approximately 4 months. All results were compiled from 3-year simulation runs.

Projecting the effects of increasing surgical volume on ED boarding

There were 15,296 surgical procedures consisting of 1,578 (10%) cardiac surgeries performed over the study period. The simulation was used to determine the effects increasing surgical volume on cardiac patient boarding time in the ED. The number of simulated weekly surgical procedures was increased by 10% increments keeping the proportion of cardiac surgeries (10%) constant. The increase in surgical volume was distributed by day-of-week and hour-of-day in proportion to scheduling in the current system. The effects of increasing surgical volume on boarding time to the telemetry unit and CVICU is seen in Figure 13. Increasing surgical volume 10% resulted in a 37 min (12%) increase in average boarding time to telemetry and a 33 min (20%) increase in average boarding time to the CVICU.

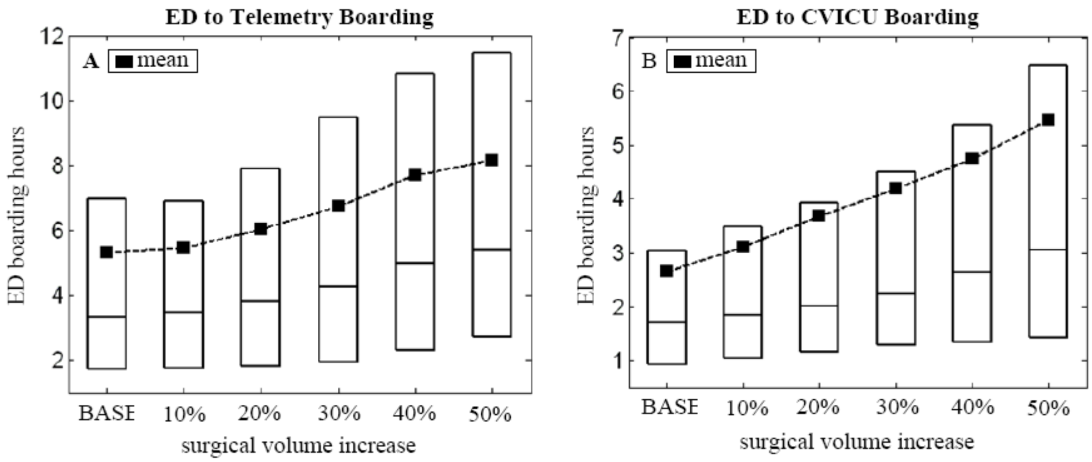

Figure 13. The effect of surgical volume increases on ED boarding time:
A) Boarding time to the telemetry unit
B) Boarding time to the CVICU

Reducing length-of-stay (LOS)

Reducing LOS for telemetry and CVICU patients results in an increase in available staffed bed-hours that can be used to improve ED patient access or accommodate more surgical volume. The LOS distribution is easily altered within the simulation, however not all real patients' LOS may be affected by new cardiology processes. LOS for patients destined to the OR, CATH LAB or other hospital units may be dependent upon the operations of their future location. Cardiology has the most control over LOS for; (1) telemetry patients discharged home; representing 73% of telemetry exits, and (2) CVICU patients either transferred to telemetry or discharged home; representing 69% of CVICU exits. Improving the efficiency of transfer and discharge processes, introducing provider incentives to discharge patients home earlier in the day and creating a discharge waiting area are the methods that hospital administrators have discussed to reduce inpatient LOS. Fast track protocols, post operative critical pathways, and staffing level improvements are methods other hospitals have used to reduce inpatients' LOS.[17-21]

Reducing LOS in the simulation for controllable telemetry inpatients by 60 minutes results in a 7 minute (2%) reduction in average boarding time to telemetry. Reducing LOS for controllable CVICU inpatients by 60 minutes results in a 8 minute (5%) reduction in average boarding time to the CVICU, with all other inputs held constant. Instead of reducing boarding time, LOS reduction can free capacity to receive an increase in surgical patients. Figure 14 demonstrates how LOS for controllable patients must be adjusted in order to accommodate increases in surgical volume and operate in the current state (i.e., current occupancy levels, current boarding time distribution). Reducing LOS for

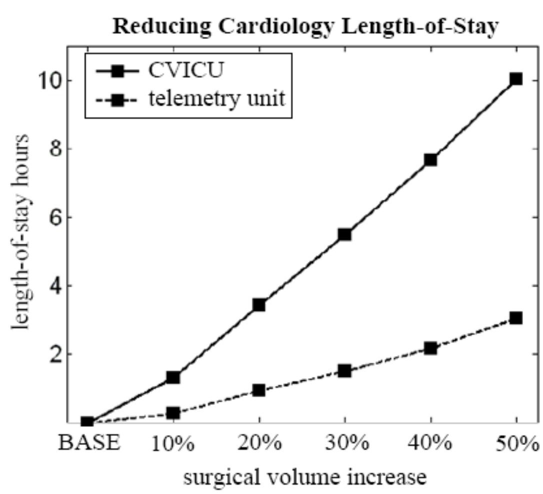

Figure 14. Reducing cardiology inpatient length-of-stay to accommodate an increase in surgical patients

controllable telemetry and CVICU inpatients by 60 minutes gives cardiology the ability to receive 296 (19%) more surgical patients annually, with 75 of these patients moving directly to telemetry and 221 moving directly to the CVICU.

Informing cardiology inpatient expansion plans

The simulation was used to demonstrate how expanding physical capacity (beds) would allow cardiology to improve ED patient access or accommodate more surgical patients. Increasing telemetry unit capacity by 1 additional bed results in a 9 minute reduction in average boarding time to telemetry. Increasing CVICU capacity by 1 additional bed results in a 7 minute reduction in average boarding time to the CVICU. In comparison the simulation results suggest that 1 additional telemetry bed be added for every 16% (270 annual cardiac surgeries) increase in surgical volume and 1 additional CVICU bed be added for every 11% (184 annual cardiac surgeries) increase in surgical volume. Again this assumed that all inputs, patient flow patterns and current system state outputs remained constant.

Conclusions

A discrete event simulation tool was created to provide information that assisted cardiology administrators in decision-making and planning for upcoming increases in surgical volume. The simulation output focused on the relationship between surgical volume and ED patient access to inpatient cardiac services. This relationship was determined by using hazard regression models that reflect the nature of competition for resources within a hospital macro-system. The models quantify how increasing demand elevates competition and creates delays in access for ED patients. Embedding the "competition" regression models into a stochastic discrete event simulation represents a novel strategy that was used to examine the effects of future demand and prospective interventions.

The simulation results demonstrate how interventions (i.e., reducing LOS or increasing capacity) have the strongest effect on the highest priority surgical patients. Reducing LOS 60 minutes can result in a relatively unnoticeable 7 or 8 minute reduction in average boarding time or an apparent 19% increase in cardiac surgery throughput. Similar results are true of adding additional cardiology beds. As long as ED patients receive low priority and management practices reflect this, the gap between surgical and ED patient access is destined to widen and ED crowding will escalate.

United States hospitals provide health care services in a conflicting environment. It is the responsibility of hospitals to adhere to the Institute of Medicine's mandate to reduce boarding and ED crowding while simultaneously providing enough remunerative services to remain financially viable. System engineering tools, such as the simulation developed in this study allows hospitals to better navigate and plan in this discordant environment.[22] Hospitals should strive to use these tools to understand how scarce resources are being distributed; how competition for these resources affects health care access and how intervening would affect and improve the system.[23]

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CHAPTER VII

CONCLUSIONS AND FUTURE WORK

Conclusions

My doctoral research focused on the use of system engineering tools to measure and improve health care work processes. The tools were designed to engage barriers to safe and efficient emergency health care delivery. Studies focused on work processes at the levels of the patient, care team and organization as displayed in Figure 15.[1,2] Preliminary research

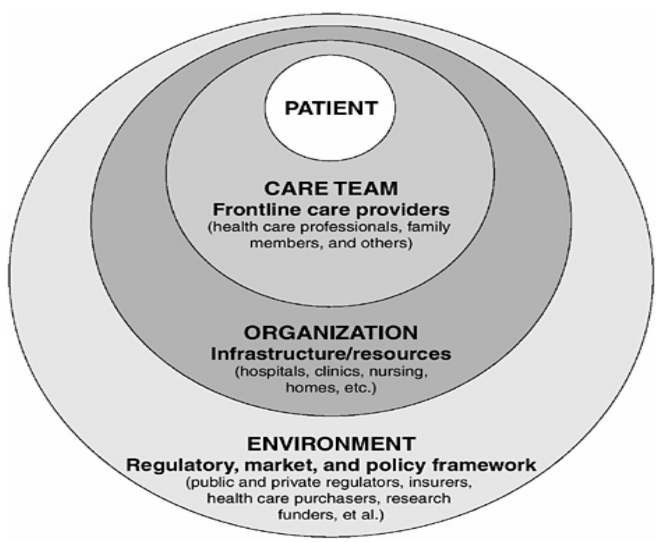

Figure 15. Conceptual drawing of the 4 level health care system[1,2]

was aimed at measuring workload and characterizing work patterns of individual physicians and physician teams.[3-5] This led to research aimed at measuring the complexity of the ED as a system.[6] Preliminary studies provided insights about the challenges of delivering high quality care under excessive demand and resource constraints.

Systems engineering tools are able to provide solutions that can help tightly coupled hospitals operate under intensifying pressures. Pressures are represented as boundaries in Rasmussen's dynamic safety model displayed in Figure 16.[1,7] Economic and workload boundaries move the operating point in the

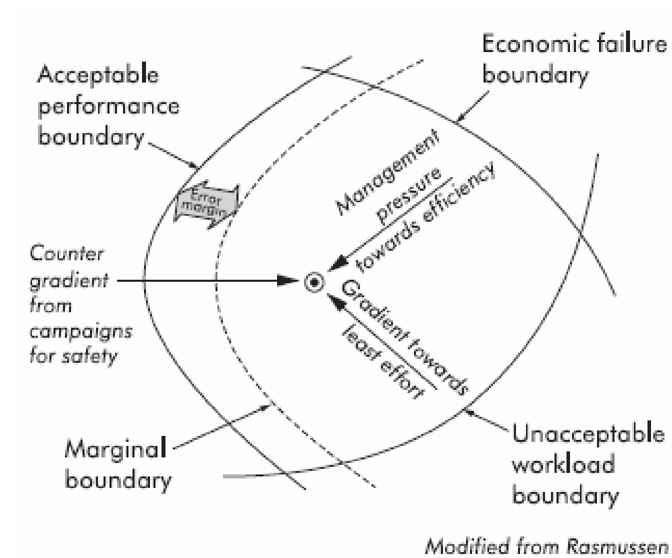

Figure 16. Dynamic safety model; The dot represents a hospital systems dynamic operating state.[7,8]

move the operating point in the direction of the performance (safety) boundary. The unacceptable workload boundary is being approached in EDs across the country and this is placing patients at risk. The risk of an accident increases as the operating state moves closer to the acceptable performance boundary. The marginal boundary represents the ambiguity associated with the position of this boundary. Accident risk is acceptably low when the operating state is within the marginal boundary.

Hospital administrators and health care providers are constantly managing the trade-offs associated with moving the operating point within the feasible space. Systems engineering tools should be designed to help define and navigate these boundaries. Using these tools to increase efficiency will allow hospitals to cope with heightening levels of demand and not approach unacceptable levels of workload and patient risk. These tools provide the means of improving quality of health care delivery while reducing health care costs and increasing provider job satisfaction.

Promising areas for improvement exist at the junctions between hospital sub-systems. Solutions designed to optimize the performance of a hospital system become difficult to implement in the presence of competing interests from inter-dependent components. Competing interests and competition for resources create inefficiencies and risk when processes are optimized for individual components, rather than the system as a whole. Isolating the analysis and optimization of separate hospital components does not support patient-centered care.[8] Individual patient care spans many components (units) yet the effects of component interactions on patient care have not been adequately studied. Using systems engineering methods to measure, analyze and improve component interactions is the best way to follow a patient centered approach to improving hospital-based health care delivery.

Despite the value and need of systems engineering tools in health care, little effort has been put forth in comparison to other industries. Systems engineering tools have proven their value in other industries such as nuclear power, aviation, manufacturing and many other service based industries. These tools have yet to prove themselves on a large scale in health care. The reasons for this may be: (1) The complexity of the health care system and patient care challenges the adaptability of systems engineering tools; (2) Professionals with system engineering skills are not routinely recruited to work in health care settings; and (3) Health care is quite resistant to change, which these tools may introduce. At the present time, systems engineering tools have a lot to offer health care and there are several hurdles that must be overcome. The NAE / IOM report, "Building A Better Delivery System" was a very important step in the right direction. The report illustrated the major quality gaps in health care delivery that may be addressed by systems engineering methods.[9] I am hopeful that over the next decade, systems engineering tools will have gained traction in health care and the tools and methods will have become more commonplace. If this happens, the health care environment will undoubtedly be a better place for all who come in contact with it.

National Heart, Lung, and Blood Institute Future Work

A National Heart, Lung, and Blood Institute (NHLBI) grant proposal involving several committee members was proposed to apply the simulation methods developed in this doctoral research to the ED cardiac care pathway. The future study seeks to use a similar simulation model to determine how variability in hospital system workload and variability in work processes designed to manage this workload, contributes to performance errors in ED cardiac care.

The simulation tool will enable testing of the following global hypotheses: (1) artificial (i.e., man-made) variability in ED and hospital work processes accounts for more of the observed variance in acute coronary syndrome (ACS) care than does the natural (i.e., random) variability of patient arrival patterns and risk severity; and (2) adherence to ACS quality indicators can be increased by eliminating artificial variability and improving the management of natural variability. The rationale for the project is that artificial and natural variability create constraints on system resources which significantly limit ED care providers' abilities to meet quality standards for ACS.

This study will examine six time-dependent quality indicators for ACS (Table 11) including three indicators endorsed by the ACC, the AHA and the National Academy of Clinical Biochemistry (NACB): electrocardiogram (ECG) readout time; door-to-balloon time; and cardiac biomarker turnaround time. The quality of care provided to patients suspected of having ST-Elevation Myocardial Infarction (STEMI) will be evaluated on the basis of ECG readout time and door-to-balloon time. For patients suspected of having Unstable Angina (UA) or Non-STEMI, the quality of ED system care processes will be evaluated using five measures: ECG readout time; laboratory turnaround time; therapeutic turnaround time; boarding time; and ED LOS.

Table 11. Selected quality indicators for STEMI and UA/Non-STEMI

STEMI Quality Indicators	Definition (Guideline)
(1) ECG readout time	Arrival time to ECG readout (<10 min)
(2) Door-to-balloon time	Arrival time to balloon inflation (<90 min)
UA/NSTEMI Quality Indicators	**Definition (Guideline)**
(1) ECG readout time	Arrival time to ECG readout (<10 min)
(2) Laboratory turn-around-time	Physician order to laboratory report time(<60 min)
(3) Therapeutic turn-around-time	Laboratory order to first anti-ischemic medication administration
(4) Boarding time	Disposition decision time to inpatient admit time (<120 min)
(5) ED length-of-stay	Arrival time to discharge (disposition decision for inpatients)

There is increasing evidence that ED crowding and acute surges in ED workload adversely affect the quality of care provided in that setting by straining the resources necessary for care delivery. [10-15] Researchers examining variation in healthcare have used queuing theory to demonstrate how ICU and ED crowding result, at least in part, from distal fluctuations in hospital system workload and patient flow. [16-18] This study proposes to integrate the current aims and methods of ED crowding research and health care operations research to model how temporal variations in hospital workload strain resources, overload inefficient work processes, and increase the likelihood of performance errors in clinical microsystems. Figure 17 is a conceptual diagram of the proposed study which illustrates the relationships between variability, system uncertainty and complexity, and the quality of cardiac care provided in the ED.

National trends in clinical performance standards for ACS illustrate the complex relationship between hospital system dynamics and quality of care in the ED. ED care providers do not strive to provide sub-optimal care to their patients. However, despite their best efforts they are predominantly failing to

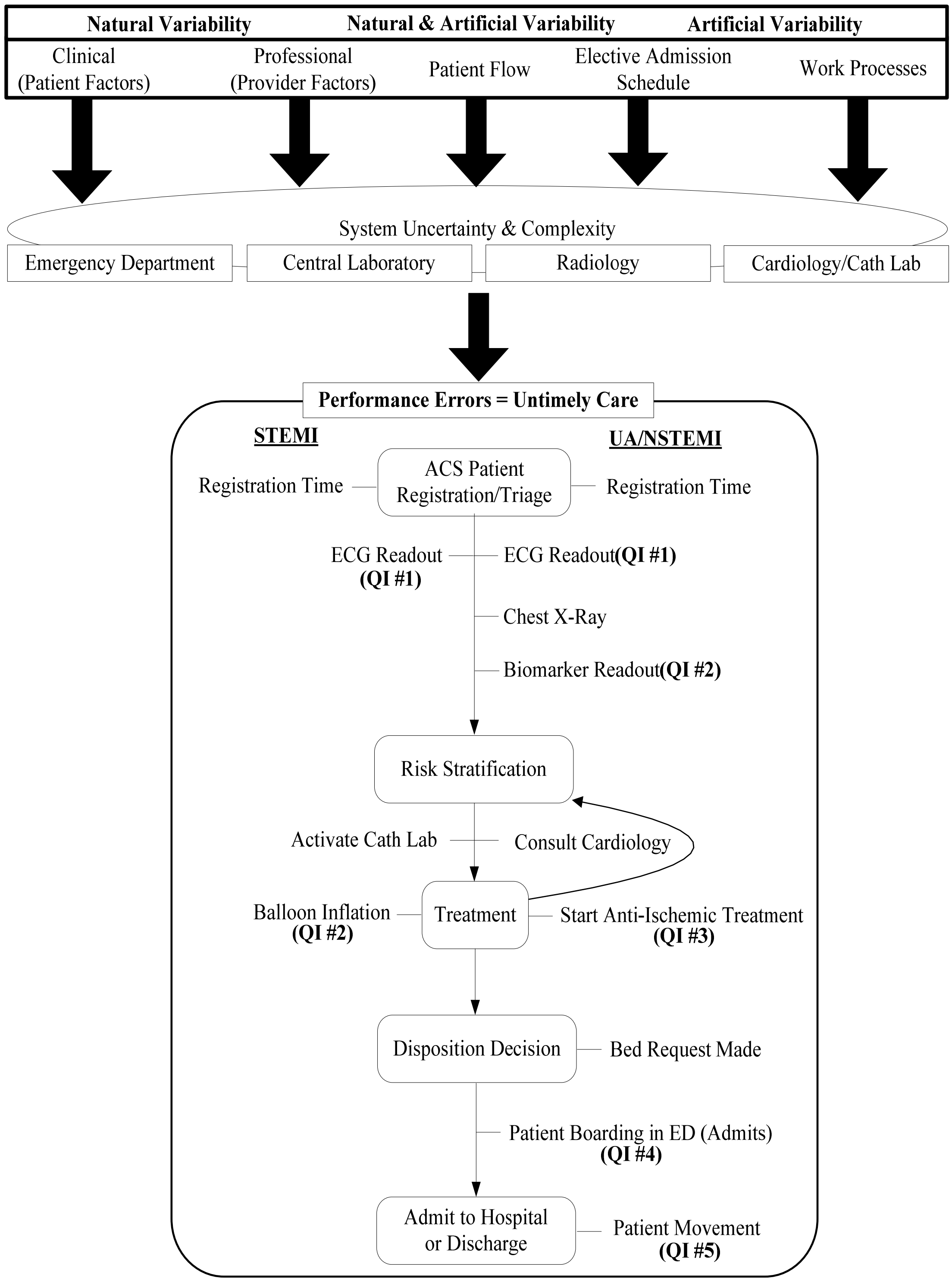

Figure 17. Cardiac pathway conceptual diagram; QI = Quality Indicator

meet the quality indicators for ACS set forth by the AHA, the ACC, and the NACB.[19-21] Further, failure to diagnose myocardial infarction is the leading cause of malpractice claims in the ED.[22] Yet, the process of ruling out ACS requires a minimum of 6 to 12 hours of evaluation and diagnostic testing.[22] The implication of such demands on ED safety and efficiency are significant considering that up to two-thirds of US EDs routinely operate at or above capacity.[23] ED providers are challenged to provide timely and thorough care for potential ACS patients without tying up critical resources and inadvertently jeopardizing the quality of care provided to other patients.

In manufacturing engineering there is an important concept involving "non-value added" processes or "non-value added time". For instance, when a part is being created it may start as a piece of raw material and with each step or process it comes closer to the final product. Steps such as drilling a hole or sanding add value to the product, where as steps such as transporting or inspecting the part are non-value added processes that contribute to non-value added time. In lean manufacturing, the goal is to minimize the time and money spent on non-value added processes. For suspected ACS patients, preventable delays are, by definition, errors. The first step towards improving the quality of ED care provided to these patients is to understand the mechanisms by which system factors, such as ancillary service delays and patient flow variability, interact to impede providers' abilities to achieve basic performance standards.

The study aims to advance the NHLBI's mission to improve cardiopulmonary care on a broad scale by eliminating performance errors caused by interactive complexity and system uncertainty. The research plan has been developed as a direct response to recommendations made by the IOM and NAE to apply tools and methods from engineering and operations management to improve the quality and efficiency of healthcare systems.[22,24-26]

Other Future Work

In addition to the research proposal submitted to the NHLBI, other efforts to engage new health care problems and extend and improve the current simulation methodologies will transpire. The near future opportunities may include; (1) Developing a patient flow simulation of the entire hospital with an emphasis on creating smart scheduling practices for electively scheduled patients; (2) Improving the current patient flow simulation models to include cost and staffing parameters, and; (3) Using the NHLBI simulation methodology to construct patient care pathways for other disease processes, such as stroke. Beyond the near future, I hope to continue to apply systems engineering tools to health care delivery problems and to convince others of the value in doing so.

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APPENDIX A

Levin S, France DJ, Hemphill R, Han J, Slagle J, Aronsky D. Shifting Toward Balance: Measuring the distribution of workload among emergency physician teams. *Ann Emerg Med.* 50:419-423, 2007.

Levin S, France DJ, Hemphill R, Jones I, Chen K, Rickard D, Makowski R, Aronsky D. Tracking Workload in the Emergency Department. *Hum Factors.* 48(3):526-539, 2006.

France DJ, Levin S. System Complexity as a Measure of Safe Capacity for the Emergency Department. *Acad Emerg Med.* 13:1212-1219, 2006.

Shifting Toward Balance: Measuring the Distribution of Workload Among Emergency Physician Teams

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Study objective: The objective of this investigation is to determine time-dependent workload patterns for emergency department (ED) physician teams across work shifts. A secondary aim was to demonstrate how ED demand patterns and the timing of shift changes influence the balance of workload among a physician team.

Methods: Operational measurements of an adult ED were collected from a clinical information system to characterize physician workload patterns during all current work shifts. Plots of patient load versus time were developed for each physician shift, in which patient load was defined as the number of patients a physician simultaneously managed at a point in time. Patient-load curves for each shift were superimposed during 24 hours to display how patient load was distributed among a team of physicians.

Results: Resident shift changes during daily peak occupancy periods caused patient load imbalances so that residents on a particular shift consistently managed a disproportionate number of patients (mean 9.4 patients; 95% confidence interval [CI] 6.7 to 12.1 patients) compared with other residents on duty (mean 3.4 patients; 95% CI 2.1 to 4.7 patients).

Conclusion: Physician patient load patterns and ED demand patterns should be taken into consideration when physician shift times are scheduled so that patient load may be balanced among a team. Real-time monitoring of physician patient load may reduce stress and prevent physicians from exceeding their safe capacity for workload. [Ann Emerg Med. 2007;50:419-423.]

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SEE EDITORIAL, P. 384.

INTRODUCTION

Background

High demand periods in the emergency department (ED), characterized by high occupancy levels, increased waiting room census, and access block to inpatient beds, are hypothesized to pose significant risks to patient safety and patient satisfaction.[1-8] High demand increases the amount of clinical workload that must be distributed among a team of attending and resident physicians on staff. While performing an observational study to characterize and quantify the workload and communication patterns of individual emergency physicians working during periods of high demand, the authors noticed an apparent imbalance in the distribution of workload among physicians working concurrently.[9,10] It appeared that although some physicians were extremely busy to the point of nearly exceeding their functional limits, other physicians were experiencing low workload.

Importance

The microenvironment of each physician must be conducive to providing safe, timely care regardless of the operational state of the entire ED. Excessive cognitive workload and increased stress have been shown to adversely affect worker performance across many industries.[11,12] O'Donnel and Eggemier[12] refer to mental workload as the portion of an operator's limited capacity required to perform particular tasks. The assumption behind this theory is that humans have a fixed amount of processing capacity, and if at any time the processing demands exceed the available processing capacity, performance quality decreases. High levels of workload can lead to error and adverse patient events. In hospital care, increasing nursing

Editor's Capsule Summary

What is already known on this topic

Many studies have documented variations in total emergency department (ED) workload during a 24-hour cycle, but few have focused on the distribution of this load among individual physicians.

What question this study addressed

How physician workload varies over time and how variation in new patient arrivals and emergency physicians' shifts relates to variations in physician workload.

What this study adds to our knowledge

Shift changes occurring at peak presentation times are associated with much higher peak workloads for the oncoming physicians than other shifts.

How this might change clinical practice

This information might allow development of more equitable patterns of scheduling and organization of work among emergency physicians.

Research we'd like to see

Workload was defined as the total number of patients a physician was managing, but even within a single patient, workload varies dynamically over time. More detailed estimates of actual workload would be useful in refining these results.

patient load above 4 patients has been associated with a 7% increase in 30-day mortality rate and a 7% increase in the odds of failure-to-rescue per additional patient.[13] Increased patient load has also been distinguished as a major contributor to physician stress in the ED.[14,15]

High demand intervals in the ED increase the likelihood that physicians will experience workload levels that exceed their capacity to provide safe care. Balancing workload across all physicians on staff as determined by training level and clinical experience will reduce the chances of an individual physician managing unsafe amounts of workload.

Goals of This Investigation

The objective of this investigation was to determine time-dependent workload patterns for dynamic emergency physician teams. For this study, a physician team is defined as a group of physicians working together during a specific work shift or defined period. A secondary aim was to demonstrate how demand patterns and shift change times influence the balance of workload among a physician team.

MATERIALS AND METHODS

Study Design

The study design was a retrospective observational study of emergency physicians. Patient load and ED operational information were collected from a clinical information system during the 8-month study period, lasting from September 8, 2003, to May 14, 2004.

Setting and Selection of Participants

The study was performed at the adult ED of an urban, academic, tertiary care, Level I trauma center in the southeastern United States. The 27-bed ED was designed to handle an annual volume of 20,000 visits but received more than 43,000 visits per year during the study. All emergency physicians present during the course of the study were included.

The study focuses on daily peak operational periods (Monday to Friday) between 3 and 7 PM, during which 2 to 3 attending and 3 to 5 resident physicians are on shift. Physician shift times are staggered throughout the day, with only 1 physician working each shift, which caused individual physicians within a group on duty to be at different stages (beginning, middle, or end) of their respective shift during peak operational periods. Specific physician shifts that start immediately before daily peak operational periods will be referred to as "burdened" shifts. Burdened shifts are characterized by physicians managing high patient loads as a result of daily peaks in occupancy.

Methods of Measurement and Data Collection

ED operational metrics were collected from the ED information system database. Time-stamped information pinpointing the step (ie, waiting room, treatment area, boarded) in ED care each patient was experiencing was extracted from the database. Corresponding patient records documenting the managing attending and resident physicians allowed us to determine the patient load for each physician on duty. Patient load was defined as the number of patients a physician simultaneously managed at a point in time. Minute-by-minute patient-load information was extracted for each physician on duty during the study period. Patient-load curves for each attending and resident physician were generated and then stratified by shift. Weekday (Monday to Friday) shifts and weekend (Saturday to Sunday) shifts were aggregated separately. Patient-load curves averaged during the 8-month study period (ie, ensemble average) for each shift were superimposed during 24 hours to display how patient load was distributed among a team of physicians as a function of time of day.

We used staffing schedules to determine the physicians on duty at specific points. We assumed that attending and resident physicians start their shift on time; we assumed that attending physicians end their shift 1 to 2 hours and residents 1 hour after their formal shift end time. Knowledge gained through physician interviews led to the creation of these assumptions, which are intended to reflect the actual behavior of the emergency physicians studied.

Primary Data Analysis

Descriptive statistics, including mean and 95% confidence interval (CI), were used to characterize the operational state of the ED and physician patient load.

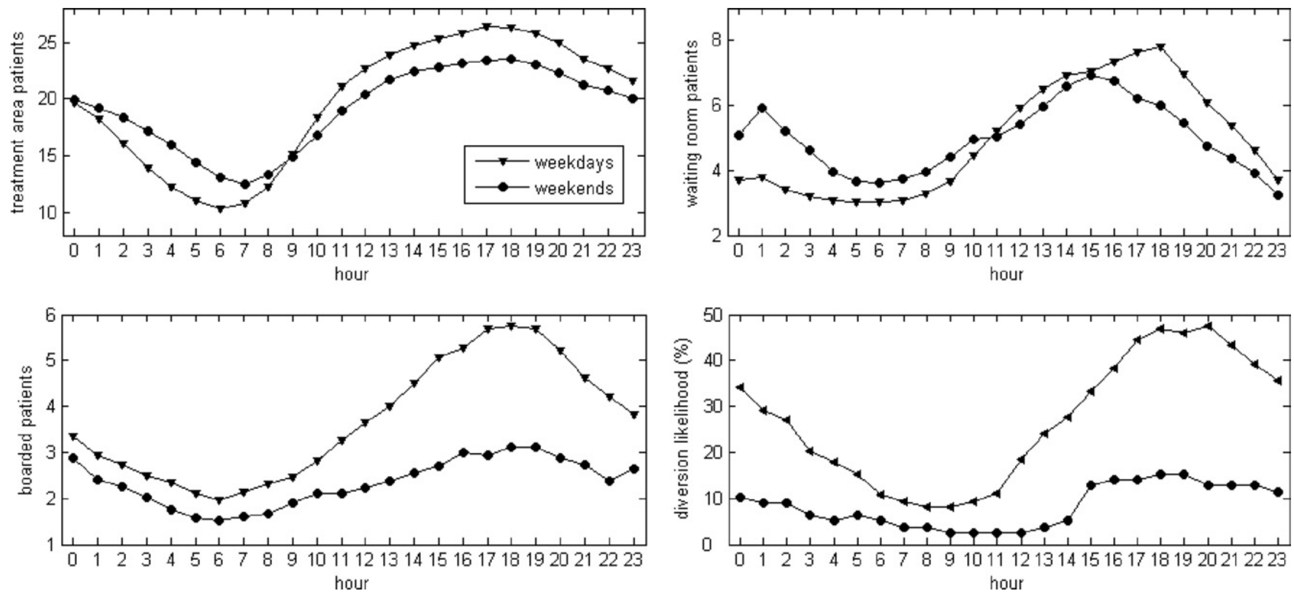

Figure 1. Operational characteristic by hour of day for the 27-bed ED of study.

RESULTS

Operational characteristics of the ED with respect to time are displayed in Figure 1. The ED of study reached peak operations during weekdays (Monday to Friday) between 3 and 7 PM, which is when all observations took place. The average treatment area census was 25.9 patients (95% CI 25.1 to 26.2), the average boarding burden was 5.5 patients (95% CI 5.3 to 5.7), the average waiting room census was 7.4 patients (95% CI 7.1 to 7.6) and the likelihood of the ED being on diversion was 41.7%. ED diversion occurred when occupancy levels exceeded 100% and there were more than 10 patients present in the waiting room.

Average patient loads over time for attending and resident physicians stratified by weekday shift are displayed in Figure 2A and B. Each curve is representative of the time-dependent patient load experienced by the physician on a routine shift during a typical weekday. Patient-load curves for attending and resident physician shifts demonstrate the common pattern of accumulating patients at the beginning of a shift and then decreasing patient load as shift draws to an end. The "burdened" resident or attending shifts highlighted are distinguished by their start times, which occur immediately before daily peak operational (weekdays 3 to 7 PM) periods. The burdened resident shift begins at 3 PM and the burdened attending physician shifts begin at 2 PM and 3 PM. Burdened shifts are characterized by high patient loads and are most affected by the peaking censuses displayed in Figure 1. Residents working the burdened shift accumulate 1 new patient every 15 minutes and reach their maximum patient load 2.5 hours after their shift begins. Attending physicians working burdened shifts accumulate 1 new patient every 22 and 30 minutes, reaching their maximum patient load within 5 hours and 5.8 hours, respectively. Figure 2C represents the distribution of patients among the team of resident physicians at 6 PM on weekdays. Resident shift changes during daily peak occupancy periods caused patient-load imbalances at 6 PM on weekdays so that residents on a particular shift consistently managed a disproportionate number of patients (mean 9.4 patients; 95% CI 6.7 to 12.1 patients) compared with other residents on duty (mean 3.4 patients; 95% CI 2.1 to 4.7 patients).

LIMITATIONS

The ED information system used to collect patient-load information only recorded the physician who discharged a patient. Missing information concerning which physicians managed patients before a handoff was estimated. The results of the estimation were verified by data collected from a sample of observed physicians. In addition, missing information was captured from an alternate clinical information system and matched to estimates to ensure accuracy. The study was also limited to 1 academic ED; thus, results may not be generalizable to other EDs.

This research has produced 2 previous publications that characterize the subjective workload and task and communication patterns of the emergency physicians on whom this study is based. The research designs for the previous studies were created before patient-load imbalance findings and were not developed to support hypotheses on workload imbalances. However, our previous findings have relevant implications to the current work and should be referred to if more detailed information on physician work characteristics is desired.[9,10]

DISCUSSION

There are numerous factors that may influence the distribution of emergency physician workload during the period of a work shift: the total number of patients being managed, the complexity and

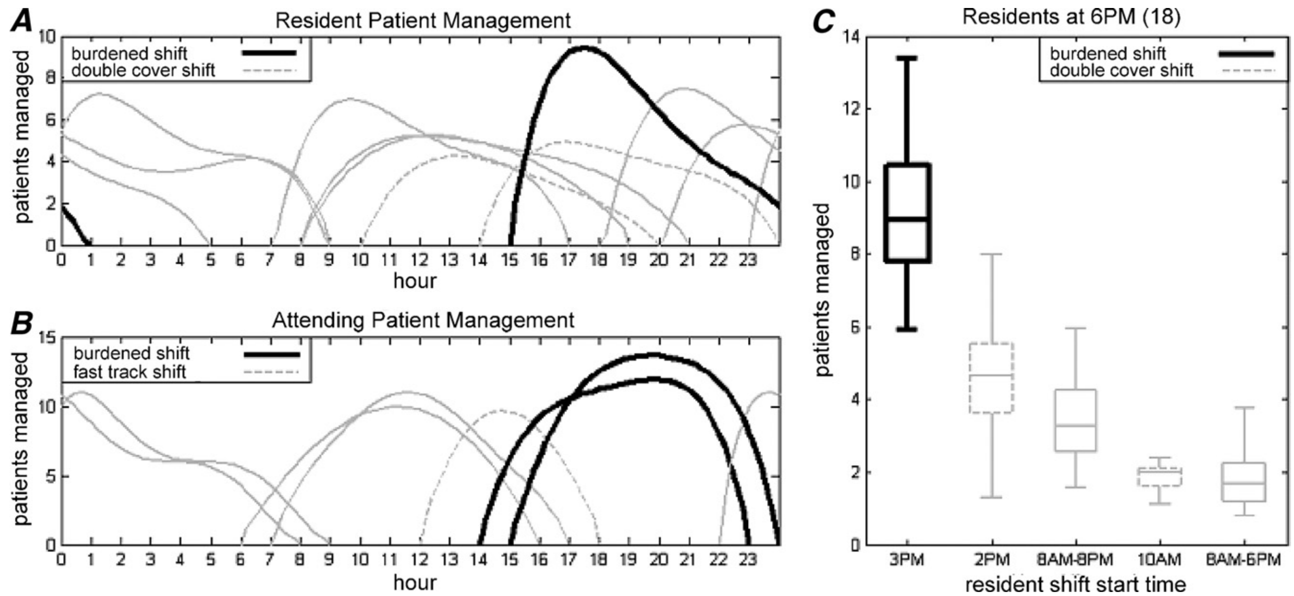

Figure 2. Physician patient load distribution. Burdened shifts are most affected by peaking censuses displayed in Figure 1. Double-cover shifts represent resident shifts that were not permanently scheduled. Double-cover shifts starting at 10 AM and 2 PM were filled 38% and 67% of the time, respectively.

severity of these patients, or the level of training and experience of the physician providing care to these patients. This study focused on the distribution of patient load among residents working weekday afternoon shifts characterized by high patient demand because we perceived, during direct observations for a previous study, an imbalance of workload among resident physicians on duty. Time-varying plots of patient load were created for each of the on-duty residents to examine the distribution of workload across residents working either the same or overlapping afternoon shifts. The study revealed that residents working a particular weekday afternoon shift (starting at 3 PM) were managing much higher patient loads than other residents working at the same time but on different shifts (ie, as defined by shift start time). The results indicate that shift timing relative to peak operational periods may consistently produce workload imbalances among a team of residents and produce unsafe conditions for the providers working those shifts and for their patients.

During periods of high demand, physicians approaching the end of their shift are unlikely to take on new patients; thus, the surge of incoming patients falls on the shoulders of physicians who are, depending on scheduling structure, either at the beginning or middle of their shifts. Residents accumulate patients more quickly because they are assigned patients as they enter the treatment area. Attending physicians are relayed information and assigned to these patients after residents are assigned them. Thus, the surge of incoming patients between 3 and 6 PM on weekdays is rapidly absorbed by residents working the burdened shift. This behavior influences patient-load imbalances among a team of resident physicians. Although the physicians on burdened shifts record the highest patient loads, other physicians such as the residents on shifts starting at 7 AM, 6 PM, or 11 PM also managed high patient loads.

However, during these shifts there was not a daily surge of incoming patients, fewer physicians were on duty, and patient load was distributed more evenly. During peak ED operations (6 PM on weekdays), a resident working a burdened shift (start time 3 PM) typically managed 43% of patients in the ED while there were generally 3 other residents present. The average patient load distribution at 6 PM on weekdays in the ED is displayed in Figure 2C. Third-year residents were placed in the burdened shift 92% of the time during the study period. This situation makes it difficult to determine the exact cause of the high patient loads experienced. It is undetermined whether these high loads were caused by senior residents accumulating the most patients or by shift timing during periods of high demand. It is the authors' hypothesis that both factors contribute. Thus, it is important to monitor physicians (especially residents) who come on shift during these busy times. This occurrence may be alleviated by placing shift start and stop times farther from (not during) daily high demand time periods (3 PM to 7 PM) or by creating an overlapping shift during these times.

The workload imbalance may be detrimental to the resident on the burdened shift, considering that high patient loads increase physician stress.[14,15] In addition, this resident has a greater likelihood of reaching cognitive workload limits at which performance degradation and human error is probable, which may especially be true for burdened residents 2.5 hours into their shift, when it is common for them to be managing more than 9 patients. Within the first 2.5 hours of the burdened shift, a resident must absorb and process a large quantity of new information. During this time, the physician's working environment is rapidly changing and uncertain, which has been proposed to further strain an emergency physician's capacity to deliver safe care.[16] Coupling these circumstances with the highly disruptive, time-pressured environment that is present within emergency medicine increases the potential for clinical errors to be made.[9,17-19] Junior clinicians have been noted to be particularly vulnerable to the rigors of this work environment.[20] Situations are most hazardous during periods of high demand. Circumstances in which specific staff members (ie, burdened resident) are feeling the brunt of high demand periods only decrease the safety of the ED. Physicians must be cognizant of their own workload management abilities, along with the abilities of other staff members, which is of particular concern in an academic medical setting in which a broader range of abilities and experience is present. A complete understanding of each physician's microenvironment, along with how they operate as a team, is essential in safely managing high levels of ED workload.

Studying ED operational patterns and physician behaviors collectively shed light on a situation that is potentially hazardous and occurring almost daily in the ED of study. Further studies delving into the components of emergency medicine work processes have potential to uncover similar deficiencies that may be corrected. Emergency medicine is characterized by a wide variety of task complexity, uncertainty, continual multitasking, and production pressure, which may contribute to the higher risks for error compared to that in other hospital settings.[17,21] It is unlikely that a simple set of improvement strategies will improve the emergency medicine system to deliver health care flawlessly. Numerous studies aimed at characterizing ED work processes, identifying flaws, and subsequently developing knowledge-based strategies for improvement will undoubtedly have a cumulative effect on the progression of emergency medicine.

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Tracking Workload in the Emergency Department

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Objective: The primary objective of this study was to create a methodology for measuring transient levels of physician workload in a live emergency department (ED) environment. **Background:** Characterizing, defining, and measuring aspects of this interrupt-driven work environment represent the preliminary steps in addressing impending issues concerning ED overcrowding, efficiency, and patient and provider safety. **Methods:** A time-motion task analysis was conducted. Twenty emergency medicine (EM) physicians were observed for 180-min intervals in an ED of an academic medical center. Near continuous workload measures were developed and used to track changing workload levels in time. These measures were taken from subjective, objective, and physiological perspectives. The NASA-Task Load Index was administered to each physician after observational sessions to measure subjective workload. Physiological measurements were taken throughout the duration of the observation to measure stress response. Additional information concerning physicians' patient quantity and patient complexity was extracted from the ED information system. **Results:** Graphical workload profiles were created by combining observational and subjective data with system state data. Methodologies behind the creation of workload profiles are discussed, the workload profiles are compared, and quantitative and qualitative analyses are conducted. **Conclusion:** Using human factors methods to measure workload in a setting such as the ED proves to be challenging but has relevant application in improving the efficiency and safety of EM. **Application:** Techniques implemented in this research are applicable in managing ED staff and real-time monitoring of physician workload.

INTRODUCTION

The State of Emergency Medicine

Modern emergency medicine (EM) is in a time of crisis because of a variety of interdependent perils that have been recently discovered and substantiated. Emergency department (ED) overcrowding, efficiency, and patient and provider safety are at the forefront of many issues that the EM community is addressing. Data published in the U.S. Department of Health and Human Services (2004) report *National Hospital Ambulatory Medical Care Survey: 2002 Emergency Department Summary* indicate that EDs in the U.S. are approaching a boiling point in terms of increasing patient demand and shrinking bed capacity. Just prior to this report the Institute of Medicine (2000) released *To Err is Human: Building a Safer Health System,* which estimated that between 44,000 and 98,000 patients die of iatrogenic injury annually. Accompanying these reports are numerous research studies capturing the negative effects of the ED environment on physicians, nurses, and patients (Doan-Wiggins, Zun, Cooper, Meyers, & Chen, 1995; Forster, Stiell, Wells, Lee, & van Walraven, 2003; Goldberg et al., 1996; Houry, Shockley, & Markovchick, 2000; Kalemoglu & Keskin, 2002; Lloyd, Streiner, & Shannon, 1994; Losek, 1994; Whitley et al., 1991; Whitley, Gallery, Allison, & Revicki, 1989; Wyatt, Weber, & Chudnofsky, 1998; Zautcke, Neylan, & Hart, 1996). Despite these ominous circumstances EDs continue to be effective, which is easily attributable to the numerous ED staff members who painstakingly do their job well.

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The nature of EM contributes to a rather unfavorable clinical setting for both the patients and providers. The ED is notorious for being a stressful, chaotic, and unpredictable environment within the hospital. When the fluctuant nature of the ED is coupled with punctuations of high-risk time-critical activities, there is an increased likelihood that serious consequences may result for both the providers and patients. For this reason, it is as important to study the effects of this volatile surrounding on ED providers as it is to assess patient safety. It is hoped that further understanding about how ED physicians interact with their environment will produce evidence supporting ED system changes linking provider wellness, job satisfaction, and efficiency to a higher quality of patient care.

Impact on Emergency Department Providers

Currently, the situation for ED providers remains hectic. Occupational stress and depression among EM physicians are extremely high in comparison with other medical specialists (Whitley et al., 1989). The term "burnout" has been utilized quite frequently in this setting. Burnout can be characterized by three main components: "overwhelming exhaustion, feelings of cynicism and detachment from the job, and a sense of ineffectiveness and lack of accomplishment" (Maslach, Schaufeli, & Leiter, 2001, p. 399). A study of Canadian EM physicians who used the Maslach Burnout Inventory scales discovered that 46% of the sample experienced medium to high levels of emotional exhaustion, 93% fell in the medium to high range for depersonalization, and 79% were within the medium to low range for personal accomplishment (Lloyd et al., 1994). High rates of burnout and stress are known to contribute to the relatively high levels of projected attrition within the specialty (Doan-Wiggins et al., 1995). In a population of pediatric EM physicians from 37 separate departments, it was found that only 22% believed they could practice pediatric EM after the age of 50 (Losek, 1994). This environment is having a similar effect on the nursing and clerical staff as well (Zautcke et al., 1996). It is a clear and general consensus that the ED setting has a profoundly negative impact on workers who are exposed to it constantly.

Although research findings indicate that ED physicians tend to be more stressed and burned out than other physician groups, there is less of a consensus on the source of these stresses. A study conducted in 1988 listed time pressure, critical decisions, provider-patient dissonance, and patient stress as the major sources of stress for doctors and nurses in the ED (Phipps, 1988). Keller and Koenig (1989) questioned 104 EM physicians at 24 separate hospitals in the greater Los Angeles area and concluded that (a) patient load, (b) interaction with patients and families, and (c) lack of administrative support were the major contributors to provider stress in the ED. High patient loads, high patient mortality, peer competition, long hours, and lack of sleep were noted to be major stressors among ED residents (Schwartz & Overton, 1987). In the report *Wellness Issues and the Emergency Medicine Resident,* Houry et al. (2000) concluded that the most common stressors in the ED involved long shift work, the disruption of circadian rhythms, chemical dependence, women's issues such as sexual harassment and discrimination, interpersonal relationships, and personal safety. Workload also claimed its stake as among the top stressors in the ED. Among pediatric EM physicians, 46% believed that clinical workload was excessive and that total work hours was the most common reason for this excess (Losek, 1994). Although some discrepancies exist, it is quite clear that many of the factors mentioned aggregate to create a stressful work environment that is conducive to burnout.

Impact on Emergency Department Patients

The current ED conditions may sacrifice the quality of patient care. Compared with nondistressed residents, residents experiencing burnout are more likely to say they "discharged patients early to make their work manageable, did not fully discuss treatment options or answer a patient's questions, or made medical errors" (Bradley, Wipf, & Back, 2002, p. 1). The stressful, chaotic environment is conducive to performance errors. A study of an ED in western Massachusetts found that errors were reported 18 times among every 100 registered patients. However, 98% of these errors did not result in a significant adverse patient outcome (Fordyce et al., 2003). Oftentimes, these errors are caught or blocked before affecting the patient by system safeguards or provider adaptation. However, there are also times when these errors result in poor patient outcomes. The ED has been specifically identified as a location where adverse events are highly likely to be attributable to error. Studies estimate that the proportion of ED adverse events deemed preventable are between 53% and 83%, in comparison with the overall estimates of 27% to 51% for hospital-based events (Fordyce et al., 2003).

There are several theories as to why errors are more prevalent and hazardous in EM than in other specialties. A wide variety of task complexity, uncertainty, unpredictability, continuous multitasking, and production pressures may contribute to the higher risk for error found in EM (Wears, 2000). Communication patterns and interruptions have been suggested as a source of error production (Coiera & Tombs, 1998). High levels of workload and stress have also been recognized as a contributor to high error rates. Human reliability analysis has demonstrated that high stress levels can increase human error probability by factors up to 10 in less experienced personnel during the most routine tasks (Park, 1997). The concept that excessively high levels of workload can lead to human error and system error is fundamental (Braby, Harris, & Muir, 1993). In addition to this, excess loads of the entire health care delivery system are passed directly to and through the ED, adding to the complexity and strain already being experienced (Wears, 2000). These factors intermingle to create an EM system that is prone to error production and can be susceptible to adverse events.

Studying Workload

The impending issues that EM is facing underscore the need for a systematic approach of analysis and improvement. It is obvious that a single solution will not solve the complex, interdependent problems of EM. The combined effect of research from different disciplines focusing on different aspects of the ED will allow for a holistic improvement of the system so that it may be able to better cope with the heavy demands it faces. The human factors engineering (HFE) approach taken in this report focuses on the measurement and dissection of ED physicians' workload.

Workload is a multidimensional, multifaceted concept that is difficult to define concisely (Tsang & Wilson, 1997). The elusiveness of a single satisfactory definition has challenged HFE researchers on many fronts and has fueled a lively and active debate among them. Even without consensus on a definition, HFE professionals agree that workload is a very valuable concept to understand and to measure in sociotechnical systems. Currently, the onset of technology and automation has greatly shifted the workload paradigm from the physical domain to the mental domain. The following widely accepted definition of mental workload was created by O'Donnell and Eggemeier (1986), p. 2: "The term *workload* refers to that portion of the operator's limited capacity actually required to perform a particular task." The assumption behind this theory is that humans have a fixed amount of processing capacity. Tasks inherently demand processing resources, and the more difficult the task or tasks, the higher the processing capacity required for acceptable performance. If at any time the processing demands exceed the available processing capacity, performance quality decreases.

Workload can be assessed at multiple levels. This could mean quantifying workload for an entire job, a shift, or a specific task or on a temporal basis. The measurement technique used determines the level of workload to be captured and quantified. Ideally, the decision to utilize a specific workload measurement tool should be dependent upon the research questions that one is attempting to answer. Thus, a desirable tool will effectively encompass the workload level needed to appropriately address the questions asked and the environment being studied.

Types of Workload Measurement

There are three primary methods for measuring workload: (a) procedural, (b) subjective, and (c) physiological. Each of these methods can be applied in isolation, but they may be measured concurrently to obtain a more comprehensive assessment of workload. This article describes methodologies for integrating and comparing different types of workload measures used in the ED. The different types of workload measures employed capture different levels of workload. They provide information about workload in a 3-hr time window, at the task level, at uniform time intervals, and from the more objective viewpoint of productivity. The methods demonstrated create time-varying workload profiles for each EM physician by integrating and transforming data collected by several workload measurement techniques.

Procedural Measures

Monitoring human behavior in the working environment is the basic and most direct way to measure workload. The most common HFE methods for studying human behavior in the natural or simulated work environment are primary task analysis and secondary task analysis. Task analysis includes any means of assessing what actions a human performs and why these actions are being performed. Task analysis methods involve the structured decomposition of work activities or decisions and classification of these activities as a series of tasks, processes, or classes (Luczak, 1997). A primary task analysis is the most fundamental means of evaluating workload using procedural measures. This involves observing the participant in some way and discerning changes in behavior as task loads vary. Primary task measures are the most direct and "objective" way to measure workload. Primary task metrics collected by human observers are affected by subjective biases, but they are associated with high face validity, which is frequently the most important aspect of the workload measure.

In this study primary task analysis was used to sequentially record the type and duration of discrete primary tasks performed by EM physicians during a segment of a work shift.

Subjective Measures

Subjective workload measures require an operator to distinguish a level of workload for a task or at a specific instance in time. Unidimensional and multidimensional assessment techniques can be performed either immediately or retrospectively. Unidimensional techniques involve asking the participant for a scaled rating of overall workload for a given task condition or at a given point in time. More comprehensive multidimensional methods include various characteristics of perceived workload and are able to diagnose causes and determine the nature of workload. Immediate techniques require evaluations without delay following each single task or at specific point in time. Retrospective techniques require the evaluation of each task to take place after all tasks in a given time frame have been completed. Finally, there is a distinction between absolute and relative methods. Relative techniques involve the participant rating the task circumstance in reference to a single standard. Absolute techniques call for the participant to compare a specific task condition with multiple tasks. Subjective workload assessment techniques are frequently used because of their high face validity, ease of use, participant acceptability, low cost, and known sensitivity to workload variation.

In this study investigators administered the NASA-Task Load Index (NASA-TLX) at the end of each observational period to retrospectively measure physician subjective workload on the most frequently performed clinical tasks.

Physiological Measures

Physiological evaluation techniques measure changes in a participant's physiology that correspond to different task demands. Studies have used physiological parameters such as heart rate, heart rate variability, eye blink rate, galvanic skin response, and brain activity to assess the participant's state (Miyake, 2001). Measuring physiological parameters for workload evaluation has been fairly well validated, but much of the research done involves controlled experiments with controlled stimuli.

In this study, physicians' galvanic skin response was measured continuously (i.e., sampled at 1-min intervals) during the observational periods. Galvanic skin response (GSR) is the change in electrical conductance of the skin attributable to the stimulation of the sympathetic nervous system and the production of sweat. Perspiration causes an increase in skin conductance, thus GSR (measured in siemens) is proportional to workload and stress levels.

RESEARCH OBJECTIVE

The primary objective of this study was to measure different aspects of physician workload in a live ED setting and to create a methodology for transforming the subjective and objective (productivity-based) components of workload into time-dependent measurements. The study used four distinct measurement techniques to characterize physician workload in the ED: (a) observational task analysis, (b) subjective workload assessment, (c) objective workload assessment, and (d) physiological workload assessment. Data collected using these techniques were synchronized, integrated, and analyzed. A new methodology for creating a time-based measurement of subjective and objective workload in the ED was implemented. The subjective measurement overlays NASA-TLX workload scores with a formal procedural time-motion task analysis. The objective workload measure is a score derived from the number of patients concurrently managed by the physician and the acuity of each patient as assigned by the triage nurse. Both measurements allow for the creation of two separate workload profiles for individual physicians during the measurement period. The subjective measurement characterizes changes in a physician's self-perceived workload over an observational time period, and the objective measurement characterizes fluctuations in the clinical demands a physician experiences over this same time period. The temporal nature of these profiles facilitates comparison with each other and with physiological measures.

METHODS

Participants

The study was performed at the Vanderbilt University Medical Center Adult ED between September 8, 2003, and May 14, 2004. This ED is a Level 1 trauma center in a large urban tertiary care hospital in Nashville, Tennessee. The department receives approximately 43,000 visits per year. The population observed consisted of a convenience sample of 10 faculty (attending) physicians, 5 third-year postgraduate (PGY-3) residents, and 5 second-year postgraduate (PGY-2) residents. The Vanderbilt University Internal Review Board approved the study, and all participants gave appropriate verbal consent prior to their observation.

Study Design

Time-motion primary task analyses lasting approximately 180 min were conducted on individual EM faculty and resident physicians. This time interval was selected to allow for comparative analyses with previous research on physician work and communication patterns in the ED (Chisholm et al., 26; Coeira & Tombs, 1998). All observations were performed on weekdays (Monday–Friday) between 3:00 p.m. and 6:30 p.m. This time period was chosen because it includes the peak activity in the ED during the work week (U.S. Department of Health and Human Services, 2004). A single trained observer used a standardized data collection form to sequentially record the type and duration of preidentified primary clinical tasks (Table 1) and work interruptions (Table 2). These task categories were developed from previous ED task analysis studies, physician interviews, and several preliminary (i.e., prestudy) direct observations.

TABLE 1: Categorization of Tasks

Task Name	Description
Charting	Written charting
Dictating	Verbal charting
Direct patient care	Physician at patient's bedside
Electronic whiteboard viewing	Physician views or scans electronic whiteboard for information
Electronic whiteboard interaction	Physician uses touch screen to pull or add information from the electronic whiteboard
Exchanging patient information	Provider-to-provider verbal exchange of patient-specific clinical information
Getting charts/records/documents	Physician retrieves paper charts, records, or documents
Phone calls and consults	Phone consultation with another provider
Supervising	Supervision (observation) of a junior physician or resident
Teaching/learning	Formal interactive clinical teaching or learning
Viewing diagnostic test results	Viewing laboratory results or radiology
Answering EM Services calls	Physician responding to phone call from EM Services
Verbal orders to a provider	Physician gives verbal orders to a resident, nurse, or other clinical staff member

TABLE 2: Categorization of Interruptions

Interruption Name	Description
Equipment malfunction	Computer or diagnostic equipment malfunction interrupts task
Face-to-face physician	Another physician interrupts task with verbal communication
Face-to-face nurse	Nurse interrupts physician task with verbal communication
Face-to-face other	Another provider interrupts physician task with verbal communication
Lost chart, form, or document	Lost chart or documentation interrupts task
Page	Alphanumeric page alert interrupts task
Direct patient care	Urgent patient care interrupts current task
Phone call	Phone call (clinical or nonclinical) interrupts task
Other	Any other event that interrupts physician tasks

These clinical activities or tasks were determined to represent the majority of the work activities undertaken by EM faculty and residents during typical work shifts. The data collection form incorporated Chisholm, Collison, Nelson, & Cordell's (2000) method of categorizing task outcomes and interruptions – that is, tasks could have any one of the following outcomes: (a) task completed without interruption (i.e., "end task"), (b) task interrupted and new task started (i.e., "break in task"), or (c) task temporarily interrupted but completed before new task started (i.e., "temporary interruption"). Table 2 summarizes the nine major types of interruptions recorded during the observations.

The data collection form was installed on a wireless handheld computer to facilitate mobile data collection. All tasks and interruptions were time stamped throughout the duration of the observation. An example output table from the data collection form can be seen in Table 3. Observational data were used to evaluate interrater reliability between observers trained in primary task analysis methods. Observers (i.e., one graduate student and two medical students) were paired during prestudy observations to evaluate the reliability of the data collection processes. Each observer pair exceeded an interrater reliability of .80 (kappa statistic) for task and interruption classification after two 3-hr observation sessions.

The NASA-TLX was administered to all study participants immediately following the conclusion of the 180-min observational time period. The NASA-TLX is a "multi-dimensional rating that provides an overall workload score based on a weighted average of ratings on six subscales: mental demands; physical demands; temporal demands; operator performance; effort; and frustration" (Hart & Staveland, 1988, p. 3). Separate weights for each subscale were elicited from each physician observed. The retrospective method of test administration proved to be most feasible in a live ED setting because it minimized the

TABLE 3: Data Collection Form Output

Current Task	Start Time	Stop Time	Event Type	Interruption
EWB viewing	3:45:12 p.m.	3:45:23 p.m.	End task	
Charting	3:45:28 p.m.	3:46:23 p.m.	Break in Task	Phone call
Phone calls/consults	3:47:29 p.m.	3:49:05 p.m.	End task	
Exchanging patient info	3:49:15 p.m.	3:49:22 p.m.	Temporary	Phone call
Continued	3:49:43 p.m.	3:50:33 p.m.	End task	
EWB viewing	3:50:43 p.m.	3:51:18 p.m.	Temporary	Face-to-face nurse
Continued	3:51:35 p.m.	3:51:48 p.m.	End task	
Phone calls/consults	3:52:49 p.m.	3:53:40 p.m.	End task	

Note. EWB = electronic whiteboard.

number of occasions on which the observer interrupted the physician to administer the survey tool. This retrospective evaluation method has proven to be superior in that it enables the participant to make more relative judgments of each task after all tasks have been experienced (Tsang & Vidulich, 1994). The test focused on each of the primary task categories that were recorded during the observation. Electronic whiteboard viewing and interaction were combined before physician scoring. Dictating was excluded from scoring because only attending physicians performed this task. The task category "verbal orders to provider" was also excluded because of lack of frequency. Thus, NASA-TLX scores were recorded for 10 task categories instead of the 13 listed in Table 1.

System workload metrics were collected concurrently from the ED information system. Central to the ED information system is a 60-inch (152-cm) plasma touch-sensitive electronic whiteboard (EWB) that serves as the command and control center of the ED. ED information system display screens are also accessible from any networked computer in the ED. The EWB displays and records patient data and a number of system workload metrics, including chief complaint, patient wait time, patient length of stay, patient acuity at triage, managing physician, number of patients in the waiting room, ED occupancy, diversion status, average wait times, and length of stay for all patients. The EWB also monitors and displays ED bed status for providers and cleaning staff. These parameters are recorded and stored in the central ED information database at a sampling rate of once per minute. System workload metrics were collected for both observed and randomly selected unobserved periods (i.e., 180-min blocks of time) and compared to confirm that observed periods were truly representative of the overall ED work picture.

Each physician observed during the study was equipped with body worn devices to take minute-by-minute physiological measurements. A SenseWear™ wireless armband monitor recorded GSR, skin temperature, upper body motion, and total body energy expenditure (Liden et al., 2000). A 3-D accelerometer was clipped at the waist of the physician. This monitor recorded lower body movement and total body energy expenditure. The GSR measurement was the only physiological measurement of interest in regard to workload.

Workload Profile Creation

Two unique workload metrics were calculated for each physician. The first measurement, smoothed workload density, represents the physician's subjective self-assessment of workload over his or her observational time period. The second measure, whiteboard metric (i.e., system workload), represents the objective workload or productivity of the physician over this same time frame. Both these measures spawn two separate workload profiles for each physician that represent the physician's subjective and objective workload.

The subjective measurement integrates the observational task analysis with the work scores generated for each task from the NASA-TLX. The work score is placed at the stop time (t) of its corresponding task during the observation. That work score is then multiplied by the duration of that particular task to render a point, $W_{(t)}$, that is used in the creation of a workload density profile for a specific observational period. For tasks that ended with an "end task" or a "break in task," the task duration was simply the start time subtracted from the stop time. Temporarily interrupted tasks were calculated by subtracting the temporary interruption time duration from the total duration of the task. The workload density profile ($W_{(t)}$) is located in the top left corner of Figure 1. This graphical depiction consists of peaks, which represent times of high workload as characterized by that particular physician. However, the erratic nature of the profile does not accurately signify how the effects of previous work tasks influence a provider's current subjective workload score. For this reason a smoothing algorithm is run on the workload density profile. The transform is displayed below and the corresponding smoothed workload density curve ($S_{(t)}$) can be seen in the top right corner of Figure 1:

$$S_{(t)} = S_{(t-1)} + \alpha \times \left[W_{(t)} - \mu(W)\right], \qquad (1)$$

in which $S_{(t)}$ = smoothed workload score at time point (t), $W_{(t)}$ = workload density score placed at time point (t), and $\mu(W)$ = average workload density score across all tasks for the observational period.

The α coefficient can be chosen based upon the degree of change desired in the profile. However,

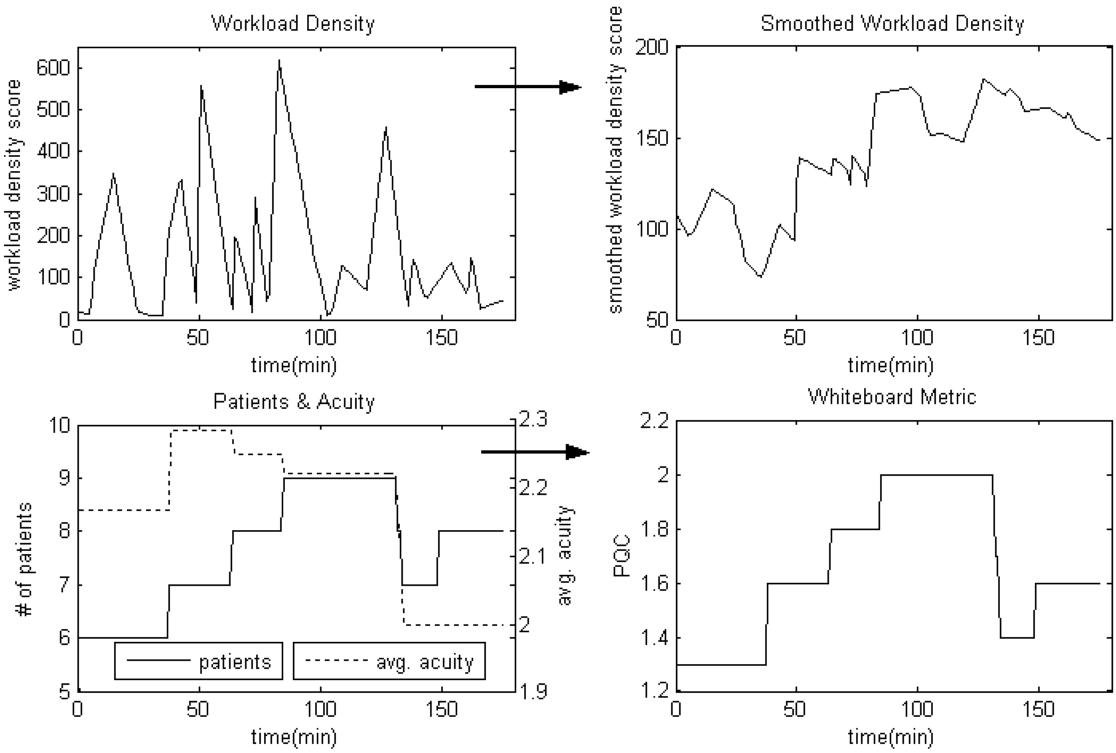

Figure 1. Subjective and objective workload profiles (right) and their corresponding components (left).

changing the coefficient will never change the shape of the curve. An α of .1 was selected for this study.

The objective whiteboard metric incorporates two critical components that help define the productivity level or actual workload a physician is experiencing. This involves the number of patients being managed simultaneously by a physician ($P_{(t)}$) and the severity of injury or acuity's for those patients. An acuity level is an integer from 1 to 4, in which 1 is considered most severe. An acuity value is assigned to each patient soon after arrival to the ED. On rare occasions a patient's acuity may change during the course of the ED visit; however, this is not reflected in any of the hospital information systems. The average acuity ($A_{(t)}$) of all patients seen simultaneously by a physician is used. These two time-dependent measures are depicted in the same plot in the bottom left corner of Figure 1, labeled, "Patients & Acuity." These two measures, $P_{(t)}$ and $A_{(t)}$, are then combined to create a measurement designated patient quantity and complexity ($PQC_{(t)}$) using the transfer function

$$PQC_{(t)} = \left[\frac{P_{(t)}}{\mu(P)} \right] \times \left[\frac{\mu(A)}{A_{(t)}} \right], \quad (2)$$

in which $PQC_{(t)}$ = patient quantity and complexity at time point (t), $P_{(t)}$ = number of patients being managed simultaneously at time point (t), $\mu(P)$ = average simultaneous patients managed across all physicians observed, $A_{(t)}$ = average acuity of patients being seen simultaneously, and $\mu(A)$ = average acuity for all patients across all physicians observed.

The $PQC_{(t)}$ profile developed from corresponding $P_{(t)}$ and $A_{(t)}$ time measurements is displayed in the plot labeled "Whiteboard Metric" in the bottom right of Figure 1. The two constants used for the objective workload calculations are $\mu(P)$ = 6.75 ± 1.50 patients (mean ± standard deviation) and $\mu(A)$ = 2.28 ± 0.20 average acuity. The subjective metric ($S_{(t)}$) and objective metric ($PQC_{(t)}$) were created for every physician observed.

Smoothed workload density ($S_{(t)}$) and the whiteboard metric ($PQC_{(t)}$) have been linearly interpolated to 1-min intervals to create data points that correspond to GSR minute-by-minute measurements. Correlation coefficients were then calculated to compare the associations among the time series profiles representing smoothed workload density ($S_{(t)}$), objective workload ($PQC_{(t)}$), and GSR. This analysis was performed on a participant-by-participant (i.e., EM physician) basis to characterize within-subject workload processes.

RESULTS

EM Physician Primary Task Analysis

In summary, three observers recorded over 50 hr of work activity. This number falls below 60 hrs because tasks not listed in Table 1, periods of inactivity, and personal breaks were not recorded. Physicians performed an average of 103.0 (95% confidence interval [CI], range 94.7–111.3) tasks and were interrupted 14.9 times (95% CI, range 13.3–16.5) per 180-min period. The distribution of tasks based upon frequency and duration can be seen in Figure 2. A recent by-product of this study illustrates the effects of the whiteboard on physicians' behavior and workload (France et al., 2005). More detailed results from the observations and task analysis are summarized in that paper.

Subjective Workload

In analyzing data provided by the NASA-TLX, we were able to better understand the characteristics of different physicians' workload. Previously published summary statistics of NASA-TLX scores showed that temporal demand (TD) was on average the dimension that contributed the most to a physician's self-assessment of workload (France et al., 2005). Forty percent of physicians ranked TD the highest contributor to overall workload and 86% of physicians had an average TD workload score that exceeded their average overall weighted workload score. The average dimensional scores for each type of physician in the ED can be seen at the top of Table 4. The average workload scores for each task can be seen at the bottom of Table 4. On average, residents recorded frustration scores that were notably higher than scores

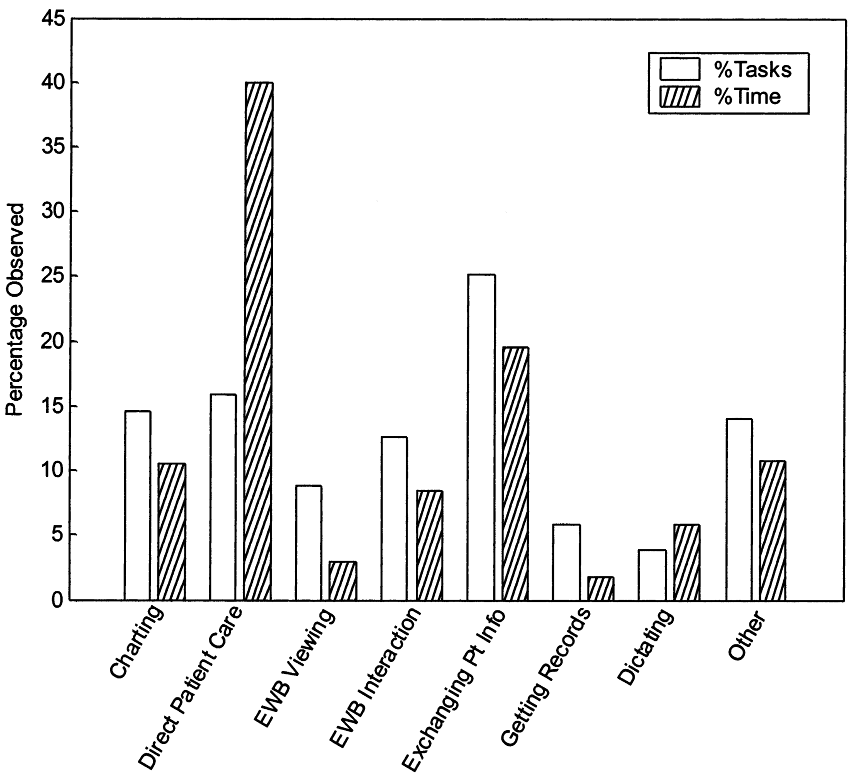

Figure 2. Distribution of tasks observed based upon frequency and duration. EWB = electronic whiteboard; Pt = patient.

TABLE 4: Subjective Workload Scores

	Attending (*N* = 10)	PGY-3 (*N* = 5)	PGY-2 (*N* = 5)
Workload Dimension NASA-TLX Scores (mean ± *SD*)			
Mental demand	56.3 ± 19.5	59.9 ± 19.8	44.9 ± 17.2
Physical demand	24.8 ± 12.9	20.4 ± 17.9	46.2 ± 15.2
Temporal demand	62.8 ± 17.7	74.4 ± 13.2	63.5 ± 25.8
Effort	50.8 ± 22.0	61.1 ± 22.7	63.8 ± 5.6
Performance	45.6 ± 20.9	41.4 ± 19.8	45.8 ± 14.1
Frustration	45.3 ± 14.2	65.8 ± 18.1	61.2 ± 18.9
Weighted workload	50.6 ±12.7	61.9 ± 12.8	61.0 ± 7.7
Task NASA-TLX Scores (mean ± *SD*)			
Answering EM Services calls	26.0 ± 18.9	39.6 ± 25.8	28.5 ± 22.9
Charting	52.7 ± 15.7	59.8 ± 13.5	67.5 ± 11.5
Direct patient care	53.7 ± 18.8	71.8 ± 8.9	61.5 ± 13.5
Electronic whiteboard interaction	35.5 ± 18.2	42.0 ± 19.7	48.8 ± 4.6
Exchanging patient information	53.8 ± 11.7	66.2 ± 22.4	58.8 ± 13.3
Getting old records	30.2 ± 25.2	46.2 ± 32.6	40.8 ± 28.7
Phone calls/consults	51.0 ± 15.4	65.2 ± 21.4	65.8 ± 13.6
Supervising	54.8 ± 12.8	41.3 ± 25.5	20.5 ± 41.0
Teaching/learning	54.6 ± 11.9	55.6 ± 15.9	57.5 ± 19.0
Viewing diagnostic results	43.6 ± 20.9	52.8 ± 15.1	54.0 ± 20.0

recorded by attending physicians. Previous published analyses revealed that residents, more so than faculty physicians, identified frustration as a major contributor to workload (France et al., 2005).

Smoothed workload density curves were plotted for each physician. An example of a smoothed workload density profile and the corresponding workload density profile is presented in Figure 1.

Objective Workload

A summary of the objective workload data collected from the electronic whiteboard is shown at the bottom of Table 5. The average number of patients simultaneously managed, $\mu(P)$, across all physicians was 6.8 (95% CI, range 6.1–7.4). The average acuity, $\mu(A)$, for all patients across all physicians observed was 2.28 (95% CI, range 2.19–2.37). These values were used for all subsequent objective workload calculations.

An objective workload profile, $PQC_{(t)}$, and its corresponding components $P_{(t)}$ and $A_{(t)}$, are displayed in Figure 1.

Physiological Workload

GSR measured across all physicians was 0.30 microsiemens (95% CI, range 0.26–0.34). A

TABLE 5: Task and Interruption Counts and ED System Workload Metrics

	Attending (*N* = 10)	PGY-3 (*N* = 5)	PGY-2 (*N* = 5)
Tasks and Interruptions (mean ± *SD*)			
Tasks	102.4 ± 23	108.0 ± 10	97.8 ± 13
Interruptions	16.0 ± 3.4	17.6 ± 5.5	11.0 ± 2.0
ED System Workload Metrics (mean ± *SD*)			
Total # of patients seen	11.4 ± 5.3	12.6 ± 2.7	6.4 ± 5.0
Maximum # of patients simultaneously managed	9.8 ± 4.0	10.8 ± 1.6	5.6 ± 4.3
Acuity of patients seen	2.6 ± 0.2	2.1 ± 0.2	2.2 ± 0.2
Patient length of stay (hr)	5.9 ± 2.2	9.8 ± 0.9	6.4 ± 3.7
ED occupancy (%)	92.7 ± 3.8	94.8 ± 11.7	92.0 ± 6.5

minute-by-minute measurement of GSR for one particular physician observed can be seen at the bottom of Figure 3.

Workload Profile Comparisons

Workload measured subjectively (smoothed workload density), objectively (whiteboard metric), and physiologically (GSR) for 1 physician can be seen in Figure 3. These three profiles are aligned in time. A product-moment correlation coefficient (r) is used to measure the association between any two workload profiles. A probability (p) value using a 95% CI is calculated for each r to determine the significance of the correlation. The ranges of r values across all physicians are displayed at the top of Table 6. The wide ranges of coefficients (rs) exhibit the high variation in correlation for each pairing across all 20 physicians. The number of physicians who recorded a positive, negative, and nonsignificant correlation coefficient (r) for each workload profile pairing can be seen at the bottom of Table 6. Physicians recording a positive correlation in one workload profile pairing did not necessarily record a positive correlation in either of the other two pairings. There were no significant correlation patterns found within the data set.

DISCUSSION

The measurement of physician workload in the ED using a variety of techniques has proven to be a complex task. The nondeterministic nature of physician workflow, rapidly changing clinical

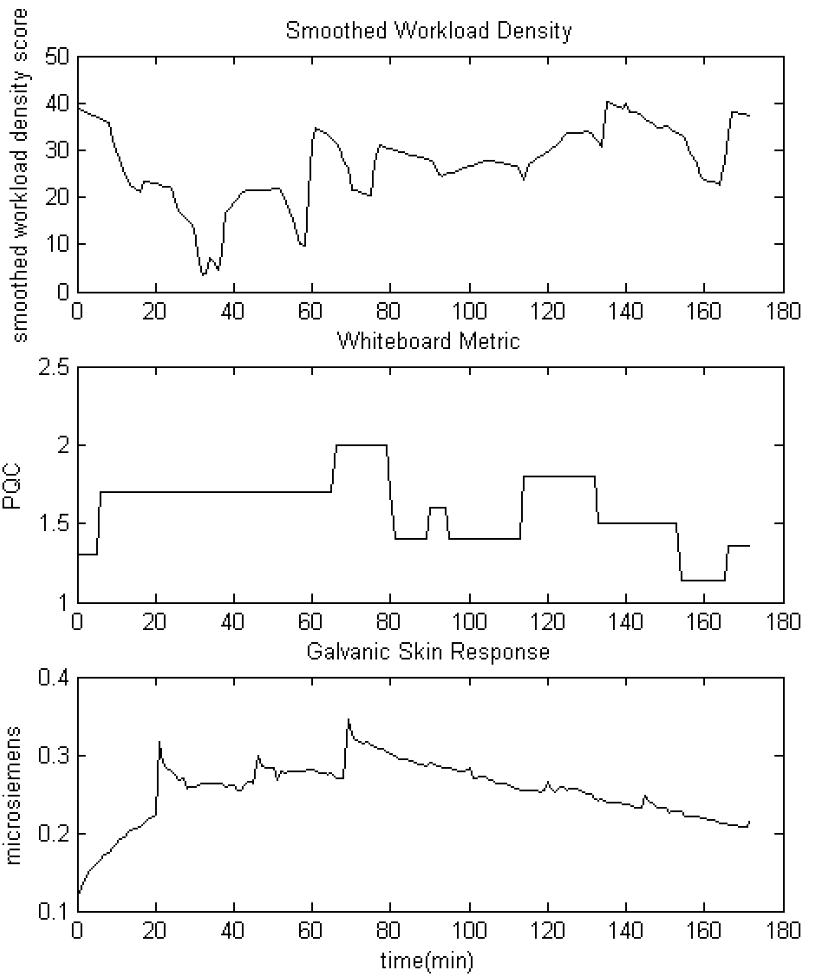

Figure 3. Aligned subjective, objective, and physiological workload profiles.

TABLE 6: Correlation Coefficient (*r*) Comparing Workload Profiles

	Smoothed Workload Density vs. Patient Quantity Complexity	Smoothed Workload Density vs. Galvanic Skin Response	Patient Quantity Complexity vs. Galvanic Skin Response
Correlation coefficient (*r*) range	–.68 to .75	–.63 to .51	–.94 to .55
Total number of physicians			
r (+)	9	5	5
r (–)	7	3	7
r (not significant)	4	12	8

demands, and interactive nature of EM makes measuring workload difficult in this setting. However, these are the very factors that perpetuate the unsafe conditions that patients and providers are experiencing. Static measures (i.e., summary statistics such as mean and median) cannot adequately characterize workload in the ED and do not provide information about the multiple time-varying factors and conditions that increase the likelihood of adverse events. This is the value in acquiring time-dependent measures of workload using the measurement tools available.

In tracking workload over time, the creation of a workload density ($W_{(t)}$) profile for each physician allows an investigator to pinpoint finite periods of high or low workload. However, this profile becomes hard to compare with other measures and lacks the ability to realistically characterize changes in workload over time. The smoothing algorithm implemented considers workload density scores of past tasks in creating the new measure at time point (t). A current smoothed workload density ($S_{(t)}$) score is affected by past scores that are closest to the time point (t). The effect of past tasks decreases exponentially as the time difference to (t) increases.

The objective measure of patient quantity complexity ($PQC_{(t)}$) utilized can be considered a fundamental measure of how much work the physician is performing at a given time point. In previous ED research, a team of investigators assigned to the task of developing measures of workflow in EDs designated 38 potentially effective measurements (15 input, 9 throughput, and 14 output; Solberg, Aspilin, Weinick, & Magid, 2003). ED workload was characterized as the "demand and complexity of patient care that is undertaken by the ED within a given period" (Solberg et al., 2003, p. 829). A throughput measure of a particular physician's workload was defined as a function of the number of patients treated and those patients' acuity levels for a particular period of time during a shift. In this study we created the system workload metric (i.e., whiteboard metric) from the electronic whiteboard data to characterize the workload of a particular physician within the ED system.

Smoothed workload density ($S_{(t)}$) and patient quantity complexity ($PQC_{(t)}$) are both measures of circumstances that relate to mental workload: $S_{(t)}$ considers task difficulty and intensity in relationship to mental workload, whereas $PQC_{(t)}$ is an objective measure that assesses the amount and complexity of the work being managed by a physician. These measurable circumstances affect physicians' available processing capacity to complete tasks satisfactorily. As smoothed workload density ($S_{(t)}$) or patient quantity complexity ($PQC_{(t)}$) levels rise past a certain point, it is estimated that a physician's ability to perform a task adequately is jeopardized. An operator's available capacity to perform a task may be exceeded by the information-processing capacity necessary to successfully perform that task. However, limitations in physicians' available processing capacity during different circumstances must be measured and modeled in order to attribute performance degradation to specific mental workload levels. An interesting finding specific to the environment focused on in this study was that PGY-3 residents proved to be the workhorses of the Vanderbilt ED. On average, they cared for the most patients, completed the most tasks, experienced the most interruptions, and slightly edged out PGY-2 residents in recording the highest average work scores.

The original motivation for developing several time-varying measures of workload was previously discussed. It was to provide insights about the changes that occur in an ED physician's workload over time that are otherwise indiscernible using static measures. Several different measurement techniques were used, but they all encompassed workload at different levels. The procedural (task analysis) and subjective (NASA-TLX) tools measured workload at the task level. Common productivity measures captured physician workload over an entire shift. The physiological measures recorded GSR minute by minute. Globally assessing workload by using and comparing all the information available from each tool was difficult because of the heterogeneity of measurement levels.

The transformation of the subjective and objective workload metrics to time-based measures created a foundation for comparison in which each measure was taken at the same level. An initial hypothesis arose regarding the comparison of these measures. These measures (subjective, objective, and physiological) are all designed to measure workload; thus they should be highly correlated. The flaw in this reasoning was that these metrics do not measure the same workload construct. This is what may have resulted in the inconsistent correlation measures calculated. Future studies using larger populations are needed to further explore the causes of the highly varying correlations found across all physicians. Additionally, the standard statistical methods, such the correlation analysis used in this study, are not optimal for analyzing rich time series data.

As mentioned earlier, workload is a multidimensional concept that is made up of several components and perceived differently by different people. The challenge arises in constructing one single global workload measure that accurately encapsulates information available from subjective, objective, and physiological standpoints. This measure must also be robust enough to control variance from differing perceptual (subjective), performance (objective), and physiological traits. These characteristics make workload hard to globally assess using these differing work components in any setting. Studying this in a live setting compounds the difficulty in that it limits the measurement tools available and sacrifices control for realism. So, in considering these challenges, maybe the goal of future research should not be to obtain an integrated global workload metric but, rather, to effectively characterize the time-varying relationships within and among time series workload measurements. Time series regression models such as autoregressive integrated moving average (ARIMA) models are capable of handling nonstationary and serially correlated data (Chatfield, 2004). Further, linear mixed models enable investigators to model the relationships among random effects (i.e., individual ED provider effects) and fixed effects (i.e., interruptions and objective workload) on the outcome of interest (i.e., subjective workload or physiological workload). Linear mixed models are advantageous to general linear models because they can handle correlated data, unequal variances, and unbalanced designs (McCulloch & Searle, 2000).

The introduction of HFE techniques to the live ED environment is a unique and complex task. The chaotic nature of this environment makes it difficult to capture and describe using human factors methodologies. The current trend in researching quality in the ED focuses on medical errors. Kyriacou and Coben (2000) described three major categories of research on error: (a) research summarizing the magnitude of errors, (b) research identifying casual factors behind these errors, and (c) research evaluating interventions that are meant to reduce errors. Studies falling within these categories have made an impact on quality in EM. However, the study of human performance within an ED is a rare occurrence. James Reason's contention is that "correct performance and systematic errors are two sides of the same coin" (Reason, 1990, p. 36). Human factors methods concerning human performance and human errors will fill a void in EM research and may be able to improve the conditions for all who set foot through ED doorways. Studying human performance and analyzing how physicians function and interact with the normal ED environment seems to be the key in justifying system changes that will improve the EM delivery system for both the patients and the providers.

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System Complexity As a Measure of Safe Capacity for the Emergency Department

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Abstract

Objectives: System complexity is introduced as a new measure of system state for the emergency department (ED). In its original form, the measure quantifies the uncertainty of demands on system resources. For application in the ED, the measure is being modified to quantify both workload and uncertainty to produce a single integrated measure of system state.

Methods: Complexity is quantified using an information-theoretic or entropic approach developed in manufacturing and operations research. In its original form, complexity is calculated on the basis of four system parameters: 1) the number of resources (clinicians and processing entities such as radiology and laboratory systems), 2) the number of possible work states for each resource, 3) the probability that a resource is in a particular work state, and 4) the probability of queue changes (i.e., where a queue is defined by the number of patients or patient orders being managed by a resource) during a specified time period.

Results: An example is presented to demonstrate how complexity is calculated and interpreted for a simple system composed of three resources (i.e., emergency physicians) managing varying patient loads. The example shows that variation in physician work states and patient queues produces different scores of complexity for each physician. It also illustrates how complexity and workload differ.

Conclusions: System complexity is a viable and technically feasible measurement for monitoring and managing surge capacity in the ED.

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Keywords: surge capacity, complexity, uncertainty, workload, safety

Emergency departments (EDs) are a critical component of our health care infrastructure because they provide essential emergent and urgent care services during ordinary times and rapid response care during times of crisis or disaster. Data published in the Centers for Disease Control and Prevention's 2004 report, *National Hospital Ambulatory Medical Care Survey: 2002 Emergency Department Summary*,[1] indicate that EDs in the United States are quickly losing their reserve capacity due to increasing patient demand and shrinking bed capacity. The Centers for Disease Control and Prevention estimates that between 1992 and 2002, ED visits increased 15%, while the number of hospitals operating EDs decreased 23%.[1] U.S. EDs received more than 110 million patient visits in 2002, compared with 89 million in 1992.

The increased production pressures have exposed the nation to the complexities and inefficiencies of the ED system and the ED–hospital interfaces.[2,3] Frequently, crowding caused by these system factors results in ambulance diversion, increased patient wait times, increased lengths of stay, patient boarding in the ED, and decreased patient satisfaction.[4–11] Although insufficient research has been conducted to establish a definite link between ED crowding and adverse patient and provider outcomes, there is growing evidence to suggest that such a link is both reasonable and likely.[12–19] Research has shown that EDs generate high rates of preventable adverse events, risk management claims, and patient complaints.[13,20–23] Other studies have shown that ED providers experience high levels of workload and stress and high rates of depression and career burnout.[24–35]

Emergency department systems researchers have largely focused on crowding measures as indicators of system state, despite their recognition that system complexity, as created by patient factors, work process factors, and ED–hospital interface factors, affects provider and system performance.[36] Although investigators have made important progress in diagnosing the causes of overcrowding and their effects on ambulance diversion,

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they have not adopted a standard definition of overcrowding or defined standard criteria for diversion.[36,37] While overcrowding is a critical factor influencing ED safety and efficiency, we assert that it is an inadequate measure of system state for evaluating ED capacity or for the purposes of safety research, operations research, and quality improvement.

In this report, we introduce a measure of system complexity for the ED based on research in manufacturing and information theory. In its current form, it can be used to quantify the uncertainty of the demands on ED resources (i.e., providers and systems). Quantifying uncertainty is especially appealing and important because there is growing evidence that uncertainty as created by variability in patient volume, patient acuity, and inpatient bed availability is one of the major determinants of ED capacity.[8,38–41] Further, system complexity has the potential to be a truly comprehensive ED system metric compared with crowding measures, such as occupancy or system workload, because it can be modified to include the magnitude of work demands in the ED. This would produce a single integrated measure of ED workload and work uncertainty for the ED.

Another attractive feature of the proposed measure is that it will enable ED system researchers to consider and evaluate the concept of capacity in a new light. Specifically, we believe this measure can be used to show that there is a difference between the efficient (or physical) capacity of an ED and its safe capacity. We define the safe capacity of the system as the capacity at which human performance and the safety of the ED system begins to deteriorate. We believe that under conditions or circumstances of high complexity, the safe capacity can be well below the physical capacity of the ED (i.e., number of staffed beds). Therefore, it is the uncertainty of the ED system at a point in time, in addition to its workload, that ultimately dictates capacity. Finally, because the proposed measure is based on information theory, it will lend itself well to human factors and cognitive systems research (i.e., study of human performance in complex, high-risk domains). Ultimately, we believe this research will improve public health by creating a new framework to study and improve ED safety and efficiency.

SYSTEM COMPLEXITY

Complexity is a fundamental but abstract property of sociotechnical (i.e., man–machine) systems that represents the expense or consequence of increased system functionality, efficiency, or flexibility.[42] Complexity has been identified as one of the major determinants of susceptibility of high-risk systems to accidents and thus remains a primary focus of modern systems and safety research.[43,44] Some experts have gone so far as to refer to complexity as the "enemy of very high levels of human-systems performance."[45] Leading patient safety researchers have recommended that health care should focus on complexity rather than error.[46] Similarly, leading ED systems researchers have recently recommended that health care use the techniques of operations management, including queuing theory, to study and model the natural and artificial variabilities within the ED and throughout the ED–hospital system.[39,47] These recommendations are in direct alignment with the recommendations put forth by the Institute of Medicine and National Academy of Engineering in their 2005 report, *Building a Better Delivery System*.[48] That report recommended that health care entities apply methods and tools from engineering disciplines to improve the safety and efficiency of the health care system.

The transition from current qualitative understandings of system complexity toward a quantitative representation of this critical system property is becoming more imperative as the need to improve the efficiency, effectiveness, and safety of EDs grows. A measure or set of measures that would quantify ED system complexity would provide opportunities to analyze and model system and provider performance as a function of system parameters. It would help researchers understand the processes individuals and clinical work teams use to manage complexity. Further, it may improve our ability to control and even predict complexity and its short-term impact on ED crowding, capacity, and safety.

In the past decade, operations researchers and manufacturing engineers have introduced and developed several theoretical measures of complexity of manufacturing systems.[49–52] These researchers define complexity "as a system characteristic which integrates several key dimensions of the manufacturing environment which include size, variety, concurrency, objectives, information, variability, uncertainty, control, cost and value."[50] In manufacturing, complexity has the effect of impeding flow by building ever-bigger obstacles. This has the effect of extending lead times and making operations less predictable.[50]

Managers of supply chains have used an information-based (i.e., entropy) measure of complexity to achieve a better understanding of manufacturing processes and how their complexity creates barriers that disrupt the flow of materials and information between the customer and supplier. The complexity measure has also been used by production line managers to determine which system factors (e.g., queue variability, labor shortages, inefficient inspection processes) contribute most to bottlenecks.[50] The strength of the measure is that it can actually guide managers and operators to the most appropriate solution to improve the performance of the manufacturing system. For example, one form of complexity, static or structural complexity, is best addressed through the simplification of processes. The other major form of complexity, dynamic or operational complexity, is best reduced by improving management of processes or targeted quality improvement interventions.

METHODS

The information-theoretic approach of manufacturing to quantifying system complexity appears to be very relevant to the study of complexity in the ED. This work is based on Shannon's mathematical theory of information that uses entropy to quantify uncertainty.[53,54] A system's entropy represents the amount of information required to describe or control the state of the system.[55] The entropic measure of complexity specifically integrates principles from queuing theory with Kolmogrov–Sinai entropy. Complexity (H(s) in Equation 1) is the sum of a system's static and dynamic complexities. Its unit of measure is bits.

$$H(s) = H_{Static} + H_{Dynamic} \quad \text{(Equation 1)}$$

Static complexity is the measure of the expected amount of information needed to describe the system and its components.[49,56,57] It is a function of the structure of the system, the variety of subsystems, and strengths of interactions. Specifically, the static complexity of a system (H_{Static}) is determined by the number of resources (M) it has (i.e., people, machines, and so on), the number of possible states (S) for each resource, and the probability p_{ij} that a resource *i* is in state *j* at a given point in time.

$$H_{Static} = -\sum_{i=1}^{M}\sum_{j=1}^{S_i} p_{ij} \log p_{ij} \quad \text{(Equation 2)}$$

In the ED, resources are physicians, staff, and medical equipment or diagnostic devices, and their states may be defined as discrete tasks or specific categories of activity. For example, clinician work states may include tasks such as direct patient care, charting, or teaching. Medical equipment, such as a magnetic resonance imaging scanner, has only two possible work states: in use or not in use. In many practical situations, measuring discrete tasks (states) may become very cumbersome. A solution to this impracticality involves merging states into specific categories or "macro states." All discrete tasks are mapped to a "coarser" set of states.[57] This method may be translated to the ED by considering a macro state to be all tasks a resource performs on one specific patient. Static complexity can be calculated on the basis of direct observation or other data sources (such as databases) that store information on production demand. In manufacturing, static complexity is generally calculated from administrative databases that store bills of materials, routings, and work centers. Static complexity can be reduced by simplifying work processes, and it also can be planned. Static complexity has predictive capabilities (Equation 2).

Dynamic complexity is the measured (actual) amount of information required for defining the state of the system and is typically calculated on the basis of direct observation and measurements of the system for a given time.[49,56,57] In manufacturing, it has been shown that observational periods of two to four weeks are sufficient to characterize the properties of the system for the purposes of analysis. The sampling rate and sampling duration required to adequately characterize the intensity and variability of ED workflow have not been determined. Sampling requirements will be different for each ED and will be most dependent on ED type (rural, suburban, urban, teaching, and so on), the degree of information technology integration, and the variability of system demands (i.e., patient volume and acuity) experienced by the ED in the past. EDs equipped with advanced information technology systems will be able to determine the nature of system queues almost entirely through retrospective analyses of electronically stored data. Regardless of the method of acquisition, longer observational periods are recommended to account for seasonal effects.

Dynamic complexity reflects the extra amount of information required for defining the state of the system when it deviates from the expected behavior. It is primarily a function of queues (queue variability or queue changes). In the ED, queues are made up of several different entities. Entities are patients or objects (e.g., laboratory specimens, x-rays) that must be processed for the ED to properly deliver health care. Every resource that is utilized by the ED manages a queue. A physician's queue consists of the number of patients he or she simultaneously manages (i.e., patient volume). A triage nurse's queue consists of the number of patients waiting to be triaged at any given point in time. A laboratory technician's queue consists of the number of laboratory tests ordered and awaiting completion. The measure of dynamic complexity quantifies uncertainty of the demands on the ED resources (Equation 3):

$$H_{Dynamic} = -P\log_2 P - (1-P)\log_2(1-P) - (1-P)\left(\sum_{i=1}^{M^q}\sum_{j=1}^{S^q} p_{ij}^q \log_2 p_{ij}^q + \sum_{i=1}^{M^b}\sum_{j=1}^{S^b} p_{ij}^b \log_2 p_{ij}^b\right) \quad \text{(Equation 3)}$$

The variables M, S, i, j, and p in Equation 3 are defined identically as they are for Equation 2.

Dynamic complexity considers both planned and unplanned events. It also separates times that the system is deemed in control from occasions where the system is out of control. For dynamic complexity, (P) becomes the probability of the system being in control, (p^q) becomes the probability of queues of varying length (>1), and (p^b) becomes the probability of Bernoulli-type process such as equipment breakdowns or any other unplanned event that stops entity processing. It should be noted that $S_j^q + S_j^b = S_j$, the number of states at resource (i). Because there is a high degree of uncertainty in emergency medicine, it would be difficult to precisely define when the system is in or out of control.

A useful alternative of this equation is to not define the system control constraints, thus setting (P) in equation 3 to zero (Equation 4). Therefore, the equation simplifies to

$$H_{Dynamic} = -\left(\sum_{i=1}^{M^q}\sum_{j=1}^{S^q} p_{ij}^q \log_2 p_{ij}^q + \sum_{i=1}^{M^b}\sum_{j=1}^{S^b} p_{ij}^b \log_2 p_{ij}^b\right) \quad \text{(Equation 4)}$$

It is also assumed that capturing variability in queue length for resource (i) when in each state (j) would be unreasonable. However, measuring overall queue length variability and the occurrence of unplanned events for each resource (i) is feasible when small sampling windows are used. The resultant modified equation is further reduced to

$$H_{Dynamic} = -\left(\sum_{i=1}^{M^q} p_{ij}^q \log_2 p_{ij}^q + \sum_{i=1}^{M^b} p_{ij}^b \log_2 p_{ij}^b\right) \quad \text{(Equation 5)}$$

Entropy (i.e., uncertainty) is captured in queue length variability in dynamic complexity as it is captured in state probability in static complexity. Complexity values are increased for systems that have highly variable queue lengths within a given time frame. Complexity also increases as more unplanned events occur that interrupt processing.

The researchers who have developed these measures suggest that greater levels of controlled complexity can increase system flexibility, increase customer satisfaction, and enable higher product variety in manufacturing.[49] Further, they suggest that these improvements can generate benefits and value that can outweigh the costs of measuring and managing complexity. Similar benefits may be obtained in emergency medicine first by quantitatively evaluating complexity and then by learning to control and manage it effectively.

EXAMPLE AND DISCUSSION

Conceptualizing the mathematical approach to measuring complexity from the equations listed may be difficult; thus, a simplified numerical example is provided to demonstrate how the proposed measure may be calculated and used for a specific set of resources in the ED. Consider a simple team of three physicians staffing an ED. Each time a patient arrives in the treatment area, a physician is assigned to provide care. When care is complete, the patient is discharged from the ED and either admitted to the hospital or discharged from the entire hospital system. Thus, each physician is managing a set of patients at a single point in time and the queue set is changed every time a patient is either assigned to that physician or is discharged. A patient set at a time point will be considered a physician's queue set. The queue behavior for each of the three physicians over a 180-minute interval can be seen in Figure 1. The numerical values at each step represent the percentage of time each physician is experiencing the corresponding queue relative to the period of time studied. Over the time interval, physician (A), who begins with nine patients, manages a total of 12 patients over the entire time window. Physician (B) begins with only five patients and ends with six, never managing more than seven at any point in time, but sees a total of 11 patients. Physician (C) begins with two and sees a total of five patients. The total number of patients a physician manages over the time window, and not simply the maximum number managed at any one time, will be called the patient group. Each physician decides how to divide his or her time with each patient within the patient group. The state of a physician at a point in time is determined by which patient the physician is directly managing. All tasks performed for a single patient comprise one macro state of a physician. All tasks that are patient nonspecific comprise an additional macro state of a physician. The distribution of time spent in each state for the three physicians is displayed in Figure 2. The state labeled "N" represents the patient nonspecific state. Examples of patient nonspecific states include paramedic radio calls, gathering ED system data such as waiting room volume and length of stay from an electronic whiteboard, general clinical communications with other emergency medicine providers, and clinical reading. The physician queuing and state behavior is what is needed to quantify complexity.

The static and dynamic complexity for each physician may be calculated. Static complexity is calculated by transforming state time distributions into probability distributions. The probability of a physician resource (i) being in state (j) is

$$p_{ij} = \frac{\textit{time in state j by each ith physician}}{\textit{total time interval being evaluated}} \qquad \text{(Equation 6)}$$

Thus, static complexity may be calculated using Equation 2. Dynamic complexity may similarly be calculated by transforming physician queue times into probability distributions. The information provided in Figure 1 may be placed into Equation 5 to render dynamic complexity values for each physician.

The elimination of state dependency (Equation 5) is desirable in that it significantly reduces the amount of information that must be collected. Because ED resources change states quite frequently, we believe this excess information would unnecessarily cloud the measure and make it harder to calculate and interpret. Dynamic

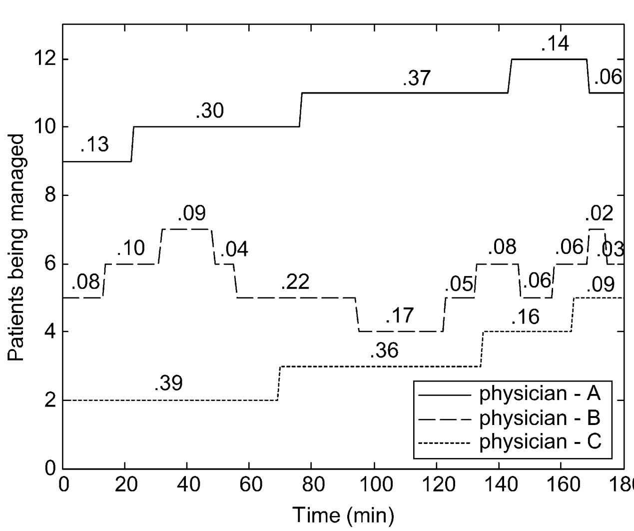

Figure 1. Physician queue behavior.

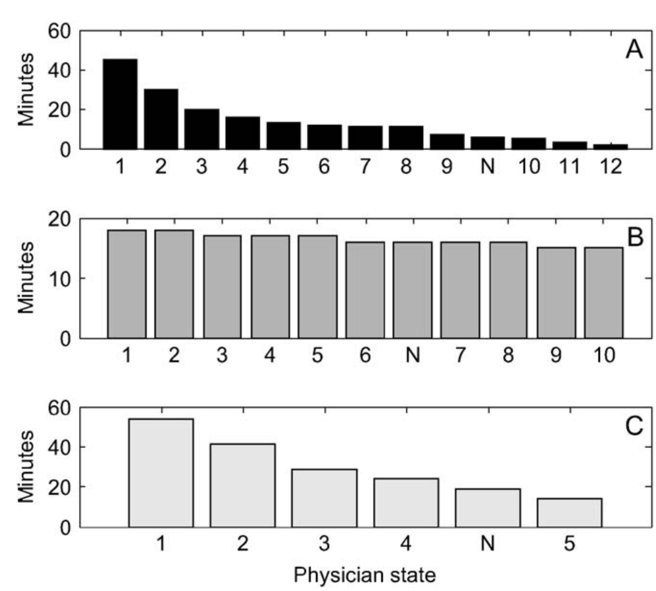

Figure 2. Physician state distribution.

Table 1
Physician Work and Complexity Statistics

Physician	Patients Seen	Average No. of Patients Managed	Average Acuity	Average Workload	Static Complexity	Dynamic Complexity	Total Complexity
A	12	10.59 ± 0.12	2.30 ± 0.01	28.60 ± 0.32	3.27	2.07	5.34
B	11	5.41 ± 0.13	2.29 ± 0.03	14.55 ± 0.30	3.46	3.34	6.80
C	5	2.96 ± 0.14	2.40 ± 0.02	7.71 ± 0.37	2.44	1.79	4.23

complexity may be computed using the information in Figure 1 and Equation 5. The probability of being in each queue (p_i^q) is displayed for each physician in Figure 1. In this example, there were no Bernoulli-type processes; thus, (p_i^b) is set to zero. Examples of Bernoulli-type processes include unexpected loss or failure of system resources, such as when a physician or nurse must leave work due to illness or family emergency or when technological resources such as computed tomographic scanners or laboratory processing systems malfunction. The static and dynamic complexity along with other work statistics are calculated for each physician and displayed in Table 1.

The uncertainty exhibited in queue and state behavior is reflected using the proposed complexity measure. The measure quantifies complexity by capturing both workload and uncertainty. Static complexity effectively incorporates workload by incorporating both the number of patients a physician manages over a given time window and the uncertainty of predicting which patient that physician is delivering care to at any point in time. The static complexity of both physician (A) and physician (B) is greater than physician (C) because they went through significantly more states as a result of seeing more patients. However, physician (B) records a higher value of static complexity by having a more equiprobable (uncertain) state distribution than physician (A) (Figure 2). Dynamic complexity measures the instability of a physicians' queue. Physician (B) records a significantly higher value of dynamic complexity than physician (A) and physician (C) as a result of having a highly transient and unpredictable work queue.

In summary, measuring change and uncertainty in work patterns adds an additional pertinent level of detail to the traditional crowding and workload measures that currently exist to attempt to quantify workload and thus to assess whether physicians are at or near their capacity.[36] The value of evaluating change and uncertainty is evident when analyzing the relationship between complexity and conventional measures of system workload.

The measure of physician workload is calculated for each of the three physicians, incorporating the number of patients a physician is managing and the average acuity of the patient set. Triage acuity values are assigned to patients on a scale from 1 to 5, with level 1 being the most severely ill or injured patients. These acuity values are redefined in reverse order to make the workload scores increase when more severe patients present. A low acuity value (1) for a severe patient is redefined as a (5) and so forth. The calculation for workload can be seen in Equation 7:

$$\textit{Workload} = \textit{number of patients} * \textit{reverse order acuity values} \qquad \text{(Equation 7)}$$

Average acuity, average number of patients being managed, and average workload calculations for each of the three physicians are displayed in Table 1. A comparison on workload versus complexity scores for each physician is displayed in Figure 3. The difference between these measures is evident when looking at physician (A) and physician (B). Physician (A) consistently managed the most patients over time compared with physician (B). Physician (A) also saw slightly more patients than physician (B). The average acuity values for both physicians' patient sets over time were nearly identical. As a result, physician (A) recorded a significantly higher workload value. However, physician (B) recorded a significantly higher complexity value. Physician (B), while never overworked during this period, was operating in the most transient and uncertain environment. The unpredictable nature of physician (B)'s work experience is much more difficult to effectively manage than the other two physicians. This uncertainty is effectively captured in the measure of complexity.

This simple example may be extrapolated to monitor an entire ED system. Measuring the uncertainty of work demands experienced by each system resource will make it possible to calculate a cumulative complexity score for the entire ED system. This will facilitate the identification of workflow bottlenecks and process hazards for clinicians and patients alike that may not be detectable using conventional overcrowding measures. The measure will also provide a means to evaluate the effectiveness of interventions designed to reduce static and dynamic complexity.

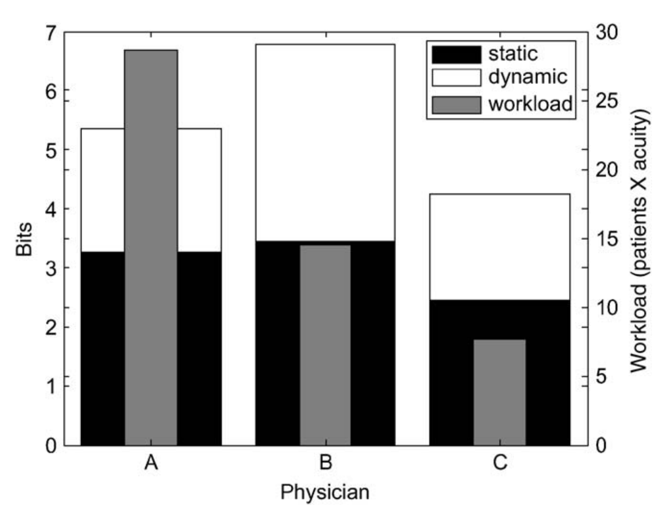

Figure 3. **Complexity versus workload.**

LIMITATIONS

System complexity shows great promise as a practical measure of system state for the ED. The ultimate value of this proposed measure, however, will be determined by whether it is possible to measure it in real time and use it to monitor and predict the safety and functional capacity of the ED, as well as to potentially mobilize resources or stimulate a decision to go on ambulance diversion, as needed. To achieve this objective, the measure must first be fully adapted to emergency medicine from manufacturing. This would include further modifying the equations for each type of resource in the ED. The equations used in this report to capture complexity in physicians may not be appropriate for nurses or patient care technicians. However, the concept of measuring complexity by incorporating workload and uncertainty must remain the same for each resource included. Monitoring each resource in an analogous fashion enables the ability to calculate a cumulative measure of ED system complexity.

The addition of other system parameters may help further customize the model for emergency medicine. For example, because it is well known that the ED is an "interrupt-driven environment" and that interruptions increase complexity, at least perceptually, it may be useful to add an interruption term to the model (i.e., probability of interruptions occurring in some time period).

Finally, a standard data collection or site sampling methodology must be developed to gather the critical data elements necessary to calculate the measure in a timely manner. Complexity must be measured periodically, perhaps every half-hour, to be an operationally useful measure. Manufacturing engineers have predominantly calculated system complexity on the basis of administrative data and direct observations. This same basic approach can work for emergency medicine. Our preliminary research has determined that modern ED information systems that collect and display system status (e.g., occupancy, patient acuity, physician and nurse patient assignments) collect most of the data necessary to calculate this in near real time.

Even with utilization of such technologies, site-specific sampling, in the form of periodic direct observational studies, will still be necessary to quantify resource utilization patterns. However, rapidly developing indoor positioning systems or electronic tracking systems (such as radio frequency identification) may soon be utilized to perform these observational studies, thus eliminating or minimizing the need for direct human observation.

Emergency departments that are less technologically advanced in terms of ED information systems could rely solely on site-sampling methodologies to calculate complexity in a near–real-time manner. This methodology would follow a similar methodology used by system researchers to calculate and track system workload measure and other indicators for diversion.[58–60]

CONCLUSIONS

Capacity is a multifaceted construct for all of health care. For an ED, unpredictable surges in patient demand, tight coupling with hospital factors such as inpatient bed availability, and complex interactions among care providers, patients, and care systems impact the daily surge capacity. Current ED crowding and workflow measures are too simplistic to account for the multidimensionality of surge capacity. As this special topics issue implies, there is a need to develop a science of surge. It is time for ED systems researchers to become innovative in the ways they think about capacity, measure it, and improve it. It is time that we heed the call from expert groups such as the Institute of Medicine and National Academy of Engineering to apply knowledge and methods from other industries to improve the quality and safety of emergency medicine.

Perhaps emergency medicine should follow the lead set forth by the Department of Defense's Operating Room of the Future program. This forward-thinking program, managed by the Telemedicine and Advanced Technologies Research Center (Fort Detrick, MD; available at: http://www.tatrc.org/), challenges clinicians and engineers to design and develop tomorrow's operating rooms today by using and integrating the best available technologies, design principles, and evidence-based clinical work processes. The program asks the simple question, "How should modern ORs be designed to maximize the performance of the clinical team and the comfort and safety of their surgical patients?" ED system researchers must adopt this same approach in developing solutions to improve the flexibility and adaptability of ED systems to handle both daily and disaster surge demands.

The objective of this report is to propose a new measure of ED system state that has potential to facilitate innovative thinking and improvement in assessment of the safety and complexity of the ED environment. We suggest a measure of system complexity, as adapted from manufacturing engineering, to quantify the magnitude and uncertainty of work demands on ED resources. By quantifying ED system complexity, the relationship between the safe capacity and physical capacity of an ED can be explored and evaluated. Ideally, system complexity can be used to prospectively track functional capacity and intelligently manage the ED.

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APPENDIX B

Medmodel™ Programming Code

SQL Query Programming Code

MATLAB™ M-File Programming Code

Remaining simulation code available on CD by contacting:

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Medmodel™ Programming Code

Led Location Processing --

```
Vcontentsed = CONTENTS(Led,Eed)
Vwaitlos = CLOCK() - Awaitstart
Atreatstart = CLOCK()
INC Vtreatcontents
INC Vedid
Aedid = Vedid
^ P6(2.38, 7.53, 11.3) hr # assigned bounded #
Atreatlos = CLOCK()-Atreatstart
Vtreatlos = Atreatlos
        WRITELINE Xed_los, Aedid
        WRITELINE Xed_los, Atreatlos/60
        WRITELINE Xed_los, CLOCK(HR)
Adaynum = CLOCK(DAY)
Ahour = CLOCK(HR) - Adaynum*24
Aday = Sdaynum(Adaynum)
# DEFINE BOARDING PATTERN
Aboard = 1
IF Aday = 1 AND Ahour < 3 THEN Aboard = Uboard90()
IF Aday = 1 AND Ahour >= 3 AND Ahour < 22 THEN Aboard = Uboard71()
IF Aday = 1 AND Ahour >= 22 THEN Aboard = Uboard85()
IF Aday = 2 AND Ahour < 3 THEN Aboard = Uboard80()
IF Aday = 2 AND Ahour >= 3 AND Ahour < 22 THEN Aboard = Uboard70()
IF Aday = 2 AND Ahour >= 22 THEN Aboard = Uboard80()
IF Aday = 3 AND Ahour < 3 THEN Aboard = Uboard85()
IF Aday = 3 AND Ahour < 22 AND Ahour >= 3 THEN Aboard = Uboard69()
IF Aday = 3 AND Ahour >= 22 THEN Aboard = Uboard95()
IF Aday = 4 AND Ahour < 3 THEN Aboard = Uboard85()
IF Aday = 4 AND Ahour < 22 AND Ahour >= 3 THEN Aboard = Uboard68()
IF Aday = 4 AND Ahour >= 22 THEN Aboard = Uboard95()
IF Aday = 5 AND Ahour < 3 THEN Aboard = Uboard87()
IF Aday = 5 AND Ahour >= 3 AND Ahour < 22 THEN Aboard = Uboard63()
IF Aday = 5 AND Ahour >= 22 THEN Aboard = Uboard90()
IF Aday = 6 AND Ahour < 3 THEN Aboard = Uboard90()
IF Aday = 6 AND Ahour >= 3 AND Ahour < 6 THEN Aboard = Uboard80()
IF Aday = 6 AND Ahour >= 6 AND Ahour < 14 THEN Aboard = Uboard53()
IF Aday = 6 AND Ahour >= 14 THEN Aboard = Uboard80()
IF Aday = 7 THEN Aboard = Uboard69()
IF Aboard = 1 THEN
        BEGIN
                ^ 1.45*Udischargetime() hr
                ROUTE 1
                DEC Vtreatcontents
                DEC Vcontentsed
                CREATE 1 AS Eturnover
        END
ELSE IF Aboard = 2 THEN
        BEGIN
                Aboardout = Uboardout()
                Aboardstart = CLOCK()
```

```
        Aboardstartday = CLOCK(DAY)
        Aboardstarthour = CLOCK(HR) - Aboardstartday*24
        Vboardstarthour = Aboardstarthour
        INC Vcontentsboard
        INC Vedadmid
        Aedadmid = Vedadmid
        IF Aboardout = 2 THEN GRAPHIC 3
        IF Aboardout = 3 THEN GRAPHIC 4
        IF Aboardout = 4 THEN GRAPHIC 2
        IF Aboardout = 5 THEN GRAPHIC 2
        IF Aboardout = 6 THEN GRAPHIC 2
IF Aboardout = 2 THEN
        BEGIN
                #COLLECTINGCOVARIATES
                INC Vboardteleid
                Aboardteleid = Vboardteleid
                        WRITELINE Xtelecovariates, Aboardteleid
                Aboardday = Sdaynum(Aboardstartday)
                        WRITELINE Xtelecovariates, Aboardday
                        WRITELINE Xtelecovariates, Aboardstart/1440
                Aboardhour = ((Aboardstart/1440) - TRUNC(Aboardstart/1440))*24
                        WRITELINE Xtelecovariates, Aboardhour
                Acath = Vcontentscath
                Asurg = Vcontentssurg
                Asurgcath = Ssurgcath(Aboardteleid,Aboardday,Aboardhour,Vcathin,…
                Acath,Vsurgin,Asurg,Aboardout)
                        WRITELINE Xtelecovariates, Asurgcath
                Atele = Vcontentstele/47
                        WRITELINE Xtelecovariates, Atele
                Atot = Vcontentstot/915
                        WRITELINE Xtelecovariates, Atot
                Acvicu = Vcontentscvicu/26
                        WRITELINE Xtelecovariates, Acvicu
                #CALCULATING HAZARD RATIOS
                Atelehr1 = EXP((-3.79*(Asurgcath-Musurgcatht))+(-1.99*(Atele-
                        Mutele))+(-1.62*(Atot-Mutot))+(-1.18*(Acvicu-Mucvicu)))
                        WRITELINE Xtelecovariates, Atelehr1
                Vtelehr1 = Atelehr1
                Atelehr2 = EXP((-3.56*(Atot-Mutot))+(-3.04*(Atele-Mutele))+(-
                        1.85*(Acvicu-Mucvicu)))
                        WRITELINE Xtelecovariates, Atelehr2
                Vtelehr2 = Atelehr2
                Atboardtime = Sboardtele(Aday,Atelehr1,Atelehr2)
                        WRITELINE Xtelecovariates, Atelemap
                        WRITELINE Xtelecovariates, Atboardtime
                Vtboardtime = Atboardtime
                ^ Atboardtime hr
                CREATE 1 AS Eturnover
                ROUTE 2
                DEC Vcontentsboard
                DEC Vcontentsed
                DEC Vtreatcontents
                Vboardout = Aboardout
        END
        ELSE IF Aboard = 2 AND Aboardout = 3 THEN
                BEGIN
```

```
        #COLLECTING COVARIATES
            INC Vboardcvicuid
            Aboardcvicuid = Vboardcvicuid
                WRITELINE Xcvicucovariates, Aboardcvicuid
            Aboardday = Sdaynum(Aboardstartday)
                WRITELINE Xcvicucovariates, Aboardday
                WRITELINE Xcvicucovariates, Aboardstart/1440
            Aboardhour = ((Aboardstart/1440) -
                TRUNC(Aboardstart/1440))*24
                WRITELINE Xcvicucovariates, Aboardhour
            Acath = Vcontentscath
            Asurg = Vcontentssurg
            Asurgcath = Ssurgcath(Aboardcvicuid,Aboardday,Aboardhour…
                Vcathin,Acath,Vsurgin,Asurg,Aboardout)
                WRITELINE Xcvicucovariates, Asurgcath
            Acvicu = Vcontentscvicu/26
                WRITELINE Xcvicucovariates, Acvicu
            #CALCULATING HR
            Acvicuhr1 = EXP((-3.32*(Asurgcath-Musurgcathc))+(-
                2.87*(Acvicu-Mucvicu)))
                WRITELINE Xcvicucovariates, Acvicuhr1
            Vcvicuhr1 = Acvicuhr1
            Acvicuhr2 = EXP((-4.81*(Acvicu-Mucvicu))+(-1.95*(Asurgcath-
                Musurgcathc)))
                WRITELINE Xcvicucovariates, Acvicuhr2
            Vcvicuhr2 = Acvicuhr2
            Acboardtime = Sboardcvicu(Aday,Acvicuhr1,Acvicuhr2)
                WRITELINE Xcvicucovariates, Acvicumap
                WRITELINE Xcvicucovariates, Acboardtime
            Vcboardtime = Acboardtime
            ^ Acboardtime hr
            ROUTE 3
            DEC Vcontentsboard
            DEC Vtreatcontents
            DEC Vcontentsed
            Vboardout = Aboardout
            CREATE 1 AS Eturnover
        END
    ELSE IF Aboardout = 4 THEN
        BEGIN
        ^ Ucclboardtime() hr
        ROUTE 4
        DEC Vcontentsboard
        DEC Vtreatcontents
        DEC Vcontentsed
        Vboardout = Aboardout
        CREATE 1 AS Eturnover
    END
    ELSE IF Aboardout = 5 THEN
        BEGIN
        ^ .25 hr
        ROUTE 5
        DEC Vcontentsboard
        DEC Vtreatcontents
        DEC Vcontentsed
        Vboardout = Aboardout
```

```
                CREATE 1 AS Eturnover
        END
        ELSE IF Aboardout = 6 THEN
                BEGIN
                ^ Sboardtime(Aday) hr
                Aboardlostot = CLOCK() - Aboardstart
        WRITELINE Xboard_los, Aedadmid
                        WRITELINE Xboard_los, Aboardlostot/60
                        WRITELINE Xboard_los, CLOCK(HR)
                ROUTE 6
                DEC Vcontentsboard
                DEC Vtreatcontents
                DEC Vcontentsed
                Vboardout = Aboardout
                CREATE 1 AS Eturnover
        END
END
```

Ltele Location Processing --

```
INC Vteleid
Ateleid = Vteleid
Atelestart = CLOCK()
Adaynum = CLOCK(DAY)
Ahour = CLOCK(HR) - Adaynum*24
Aday = Sdaynum(Adaynum)
Vteleinloc = Ateleinloc
Vcontentstele = CONTENTS(Ltele,Etele)
IF Vcontentstele <= Mtelelevel THEN ORDER 1 Etele to Ltelein
Ateleout = Uteleout_initial()
IF Ateleinloc = 1 THEN Ateleout = Uteleout_ed()
IF Ateleinloc = 3 THEN Ateleout = Uteleout_cvicu()
IF Ateleinloc = 4 THEN Ateleout = Uteleout_cath()
IF Ateleinloc = 5 THEN Ateleout = Uteleout_surg()
IF Ateleinloc = 6 THEN Ateleout = Uteleout_tot()
IF Ateleinloc = 7 THEN Ateleout = Uteleout_out()
```

Lcvicu Location Processing --

```
INC Vcvicuid
Acvicuid = Vcvicuid
Acvicustart = CLOCK()
Vcvicuinloc = Acvicuinloc
Vcontentscvicu = CONTENTS(Lcvicu,Ecvicu)
IF Vcontentscvicu <= Mcviculevel THEN ORDER 1 Ecvicu to Lcvicuin
Acvicuinloc = Ucvicuout_initial()
IF Acvicuinloc = 1 THEN Acvicuout = Ucvicuout_ed()
IF Acvicuinloc = 2 THEN Acvicuout = Ucvicuout_tele()
IF Acvicuinloc = 4 THEN Acvicuout = Ucvicuout_cath()
IF Acvicuinloc = 5 THEN Acvicuout = Ucvicuout_surg()
IF Acvicuinloc = 6 THEN Acvicuout = Ucvicuout_tot()
IF Acvicuinloc = 7 THEN Acvicuout = Ucvicuout_out()
```

Lcath Location Processing ---

```
INC Vcathid
Acathid = Vcathid
Vcontentscath = CONTENTS(Lcath,Ecath)
Vcathinloc = Acathinloc
Acathstart = CLOCK()
ACTIVATE Scathwait(Acathid)
WAIT UNTIL Vpasscathtime = Acathid OR Vsurge_get_cath > 0
IF Vpasscathtime = Acathid THEN
        BEGIN
                IF Acathout = 2 THEN
                        BEGIN
                                ROUTE 1
                                CREATE 1 AS Eturnover
                                Acathlos = CLOCK() - Acathstart
                                        WRITELINE Xcath_los, Acathid
                                        WRITELINE Xcath_los, Acathlos/60
                                        WRITELINE Xcath_los, CLOCK(HR)
                                Vcathlos = Acathlos
                                Vcathout = Acathout
                                DEC Vcontentscath
                        END
                ELSE IF Acathout = 3 THEN
                        BEGIN
                                ROUTE 2
                                CREATE 1 AS Eturnover
                                Acathlos = CLOCK() - Acathstart
                                Vcathlos = Acathlos
                                Vcathout = Acathout
                                DEC Vcontentscath
                        END
                ELSE IF Acathout = 6 THEN
                        BEGIN
                                ROUTE 3
                                CREATE 1 AS Eturnover
                                Acathlos = CLOCK() - Acathstart
                                        WRITELINE Xcath_los, Acathid
                        WRITELINE Xcath_los, Acathlos/60
                                        WRITELINE Xcath_los, CLOCK(HR)
                                Vcathlos = Acathlos
                                Vcathout = Acathout
                                DEC Vcontentscath
                        END
                ELSE IF Acathout = 7 THEN
                        BEGIN
                                ROUTE 4
                                CREATE 1 AS Eturnover
                                Acathlos = CLOCK() - Acathstart
                                        WRITELINE Xcath_los, Acathid
                        WRITELINE Xcath_los, Acathlos/60
                                        WRITELINE Xcath_los, CLOCK(HR)
                                Vcathlos = Acathlos
                                Vcathout = Acathout
                                DEC Vcontentscath
```

```
                    END
          END
ELSE IF Vsurge_get_cath > 0 THEN
          BEGIN
                    DEC Vsurge_get_cath
                    ROUTE 5
                    CREATE 1 AS Eturnover
                    Acathout = 5
                    Vcathout = Acathout
                    Acathlos = CLOCK() - Acathstart
                              WRITELINE Xcath_los, Acathid
          WRITELINE Xcath_los, Acathlos/60
                              WRITELINE Xcath_los, CLOCK(HR)
                    Vcathlos = Acathlos
                    DEC Vcontentscath
          END
```

Lsurg Location Processing ---

```
INC Vsurgid
Asurgid = Vsurgid
Vcontentssurg = CONTENTS(Lsurg,Esurg)
Vsurginloc = Asurginloc
Adaynum = CLOCK(DAY)
Ahour = CLOCK(HR) - Adaynum*24
Asurgstart = CLOCK()

ACTIVATE Ssurgwait(Asurgid,Ahour)
WAIT UNTIL Vpasssurgtime = Asurgid OR Vcath_get_surge > 0
IF Vpasssurgtime = Asurgid THEN
          BEGIN
                    ROUTE 1
                    CREATE 1 AS Eturnover
                    Asurglos = CLOCK() - Asurgstart
                              WRITELINE Xsurg_los, Asurgid
                              WRITELINE Xsurg_los, Asurglos/60
                              WRITELINE Xsurg_los, CLOCK(HR)
                    Vsurglos = Asurglos
                    DEC Vcontentssurg
          END
ELSE IF Vcath_get_surge > 0 THEN
          BEGIN
                    DEC Vcath_get_surge
                    ROUTE 2
                    CREATE 1 AS Eturnover
                    Asurgout = 4
                    Asurglos = CLOCK() - Asurgstart
                              WRITELINE Xsurg_los, Asurgid
                              WRITELINE Xsurg_los, Asurglos/60
                              WRITELINE Xsurg_los, CLOCK(HR)
                    Vsurglos = Asurglos
                    Vsurgout = Asurgout
                    DEC Vcontentssurg
          END
```

Lpacu Location Processing --

```
INC Apacuid
INC Vcontentzpacu
Apacustart = CLOCK()
IF Asurgout = 2 THEN
        BEGIN
                GRAPHIC 2
                Mpacuwait
                ROUTE 1
                CREATE 1 AS Eturnover
                Apaculos = CLOCK() - Apacustart
                        WRITELINE Xpacu_los, Apacuid
                        WRITELINE Xpacu_los, Apaculos/60
                        WRITELINE Xpacu_los, CLOCK(HR)
                Vpaculos = Apaculos
                Vsurgout = Asurgout
                DEC Vcontentzpacu
                INC Vcarsurgid
        END

ELSE IF Asurgout = 3 THEN
        BEGIN
                GRAPHIC 3
                Mpacuwait
                WAIT UNTIL Vcontentscvicu <= 24
                ROUTE 2
                CREATE 1 AS Eturnover
                Apaculos = CLOCK() - Apacustart
                        WRITELINE Xpacu_los, Apacuid
                        WRITELINE Xpacu_los, Apaculos/60
                        WRITELINE Xpacu_los, CLOCK(HR)
                Vpaculos = Apaculos
                Vsurgout = Asurgout
                DEC Vcontentzpacu
                INC Vcarsurgid
        END

ELSE IF Asurgout = 6 THEN
        BEGIN
                GRAPHIC 4
                Mpacuwait
                ROUTE 3
                CREATE 1 AS Eturnover
                Apaculos = CLOCK() - Apacustart
                        WRITELINE Xpacu_los, Apacuid
                        WRITELINE Xpacu_los, Apaculos/60
                        WRITELINE Xpacu_los, CLOCK(HR)
                Vpaculos = Apaculos
                Vsurgout = Asurgout
                DEC Vcontentzpacu
        END

ELSE IF Asurgout = 7 THEN
        BEGIN
```

```
                    GRAPHIC 1
                    Mpacuwait
                    ROUTE 4
                    CREATE 1 AS Eturnover
                    Apaculos = CLOCK() - Apacustart
                              WRITELINE Xpacu_los, Apacuid
                              WRITELINE Xpacu_los, Apaculos/60
                              WRITELINE Xpacu_los, CLOCK(HR)
                    Vpaculos = Apaculos
                    Vsurgout = Asurgout
                    DEC Vcontentzpacu
          END
ELSE
          BEGIN
                    ROUTE 4
                    DEC Vcontentzpacu
                              WRITELINE Xpacu_los, Apacuid
                              WRITELINE Xpacu_los, Apaculos/60
                              WRITELINE Xpacu_los, CLOCK(HR)
          END
```

Ltot Location Processing ---

```
Vtotinloc = Atotinloc
Atottype = Utottype()
INC Vtotid
INC Vcontentstot
Atotstart = CLOCK()
Atotid = Vtotid
ACTIVATE Stotwait(Atotid,Atottype)
WAIT UNTIL Vpasstottime = Atotid OR Vsurge_get_tot > 0 OR Vcath_get_tot > 0 OR
Vtele_get_tot > 0 OR Vcvicu_get_tot > 0
IF Vpasstottime = Atotid THEN
          BEGIN
                    ROUTE 1
                    Atotlos = CLOCK() - Atotstart
                    Vtotlos = Atotlos
                    DEC Vcontentstot
          END
ELSE IF Vsurge_get_tot > 0 THEN
          BEGIN
                    DEC Vsurge_get_tot
                    ROUTE 2
                    Atotlos = CLOCK() - Atotstart
                    Vtotlos = Atotlos
                    DEC Vcontentstot
          END
ELSE IF Vcath_get_tot > 0 THEN
          BEGIN
                    DEC Vcath_get_tot
                    ROUTE 3
                    Atotlos = CLOCK() - Atotstart
                    Vtotlos = Atotlos
                    DEC Vcontentstot
```

```
        END
ELSE IF Vtele_get_tot > 0 THEN
        BEGIN
                DEC Vtele_get_tot
                ROUTE 4
                Atotlos = CLOCK() - Atotstart
                Vtotlos = Atotlos
                DEC Vcontentstot
        END
ELSE IF Vcvicu_get_tot > 0 THEN
        BEGIN
                DEC Vcvicu_get_tot
                ROUTE 5
                Atotlos = CLOCK() - Atotstart
                Vtotlos = Atotlos
                DEC Vcontentstot
        END
```

SQL Query Programming Code

ADT_TABLE_SQL_PLUS_QUERY_BY_CASENUM.txt-----------------------------------

```
SET LINESIZE 200
SET PAGESIZE 50
COLUMN MED_REC_NUMBER HEA 'MRN'FORMAT 9999999999
COLUMN CASENO FORMAT 999999999999999
COLUMN EVENT_TIMESTAMP FORMAT A30
COLUMN EVENt_TYPE HEA 'E_TYPE' FORMAT 9
COLUMN SERVICE FORMAT A7
COLUMN UNIT FORMAT A4
COLUMN BED FORMAT A6
COLUMN PREVIOUS_LOC HEA 'PREV_LOC' FORMAT A8
COLUMN DISCHARGE_LOC HEA 'DISH_LOC' FORMAT A8

SPOOL C:\Spooled_Files\TEST.LST
Select MED_REC_NUMBER, CASENO, EVENT_TIMESTAMP,
EVENT_TYPE, SERVICE, UNIT, BED, PREVIOUS_LOC, DISCHARGE_LOC
FROM MPAC_ADT
WHERE EVENT_TYPE IN (1,2,3)
AND CASENO = 124898786092
ORDER BY EVENT_TIMESTAMP;
SPOOL OFF;
```

Matlab™ M-File Programming Code

CLEAN_ADT.M---

```
%CLEAN ADT_ RAW.MAT - 12/22/2006
format long g
tic;
% converting time to serial time
time = ADT_RAW(:,4); time = char(time);
time = time(:,1:19); time = cellstr(time);
time = datenum(time,'yyyy-mm-dd HH:MM:SS');
ADT = [ADT_RAW(:,1:2) cellstr(datestr(time)) num2cell(time) ADT_RAW(:,5:end)];
clear time;
% eliminating all Event_Type = 7 (cancel discharge)
% e_type = cell2mat(ADT(:,5)); e_type7 = find(e_type==7);
% e_type7 = setxor(1:length(ADT),e_type7);
% ADT = ADT(e_type7,:); clear e_type*;
% eliminating all Event_Type = 6 (cancel admit)
% e_type = cell2mat(ADT(:,5)); e_type6 = find(e_type==6);
% e_type6 = setxor(1:length(ADT),e_type6);
% ADT = ADT(e_type6,:); clear e_type*;
% (1) Eliminating transfers with UNIT LOC = PREV LOC
% e_type = cell2mat(ADT(:,5));
% y = ones(length(ADT),1);
%     for i = 1:length(e_type);
%         if e_type(i) == 3;
%             same = strmatch(ADT(i,7),ADT(i,10));
%             y(i,1) = isempty(same);
%         else;
%         end;
%     end;
% j = find(y == 0);
% j = setxor(1:length(ADT),j);
% ADT = ADT(j,:); clear i; clear j; clear same; clear y; clear e_type;
% (2) Eliminating admit to ED rows
e_type = cell2mat(ADT(:,5));
y = ones(length(e_type),1);
for i = 1:length(e_type);
        if e_type(i) == 1;
            emer = strmatch('EMER',ADT(i,7));
            y(i,1) = isempty(emer);
        else;
        end;
    end;
j = find(y == 0);
j = setxor(1:length(ADT),j);
ADT = ADT(j,:); clear i; clear j; clear emer; clear y; clear e_type;
% rounding each time to nearest 10 min and placing in last column
adt_time = cell2mat(ADT(:,4));
load BASELINE;
time_round = cell2mat(BASELINE(:,1));
ind = nearestpoint(adt_time,time_round);
adt_time_round = time_round(ind);
```

```
ADT(:,12) = num2cell(adt_time_round);
clear adt_time; clear adt_time_round; clear ind; clear time_round;
clear BASELINE;
% sorting ADT and placing each patient in a cell (ADT_PATIENT)
ADT = sortrows(ADT,3);
case_num = cell2mat(ADT(:,2));
   u_case = unique(case_num);
mrn_num = cell2mat(ADT(:,1));
   u_mrn = unique(mrn_num);
ADT_PATIENT = cell(length(u_case),1);
   for i = 1:length(u_case);
      adt_patient = find(case_num == u_case(i));
      adt_patient = ADT(adt_patient,:);
      ser_time = cell2mat(adt_patient(:,4));
      [ser_time,y] = sort(ser_time);
      adt_patient = adt_patient(y,:);
      ADT_PATIENT(i) = {adt_patient};
   end;
clear adt_patient; clear i; clear ser_time; clear y;
clear case_num; clear mrn_num; clear u_case; clear u_mrn;
%-----------------------------------------------------------------------
%Eliminating patients with admit = 1, for last row
% discharges = cell(length(ADT_PATIENT),size(ADT,2));
% for i = 1:length(ADT_PATIENT);
%     pat = ADT_PATIENT{i};
%     last_row = size(pat,1);
%     last = pat(last_row,:);
%     discharges(i,:) = last;
% end;
% dis_events = cell2mat(discharges(:,5));
% no_dis = find(dis_events == 1);
% x = setxor(1:length(ADT_PATIENT),no_dis);
% ADT_PATIENT = ADT_PATIENT(x,1);
% clear dis_events; clear discharges; clear i; clear last*; clear no_dis;
% clear pat; clear x; clear case_num; clear mrn_num; clear u_case; clear u_mrn;
% clear ADT;

% eliminating (1)Admits that aren't in the first row for each patient
for i=1:length(ADT_PATIENT);
   pat = ADT_PATIENT{i};
   if size(pat,1)>1;
      omit_rows = find(cell2mat(pat(:,5))==1);
         o = find(omit_rows >1);
         if isempty(o) == 0;
            omit_rows = omit_rows(o);
            keep = setxor(1:size(pat,1),omit_rows);
            pat = pat(keep,:);
            ADT_PATIENT(i) = {pat};
         end;
   end;
end;
clear i; clear keep; clear omit_rows; clear pat; clear o;

%eliminating events that happend within 15 min (.01) of each other
% (1)eliminate double discharges
for i =  1:length(ADT_PATIENT);
```

```
    pat = ADT_PATIENT{i};
    d = diff(cell2mat(pat(:,4)));
    omit = find(d<.01);
    if isempty(omit)== 0;
        omit_rows = [omit(:,1) omit(:,1)+1];
        dis = omit_rows(end,:);
        dis2 = cell2mat(pat(dis,5));
        if dis2 == [2;2];
            no_chop = dis(1,1);
            omit_rows = setxor(omit_rows(end,:),no_chop);
            keep = setxor(1:size(pat,1),omit_rows);
            pat = pat(keep,:);
            ADT_PATIENT(i) = {pat};
        end;
    end;
end; clear case_num; clear d; clear dis; clear dis2; clear i; clear keep;
clear mrn_num; clear no_chop; clear omit; clear omit_rows; clear pat;
clear u_case; clear u_mrn;

% (2)eliminate all other duplicates
for i = 1:length(ADT_PATIENT);
    pat = ADT_PATIENT{i};
    d = diff(cell2mat(pat(:,4)));
    omit = find(d<.01);
    if isempty(omit)== 0;
        omit_rows = [omit(:,1) omit(:,1)+1];
        chop = zeros(size(omit_rows,1),1);
        for j = 1:size(omit_rows,1);
            first = strmatch(pat(omit_rows(j,1),10),pat(omit_rows(j,1),7));
            second = strmatch(pat(omit_rows(j,2),10),pat(omit_rows(j,2),7));
            event_1 = pat{omit_rows(j,1),5};
            event_2 = pat{omit_rows(j,2),5};
            if isempty(first) == 1 & second == 1
                chop(j,1) = omit_rows(j,2);
            else
                chop(j,1) = omit_rows(j,1);
            end;
            if event_1 == 3 & event_2 == 2;
                chop(j,1) = omit_rows(j,1);
            end;
        end;
        keep = setxor(1:size(pat,1),chop);
        pat = pat(keep,:);
        ADT_PATIENT(i) = {pat};
    end;
end;
clear chop; clear d; clear first; clear i; clear j; clear keep; clear omit;
clear omit_rows; clear pat; clear second; clear event_1; clear event_2;
% eliminating double discharges that are more than 10 min appart
% (must do this twice to eliminate triple discharges as well)
for i = 1:length(ADT_PATIENT);
    pat = ADT_PATIENT{i};
    if size(pat,1) > 1;
        dis = cell2mat(pat(:,5));
        dis2 = find(dis == 2);
        if length(dis2>1);
```

```
            diff_dis = diff(dis2);
            omit_rows = dis2(find(diff_dis==1)+1);
            keep = setxor(1:size(pat,1),omit_rows);
            pat = pat(keep,:);
            ADT_PATIENT(i) = {pat};
        end;
    end;
end; clear i; clear pat; clear dis; clear omit_rows; clear keep;
clear diff_dis; clear dis2; clear next_dis;
% eliminating double discharges that are more than 10 min appart PART 2
for i = 1:length(ADT_PATIENT);
    pat = ADT_PATIENT{i};
    if size(pat,1) > 1;
        dis = cell2mat(pat(:,5));
        dis2 = find(dis == 2);
        if length(dis2>1);
            diff_dis = diff(dis2);
            omit_rows = dis2(find(diff_dis==1)+1);
            keep = setxor(1:size(pat,1),omit_rows);
            pat = pat(keep,:);
            ADT_PATIENT(i) = {pat};
        end;
    end;
end; clear i; clear pat; clear dis; clear omit_rows; clear keep;
clear diff_dis; clear dis2; clear next_dis;
% eliminating instances where patients were transfered back to ED
for i = 1:length(ADT_PATIENT);
    pat = ADT_PATIENT{i};
    if size(pat,1) > 1;
        emer = strmatch('EMER',pat(:,7));
        if isempty(emer) == 0;
            omit_rows = [emer];
            keep = setxor(1:size(pat,1),omit_rows);
            pat = pat(keep,:);
            ADT_PATIENT(i) = {pat};
        end;
    end;
end; clear pat; clear emer; clear omit_rows; clear keep;

% clearing rows that now have zero entries
for i = 1:length(ADT_PATIENT);
    pat = ADT_PATIENT{i};
    z(i) = size(pat,1);
end;
z = [find(z==0)]';
keep = setxor(1:length(ADT_PATIENT),z);
ADT_PATIENT = ADT_PATIENT(keep);
clear i; clear keep; clear pat; clear z;
clear ADT; clear case_num; clear mrn_num; clear u_case; clear u_mrn;
t = toc;
disp(['CLEANING ADT =' num2str(t) ' SECONDS']); clear t;
 % fixing transfer to nulls
for i = 1:length(ADT_PATIENT);
    pat = ADT_PATIENT{i};
    trans = cell2mat(pat(:,5));
    trans = find(trans == 3);
```

```
    null = strmatch('null',pat(trans,7));
    if isempty(null) == 0;
        null_id = trans(null);
        pat(null_id,7) = pat(null_id+1,11);
        ADT_PATIENT(i) = {pat};
    end;
end; clear pat; clear trans; clear null; clear null_id; clear i;

% finding event type transfer(3), discharge(2), transfer(3) for last rows
% and correcting by deleting the last transfer (3);
for i = 1:length(ADT_PATIENT);
    pat = ADT_PATIENT{i};
    if size(pat,1) >= 3;
        events = cell2mat(pat(end-2:end,5));
        if events == [3;2;3];
            pat = pat(1:end-1,:);
            ADT_PATIENT(i) = {pat};
        end;
    end;
end; clear events; clear pat; clear i;
% finding discharge(2) that aren't in last row and imposing rule:
    %if (i+1) time > 8hrs place "EXIT" else delete row
for i = 1:length(ADT_PATIENT);
    pat = ADT_PATIENT{i};
    events = cell2mat(pat(:,5));
    dis = find(events == 2);
    not_end = zeros(length(dis),1);
    for j = 1:length(dis);
        if dis(j) < size(pat,1);
            not_end(j) = 1;
        end;
    end;
    dis_row = dis(find(not_end));
    if isempty(dis_row) == 0;
        time_dif = pat{dis_row+1,4} - pat{dis_row,4};
        if time_dif >= .33333333;
            pat(dis_row,7) = cellstr('EXIT');
        else
            keep = setxor(1:size(pat,1),dis_row);
            pat = pat(keep,:);
        end;
        ADT_PATIENT(i) = {pat};
    end;
end; clear dis; clear dis_row; clear events; clear i; clear j;
clear keep; clear not_end; clear pat; clear time_dif;
```

CLEAN_BIPROD.M---

```
BIPROD = [BIPROD_RAW(:,7) BIPROD_RAW(:,12:15) BIPROD_RAW(:,25:29)
BIPROD_RAW(:,37) BIPROD_RAW(:,36) BIPROD_RAW(:,42) BIPROD_RAW(:,44:45)];
% deleting negative numbers
nums = cell2mat(BIPROD(:,2:5));
[neg_row neg_col] = find(nums<0);
pos = setxor(1:length(BIPROD),neg_row);
```

```
BIPROD = BIPROD(pos,:);
clear nums; clear neg*; clear pos;
% creating serial dates
ser_adm = datenum(BIPROD(:,11),'yyyy-mm-dd HH:MM:SS');
ser_dis = datenum(BIPROD(:,12),'yyyy-mm-dd HH:MM:SS');
str_adm = cellstr(datestr(ser_adm));
str_dis = cellstr(datestr(ser_dis));
BIPROD = [BIPROD(:,1:11) num2cell(ser_adm) BIPROD(:,12) num2cell(ser_dis)
BIPROD(:,13:end)];
BIPROD(:,11) = str_adm;
BIPROD(:,13) = str_dis;
clear ser_adm; clear ser_dis; clear str_adm; clear str_dis;
```

CLEAN_MEDIPAC.M--

```
MEDIPAC = [MEDIPAC_RAW(:,1:3) MEDIPAC_RAW(:,9:12) MEDIPAC_RAW(:,17:21)
MEDIPAC_RAW(:,33)];
adm_time = MEDIPAC(:,10); adm_time = char(adm_time);
dis_time = MEDIPAC(:,11); dis_time = char(dis_time);
adm_time = adm_time(:,1:19); dis_time = dis_time(:,1:19);
adm_time = cellstr(adm_time); dis_time = cellstr(dis_time);
MEDIPAC(:,10) = adm_time; MEDIPAC(:,11) = dis_time;
% chaning 'null' to '1900-00-00 00:00:00'
   [nu_a] = strmatch('null',MEDIPAC(:,10));
      MEDIPAC(nu_a,10) = cellstr('1900-00-00 00:00:00');
   [nu_d] = strmatch('null',MEDIPAC(:,11));
      MEDIPAC(nu_d,11) = cellstr('1900-00-00 00:00:00');
% adding in serial time
ser_adm = datenum(MEDIPAC(:,10),'yyyy-mm-dd HH:MM:SS');
ser_dis = datenum(MEDIPAC(:,11),'yyyy-mm-dd HH:MM:SS');
MEDIPAC = [MEDIPAC(:,1:10) num2cell(ser_adm) MEDIPAC(:,11) num2cell(ser_dis)
MEDIPAC(:,12:end)];
clear adm_time; clear dis_time; clear keep; clear nu*; clear ser_adm; clear ser_dis; clear x;
```

CLEAN_OR.M--

```
%CLEAN_OR
format long g;
 OR_SCHED = OR_SCHED_RAW;
 % REPLACING IN_ROOM TIME WITH SCHEDULE START FOR 'NULL' CELLS
in_null = strmatch('null',OR_SCHED_RAW(:,5));
if isempty(in_null) == 0;
   OR_SCHED(out_null,5) = OR_SCHED(out_null,4);
end; clear in_null;
in_null = strmatch('null',OR_SCHED(:,5));
if isempty(in_null) == 0;
   OR_SCHED(in_null,5) = cellstr('0000-01-00 00:00:00.0');
end;
in_room = datenum(OR_SCHED(:,5),'yyyy-mm-dd HH:MM:SS');

% REPLACING OUT_ROOM TIME WITH SCHEDULE FINISH FOR 'NULL' CELLS
out_null = strmatch('null',OR_SCHED_RAW(:,7));
if isempty(out_null) == 0;
```

```
    OR_SCHED(out_null,7) = OR_SCHED(out_null,6);
end; clear out_null;
out_null = strmatch('null',OR_SCHED(:,7));
if isempty(out_null) == 0;
    OR_SCHED(out_null,7) = cellstr('0000-01-00 00:00:00.0');
end;
out_room = datenum(OR_SCHED(:,7),'yyyy-mm-dd HH:MM:SS');
OR_SCHED = [OR_SCHED(:,1:3) cellstr(datestr(in_room)) num2cell(in_room)
cellstr(datestr(out_room)) num2cell(out_room)];
clear in_null; clear in_room; clear out_null; clear out_room;
```