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An Evaluation of Discharge Policies at a Generic Acute Care Hospital

Elizabeth A. Crawford

Wright State University

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AN EVALUATION OF DISCHARGE POLICIES AT A
GENERIC ACUTE CARE HOSPITAL

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Engineering

By

ELIZABETH A. CRAWFORD
B.S, Wright State University, 2011

2012
Wright State University
I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Elizabeth A. Crawford ENTITLED An Evaluation of Discharge Policies at a Generic Acute Care Hospital BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science in Engineering.

__________________________
Pratik Parikh, Ph.D.
Thesis Director

__________________________
Thomas Hangartner, Ph.D.
Chair
Department of Biomedical, Industrial and Human Factors Engineering
College of Engineering and Computer Science

Committee on Final Examination

__________________________
Pratik Parikh, Ph.D.

__________________________
Subhashini Ganapathy, Ph.D.

__________________________
Yan Liu, Ph.D.

__________________________
Andrew Hsu, Ph.D.
Dean, School of Graduate Studies
ABSTRACT

Crawford, Elizabeth A. M.S.Egr., Department of Biomedical, Industrial and Human Factors Engineering, Wright State University, 2012. An Evaluation of Discharge Policies at a Generic Acute Care Hospital

One of the main issues faced within the U.S. healthcare continuum is ineffective care transition. Ineffective transitions from one area of care to the next can lead to a reduction in quality of care, an increased risk of readmission, and an increase in healthcare costs. According to the National Transitions of Care Coalition (NTOCC), as many as 42% of the hospitals surveyed reported that care transitions during coordinated care delivery do not go as planned. One of the primary reasons for ineffective care transition is poor discharge planning.

The purpose of this research is to analyze the effect of various policies for determining the time to discharge a patient on a variety of performance measures at a generic acute care hospital using discrete-event simulation. Three discharge policies are compared: a static policy and two dynamic discharge policies. First, a baseline simulation was created to model the static policy in which a patient is discharged when his/her estimated risk of readmission is acceptable as determined by his/her current health status. To validate the simulation model multiple data sources were utilized, which include the U.S. national statistics on readmission rates and patient pathways, and patient arrival data and bed capacities from an 800+ bed acute care hospital in the U.S.

Once the model was validated, we designed and modeled two dynamic discharge policies that account for both the patient’s medical condition and the current resource utilization of the emergency department (ED) in determining patient discharges. The performance measures of interest include the following: average time a patient spends
waiting and boarding in the ED, the annual hours spent on ambulance diversion, fraction of patients in the ED leaving without treatment, and the total number of readmissions per year.

Results showed that the dynamic policies have substantial merit in reducing ED crowding and boarding. The results also suggested a tradeoff between reducing ED measures and the number of 30-day readmissions. The insights from this research could pave path for further research that considers other patient pathways, resource planning and flexibility, and integration with the discharge location decisions.
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1 INTRODUCTION

The United States healthcare organizations are experiencing a tremendous growth in patient volume. The total U.S. healthcare expenditure topped $2.5 trillion in 2009, more than 17.6% of the GDP, and is projected to increase further in the coming decade (CDC 2011).

Care provision in the U.S. occurs at various types of healthcare facilities that provide unique levels of care and treatment based on the patient’s need. These facilities range from hospitals and long-term care to rehabilitation centers, nursing homes, and home care; see Figure 1.

![Figure 1: The U.S. healthcare continuum](image-url)
One of the main issues faced within the U.S. healthcare continuum is ineffective care transition. Care transition refers to the movement of patients from one care facility to another or the movement of a patient within various care areas of a single facility. Ineffective transitions from one area of care to the next can lead to a reduction in quality of care, an increased risk of readmission, and an increase in healthcare costs. According to the National Transitions of Care Coalition (NTOCC), as many as 42% of the hospitals surveyed reported that care transitions during coordinated care delivery do not go as planned (NTOCC, 2011). One of the primary reasons for ineffective care transition is poor discharge planning (IHI, 2011).

1.1 Discharge Planning

Discharge planning refers to the decision making process required to release a patient from one care facility to the next. Every inpatient discharge involves four critical decisions: 1) the timing of discharge, 2) the discharge process, 3) the location of patient disposition, and 4) the post-discharge follow-up.

The planning of patient discharges is complex, and is typically influenced by patient-, provider-, and system-related factors. These decisions concerning patient discharges tend to be highly variable and, when suboptimal, they could result in increased readmissions and emergency department (ED) crowding. For instance, poor discharge planning accounted for 82-delay-related hospital days annually and $170,000 in annual costs, where 22% of reported delays were related to discharge planning (Srivastava et al., 2009). One in 5 Medicaid patients are readmitted within 30 days of the discharge,
accounting for a spending of over 17.4 billion annually (Jencks et al., 2009). ED crowding occurs when the demand for emergency services exceeds the number of resources available both in the ED and inpatient units (Hoot and Aronsky, 2008). ED crowding contributes to long wait times for patients, ambulance diversion, and ED boarding, which refers to patients continuing to utilize an ED bed while waiting on an available bed in an inpatient unit (Schull et al., 2003). According to a national survey, 91% of sampled ED staff responded that crowding was an issue (Institute of Medicine, 2007).

1.2 Research Objectives

The purpose of this research is to analyze the effect of various policies for determining the time to discharge a patient on a variety of performance measures at a generic acute care hospital (ACH) using discrete-event simulation. We refer to ACH as comprising of an emergency department (ED) and inpatient units (IUs). Discharge timing is referred to as determining the most appropriate day to discharge a patient from the facility. This decision is made based on the patient’s readmission risk, which is determined by medical complexity, and the system-wide impact on resource utilization. The performance measures of interest include average time a patient spends waiting and boarding in the ED, the annual hours spent on ambulance diversion, fraction of patients in the ED leaving without treatment (LWOT), and the total number of readmitted cases per year.
Three discharge policies are compared: a static policy and two dynamic discharge policies. We refer to a static policy as the one where a patient is discharged when his/her estimated risk of readmission is acceptable as determined by the physician based on his/her current health status. Such a determination being mostly subjective can induce inter-physician variability, which may result in likely poor post-discharge outcomes for the patient (e.g., readmission). The discharge timing decision also has an impact on the system-wide resource utilization at an ACH. If patients are discharged later than medically necessary, the inpatient units (IU) resources may not be released to patients with higher risks waiting in the ED for an IU bed. This may increase the likelihood of ED crowding and trigger ambulances being diverted resulting in denial of care to other high-risk patients. On the other hand, a discharge earlier than medically necessary may increase the chance of a patient’s unnecessary medical revisit to the ACH, which may impose additional burden to the resource utilization of the hospital. That is, there is a tradeoff between ED measures (waiting, boarding, ambulance diversion, and LWOT) and readmission numbers based on how soon or late a patient in the IU is discharged.

The two objectives, minimize ED measures and minimize readmissions, are conflicting and vary dynamically with time. Hence, a static policy like the one described above will likely not result in satisfactory values for both of these measures. To address this tradeoff, we introduce two dynamic policies that account for both the patient’s medical condition and the current resource utilization at ED in determining patient discharges, and are as follows:

**Dynamic Policy #1 (DP-W):** When a trigger based on a pre-specified number of patients waiting in the ED for an ED bed is set ON, patients in the inpatient units are
discharged starting from the lowest readmission risk stratum up to a certain higher risk stratum.

**Dynamic Policy #2 (DP-B):** When a trigger based on a pre-specified number of patients boarding in the ED is set ON, patients in the inpatient units are discharged starting from the lowest readmission risk strata up to a certain higher risk stratum.

The idea behind these two dynamic policies is that if proactive measures are taken to discharge patients in the inpatient units based on the number of patients waiting for ED beds in the ED, then crowding in the ED could be minimized. Reducing ED crowding results in lower ED waiting and boarding times. Additionally, the time spent on ambulance diversion is reduced. However, it is likely that early discharges, though proactively done to reduce ED crowding, may increase the probability of readmission for a patient discharged from the ACH.

A discrete-event simulation model of patient flow through an ACH considering the dynamics at the ED and within inpatient units is developed to compare these two dynamic policies with the static policy. These policies are compared based on ED waiting and boarding times, denial of care (due to ambulance diversion and LWOT), and readmission rates.

To validate the simulation model of patient flow multiple data sources were utilized, which include the U.S. national statistics on readmission rates and patient pathways, and patient arrival data and bed capacities from an 800+ bed acute care hospital in the U.S.
1.3 Thesis Outline

The remainder of this thesis is organized as follows. Relevant literature pertaining to emergency department crowding, discharge planning, and readmission is reviewed in Section 2. In Section 3, a detailed description of the logic behind the overall model, emergency department treatment, ambulance diversion, inpatient treatment, and 30-day readmission is presented for the static discharge policy as well as the dynamic policy models. Section 4 describes the experimental design, model validation, and comparisons of performance measures for the various discharge policies. Finally, Section 5 summarizes the results and discusses the direction for future research.
2 LITERATURE REVIEW

This chapter summarizes academic literature relevant to our study. This literature review is divided into 6 separate categories based on the research topic. The first category includes studies involving resource management and its impact on ED crowding and boarding. The second category includes research concerning ambulance diversion, which is a major concern when EDs experience overcrowding. The third and fourth categories discuss hospital readmission rates and discharge planning respectively. The final categories cover simulation models in health care and our research objective.

2.1 Emergency Department Crowding

Both healthcare spending and patient volumes are increasing. However, the available emergency resources are decreasing. Between 1993 and 2003, patient visits to the ED increased by 26% while the number of EDs available was reduced by 12% (Burt and McCaig, 2006).

The issue of ED crowding has been widely studied. Hoot and Aronsky (2008) performed a comprehensive review of ED crowding, which included literature concerning the causes, effects, and solutions. They reviewed 93 articles pertaining to the aforementioned three aspects of ED crowding. They found that some of the main causes included: non-urgent visits, inadequate staffing, inpatient boarding, and bed shortages.
Through their research they found that the major effects of crowding included patient mortality, delays in care, ambulance diversion, and financial impact. Some of the solutions reviewed included capacity planning (e.g. additional personnel and resources), non-urgent referrals, ambulance diversion policies, crowding measures, and queuing theory.

2.1.1 Resource Management and ED Boarding

Resource management, such as bed capacity and personnel scheduling, has been suggested to help reduce the ED crowding problem faced.

Cochran and Bharti (2006) utilized queuing analysis to balance the bed utilization for inpatient wards at a 411 bed, 13 tertiary unit, hospital. Discrete-event simulation was then used to maximize the flow through the system. They found that better management of bed capacities helped to reduce patient waiting times.

Green et al. (2006) used non-stationary queuing models to aid in capacity planning to reduce the number of patients who leave without treatment. They collected ED arrival data for a two 39-week periods, one before staffing changes and one after, at an urban ED. They showed that increasing staffing by 12 hours each week reduced the number of patients who left without being seen by 22.9% even though the arrival volume increased by 6.3%. They also found that without increasing staffing hours and only focusing on staff reallocation for data for 4 days of the week, the number of patients who left without being seen reduced by 21.7%. They concluded that new staffing plans based
on arrival patterns could significantly reduce the number of patients who leave without being seen.

Cochran and Roche (2009) utilize a queueing network model to identify necessary hospital capacity based on non-homogenous arrival pattern and different patient acuities. They implement a split patient flow where patients with a lower acuity level go to a separate area than those with a higher acuity level.

Allon et al. (2009) also developed a queueing network model describing the flow of patients between the ED and inpatient units. They showed that bed capacity, both in the ED and the inpatient units, play an important role in the time spent on ambulance diversion depending on the size of the hospital. Inpatient boarding has a greater impact on diversion hours if the size of the ED is large relative to the hospital. On the other hand, ED capacity has a greater impact on diversion hours if the ED is small relative to the size of the inpatient units. They also show that ambulance diversion tends to increase when there are more EDs close by.

Khare et al. (2009) utilized computer simulation to investigate the impact of increasing ED bed capacity, increasing the rate that admitted patients leave the ED, and increasing the amount of patients who visit the ED. They found that only increasing the number of ED beds increases the average ED patient LOS by 7 minutes. On the other hand, increasing only the rate that admitted patients leave the ED reduces the average ED patient LOS by 22 minutes. Similar trends occurred when the number of patients visiting the ED increased. They suggested that focusing on improvements in the boarding process
would provide more impact on ED LOS reductions than increasing bed capacity in the ED.

2.2 Ambulance Diversion

One of the major effects of ED crowding is the diversion of ambulances to nearby facilities. There have been several studies performed concerning the causes of diversion, the effects of various diversion policies, and financial impact of ambulance diversion.

Schull et al. (2003) investigated the relationship between physician, nursing, and patient factors on ED use of ambulance diversion. Data was obtained for 1 ED located in Toronto, Canada for the year 1999 on ambulance diversion during consecutive 8-hour intervals. Time series methods were used to determine the relationship between physician and nursing resources and number of patients boarding in the ED and ambulance diversion. They found that the patients boarding in the ED were significant factors in ambulance diversion hours. On the other hand, nursing and physicians resources were not.

Ramirez, Fowler, and Wu (2009) used simulation to analyze how the ambulance diversion state triggers and consecutive time on diversion, as well as the number of ED beds, impact patient waiting times, the percentage of LWOT, and percentage of time on diversion at a large-size hospital. They found that a fast-track ED could reduce the time spent on ambulance diversion. They concluded that there exists a trade-off between the time spent on diversion and patient wait time and LWOT statistics.
Handel and McConnell (2009) performed a retrospective analysis of administrative data between July 2003 and end of December 2006 for an academic medical center. They found that the weeks experiencing higher diversion hours resulted in higher inpatient revenues and profits overall ($119,000 per week). An average weekly increase of $265,000 was seen for patients admitted to the ED for periods of high diversion (>20 hours) compared to no diversion. For patients admitted electively, the average weekly revenue increased $415,000 for weeks experiencing high diversion compared to mild diversion (10-20 hours). Therefore, other rationales such as quality of care or reimbursement, to decrease ambulance diversion may be needed since no financial incentives exist.

2.3 Hospital Readmission

Readmission rate refers to the percentage of patients who are rehospitalized after discharge to the same or similar healthcare facility within a short time period (typically within 30 days) upon discharge. The rate of readmission is used as an indicator in the quality of care that a facility provides. The risk of readmission has been found to be dependent on many variables such as medical diagnosis, socio-demographics, economic-educational, comorbidities, and insurance status (Patel et al., 2010, Ross et al., 2010).

There is a great deal of literature concerning readmissions and specific medical conditions, especially heart failure due to the high readmission rate (Ross et al., 2010, Thakar, et al., 2012). However, there is less literature available concerning the other less
prevalent medical conditions and the overall health care processes contributing to the high readmission rates.

The impact of length of stay and readmission rates has been studied. Lin et al. (2006) used multivariate logistic regression to determine the relationship between readmissions and LOS for patients diagnosed with schizophrenia. They analyzed data from a National Health Insurance Research Database for 2001 through 2003. They concluded that a short LOS is related to increased readmission rates within 30-days of discharge. Heggestad et al. (2008) also found that shorter LOS increased the patient’s risk of readmission using regression analysis. They analyzed data obtained from Norwegians hospitals in 1996 for patients over the age of 67.

Jencks et al. (2009) analyzed Medicare data for 2003 and 2004 and reported that 19.6% of Medicare patients are readmitted within 30 days of discharge, and 34% were readmitted within 90 days of discharge. Additionally, they estimated that 90% of readmissions were unplanned, costing Medicare 17.4 billion.

Some efforts have been made to reduce the risk of readmission by making administrative changes such as patient follow-ups. For example, Hernandez et al. (2010) showed through an observational analysis that follow-ups within 7 days of hospital discharge for patients hospitalized with heart failure reduced the likelihood of readmission within 30-days of hospitalization for patients over the age of 65.

Additionally, the Affordable Care Act (also known as Obama Care), beginning in 2013, will aim to improve the quality of care and reduce expenditures due to readmissions. This will be done by penalizing hospitals up to 1% of Medicare payments
that experience high 30-day readmission rates for patients diagnosed with heart failure, pneumonia, and acute myocardial infarction (Johnson et al. 2012). The Affordable Care Act and programs similar could severely impact hospitals all over the country. Therefore, the need to control the number of readmissions while maintaining hospital performance measures is of utmost importance.

2.4 Discharge Planning

As mentioned earlier, decisions around planning patient discharges are complex, and are typically influenced by patient-, provider-, and system-related factors. There is little literature discussing the optimal time to discharge a patient. However, there is literature discussing the discharge process and strategies to improve the process.

Manning et al. (2007) investigated the usefulness of assigning discharge appointments for inpatients. Discharge appointments for the day and time of patient discharge were assigned to patients based on discussions between healthcare providers, patients, and families. During a 4-month study period, 60% of patients were discharged within 30 minutes of their scheduled discharge appointment and 46% of discharge appointments were scheduled 1 day in advance. However, the impact of discharge appointments on patient satisfaction and health outcomes was not determined.

Kreke et al. (2008) modeled the decision-making process of when to discharge a patient with sepsis in order to maximize that patient’s expected survival upon discharge. They modeled this process as an unconstrained Markov Decision Process (MDP) and non-stationary control limit policies were derived.
Srivastava et al. (2009) studied the delays occurring in a 233-bed tertiary-care children's hospital during August 2004. They indicated that the system-wide effect of poor discharge planning was as much as 82 delay-related inpatient days (9% of total) and $170,000 (8.9%) in excess costs. They concluded that close to 25% of patients during the 1-month study period could have been discharged earlier.

Jack et al. (2009) performed a randomized trial to evaluate the impact of employing the ReEngineered Discharge (RED) program. This program involved providing medication and an individualized instructions as well as arranging follow-up appointments for patients being discharged. Additionally, a clinical pharmacist followed up with patients 2 to 4 days after discharge to reiterate the discharge plan and review medication information. The patients involved in the RED group felt more prepared for being discharged and had lower rates of hospital utilization than those not involved in the RED group (0.314 vs. 0.431 visits per person per month). They concluded that discharge services such as RED aid in reducing hospital utilization within 30-days of discharged patients.

Wong et al. (2009) investigated how smoothing patient discharges throughout the week impacted the number of occupied ED beds by inpatients. They concentrated on historical data for 2004 from a Toronto hospital. Using system dynamics modeling they showed that by smoothing the same number of inpatient discharges over the entire week (increasing weekend discharges) reduced the number of ED beds occupied by inpatients by 27-57%. The ED LOS also decreased by 7-14 hours for these patients.
Vermeulen et al. (2009) performed a cross-sectional study of the admission to discharge ratio for hospitals in the Toronto area over a 3-year period. They found that as the admission to discharge ratio fell to 0.6 or below it resulted in an 11-minute decrease in average ED LOS for the following day. On the other hand a ratio of 1.3 to 1.4 resulted in a 5-minute increase in the following day average ED LOS. They also concluded that weekend ratios had a greater impact on the next day average ED LOS than those on the weekdays. The results suggested that by better balancing the admissions to discharge ratio, the amount of time patients spend waiting and boarding in the ED could be reduced.

Farris et al. (2010) performed a case study on a 362-bed teaching hospital in Texas. They used healthcare engineering methods such as task and functional flow analysis to identify the steps in the current discharge process and also the major causes of discharge delays. They showed that different patient groups require different discharge needs. They found that the need for healthcare engineering methods to develop scheduling needs for the discharge process could aid in reducing the delays experienced during this process.

Dobson et al. (2010) proposed a stochastic model of patient bumping within an ICU. They modeled the effects of discharging patients early when the capacity of the ICU is limited using different arrival patterns and capacity parameters. They found that the surgical schedules for elective procedures do impact the number of patients bumped in the ICU. They showed through this study the tradeoffs between capacity and surgical schedules have on patient bumping in the ICU.
Powell et al. (2012) performed a cross-sectional computer modeling analysis of data obtained at Northwestern University’s Feinberg School of Medicine for weekday admissions and discharges in September 2007. The objective of the study was to identify how discharging patients earlier in the day have an effect of patients boarding in the ED. Shifting the peak inpatient discharge time four hours earlier reduced ED boarding from the baseline of 77 hours per day to 0 hours. Additionally, they found that discharging 75% of patients by noon or discharging all patients by 4:00 pm reduced total boarding hours from 77 to 3.

Chan et al. (2012) analyzed the impact of various discharge decisions in the ICU on patient readmission. They developed a decision-support tool to aid in the discharge decision of when to discharge a patient from the ICU to make room for an incoming patient based on readmission risk. They found that delays in ICU patient admission may have an affect on the LOS and patient outcomes. They concluded that the use of a decision-support tool could help reduce the readmitted patient load.

### 2.5 Modeling Healthcare Processes with Simulation

Healthcare processes are both complex and dynamic. Therefore computer simulation has emerged as a popular decision support tool to model healthcare processes. Other decision support systems, such as mathematical programming, fail to capture the dynamic nature of the system as well as arrival and process variability.

A large body of research literature exists on the applications of simulation in healthcare. Jun et al (1999) performed an extensive literature review of the applications
of discrete-event simulation in health care. Their study included 117 articles. Their review included models used for improving and optimizing patient flows and routing, resource allocation, and capacity and staff planning. There are also more recent review articles concerning simulation modeling in healthcare by Jacobsen et al. (2006) and Eldabi et al. (2007).

One of the major avenues explored using DES in the healthcare setting is improving resource allocation and capacity planning. Duguay and Chetouane (2007) used simulation to improve system throughput and reduce patient waiting times by modifying resource allocation. They found that long wait times usually occurred because of lack of resource availability such as nurses, physicians and rooms. They simulated multiple scenarios that increased the numbers of nurses, physicians, and rooms during various shifts. Results showed that adding an additional nurse and physician between 8:00 a.m. and 4:00 p.m. made the most improvements and allowed 16 additional patients to be treated in that time frame since waiting times were reduced. The results also suggested that increasing the number of exam rooms did not play a large role in waiting time reduction unless additional staff was added as well.

Ashby et al. (2008) also utilized DES for facility planning. They focused on creating a simulation model to see the impact of transitioning from a higher bed facility to a new facility with smaller capacity. Results showed that the reduced number of inpatient beds had a negative effect on the ED wait times and congestion. Through simulation, results suggested that altering certain processes (e.g. utilizing discharge lounges and creating general inpatient units by combining more specialized units) would enable the ED to operate in a smaller facility successfully.
DES has also been used to analyze the impact of process changes on key hospital performance measures. Ruohonen et al. (2006) investigated the impact of introducing a triage team to the operations of an ED in Finland. The triage team method consisted of 3 staff members (doctor, receptionist, and nurse) to receive patients, define their urgency level and symptoms, and order tests before the patient is sent to his/her next phase. The previous triage process employed by the ED utilized only a nurse to handle patient diagnosis. The incorporation of a doctor in the early treatment stages would allow both diagnosis and tests to be run simultaneously. They simulated multiple scenarios. Results showed up to a 26% reduction in patient throughput time. The team approach allowed for better priority assignment and quicker delivery of treatment to the patient.

Beck et al. (2009) investigated the effect of bedside registration on ED congestion. The process change involved registering patients once they are administered an ED bed rather than after they have left triage. They simulated this policy on three systems: 1) the average scenario 2) a scenario in which the ED is “crowded” and 3) the scenario in which there is always an open bed. Results showed that the process of bedside registration only improved waiting times and ED length of stay when ED beds were available after the triage process. However, when the ED was already in a crowded state, this process did not reduce patient waiting times.

The use of DES models in health care settings is not limited to investigating the impact of resource planning or process changes. Hoot et al. (2008) created a simulation model to forecast ED conditions for 2, 4, 6, and 8 hours in the future. The conditions included number waiting, length of wait, level of occupancy, ED length of stay, number boarding and amount of time boarded, as well as ambulance diversion. They found that it
was possible to forecast operational measures that affect ED overcrowding by modeling patient flow.

2.6 Research Objective

Though several strategies to improve the discharge process have been proposed, there is a general lack of understanding and insights into effective patient-specific discharge timing and its system-wide implications. It is evident that decisions in the inpatient units, especially discharge timing, can affect its occupancy level (driving ED crowding) and readmission risk. The question of who to take care first, sick patients in the inpatient unit or sicker patients in the ED waiting for an inpatient bed, is critical when trying to provide quality care to the patients.

With over 136 million patients visiting the ED across 3,833 EDs in the US and over 17.2 million inpatient discharges (CDC, 2011), this question is even more critical. If medically-ready patients are held longer in the inpatient units for any reason (e.g., lack of transportation, capacity constraints at the discharge location, or simply defensive medical practice), then it may restrict the transition of sicker patients to the inpatients units. The subsequent ED crowding phenomenon and ambulance diversion policies are unwanted and dangerous to residence at large.

Our research adds to the growing body of literature by focusing on analyzing the effects of inpatient discharge timing on a variety of key performance measures. We introduce two new dynamic discharge policies and demonstrate their effectiveness via DES.
3 Model Description

A generic acute care hospital (ACH) was modeled to capture the flow of a patient from arrival to the emergency department (ED) to being admitted to the inpatient units before being discharged from the facility. The model included the main processes of an ED and medical inpatient units (IUs). A baseline model was created to simulate the current static policy typically employed by ACHs for discharging a patient from an ACH. Additionally, two dynamic discharge policies were also developed and modeled to analyze the impact on key performance measures. This section will discuss the overall flow of an ACH, the static policy model description and validation, and alternate discharge policies.

3.1 Patient Flow at an Acute Care Hospital

Before the simulation model could be developed, an in depth understanding of patient flow from the ED to inpatient units had to be established. Visiting a regional acute care hospital that is also a regional Level 1 trauma center, as well as reading current literature helped us gain this understanding. Figure 2 shows the complex movement of patients throughout an ACH.
Figure 2: Patient flow through an ACH
Patients can enter the ED via one of two ways: walk-ins or ambulance. For ACHs with a trauma center, some patients may arrive through helicopter service.

Walk-in patients move to a triage process for a quick assessment of their condition. During this process the patient is assigned an Emergency Severity Index (ESI). The ESI is a scale ranging from 1 to 5 and is used to prioritize patients based on the urgency in which they need treatment, which is determined by the acuity of the presenting symptoms (Gilboy et al., 2005). An ESI level of 1 is considered the highest priority because it is the greatest severity whereas an ESI level of 5 is considered the least severe. Walk-in patients may be categorized in any of the five ESI levels upon triage. Typically ESI 1 and 2 patients tend to require an ED bed, while ESI levels 3-5 may need to be sent to a dedicated observation unit, urgent care, or home based on their condition. An observation unit is designed to care for patients who may not immediately need to be hospitalized, but need additional care and determination of their condition. Such stays are typically less than 23 hours (as patients requiring longer stays are considered admitted and typically move to IUs). Patients with an ESI level of 4 or 5 do not typically need to be admitted; they may be treated by a nurse or physician and may leave the ED. EDs may have an urgent care unit attached to it to take care of such patients.

Patients requiring an ED bed will wait in a queue, which is referred to in this paper as ED waiting. Patients who enter via ambulance tend to be either ESI 1 or 2 and proceed immediately to an ED bed to receive treatment.

When the number of patients waiting for an ED bed increases it contributes to a crowding in the ED due to limited resources. To mitigate crowding, ED managers may
opt to divert ambulances for a period of time. If the ACH is experiencing ambulance diversion, patients who are en route to arrive to the facility by ambulance are then diverted to an alternate facility. Additionally, when an ACH is experiencing ED crowding, patients (mostly walk-ins) waiting for an ED bed may leave without receiving treatment (LWOT) due to excessive wait times.

For patients with acute conditions, if an ED bed is available, then they are moved there until they are stable, before being admitted to an inpatient unit. If an inpatient bed is available, then a patient boarding the ED is moved to an inpatient unit to initiate the treatment there. However, if an inpatient bed is not available, then the patient will continue to occupy the ED bed until an inpatient bed becomes available, a phenomenon referred to as ED boarding.

There are two major types of inpatient units: medical and surgical. Patients will follow the path that is appropriate for their condition whether that be an intensive care or ward. Patients may move between care areas within the ACH depending on their treatment requirements. Patients in an inpatient unit occupy a bed until they are deemed medically–ready to be discharged. Discharged patients then leave the system upon releasing the IU resources.

In some instances patients may require additional emergency medical treatment and are readmitted to the hospital. The rate of readmission is used as an indicator in the quality of care that a facility provides.

Patients may also enter the inpatient units based on a prior scheduled arrangement. These are considered elective admissions. Many times, an outpatient
physician (e.g., a family medicine physician) may deem that a patient be admitted to the hospital’s inpatient units during the outpatient visit. Patients admitted in this manner are generally referred to as direct admissions. We only consider emergency patient pathways (and no elective/direct admits) in this exploratory study.

3.2 A Discrete-Event Simulation Model

Health care processes are both complex and dynamic. Computer simulation has emerged as a popular decision support tool to model health care processes. Discrete-event simulation (DES), a type of computer simulation, models the system as it changes over time and the state of variables; e.g., patients, only change at discrete points of time (Law, 2007). DES models are able to capture the complexity of the dynamic systems and model the uncertainty associated with them; capturing this via a mathematical programming model is extremely difficult. DES models are able to perform what-if analyses to aid in comparing alternative designs for existing systems. DES is (and has been) a preferred methodology for modeling complex dynamic systems (Jacobsen et al., 2006), and was therefore chosen in our study.

We make the following assumptions to reduce the complexity and aid in generating meaningful insights:

1. Surgical emergency patients utilize a separate set of ED beds and all elective patients utilize a separate set of inpatient beds. These separate beds were not included in the analysis.
2. The different medical inpatient units were not modeled separately, but as one entire unit. It was assumed that once a patient occupied a bed, he/she remained in the same bed until treatment was complete.

3. All ED and inpatient beds were modeled as staffed beds. A staffed bed is considered a bed in which there is available resources to care for the patient. Therefore, there is no need to model individual medical staff members such as doctors and nurses.

We used an off-the-shelf simulation modeling software, ARENA by Rockwell Automation, Inc., for our study.

3.2.1 Modeling a Static Discharge Policy

The baseline model was built using data collected from a regional ACH and recent literature to represent a generic ACH. The simulation models the various patient flows within an ACH. We now describe the various elements of the simulation model.

Figure 3 shows the overall process flow of a patient throughout the system. The patient pathway includes arrival of the patient to the ED until this patient exits the system either by leaving after treatment in the ED, leaving without receiving treatment (LWOT), or being discharged from an IU.
Patients can enter the ED via two ways: ambulance or walk-in. Upon arrival, each patient is assigned one of fifteen diagnostic groupings or medical classes based on the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codes. Ambulance patients proceed immediately to a staffed ED bed, as they are typically of highest acuity levels. High-acuity walk-in patients will also require a staffed ED bed, while low-acuity patients may need to be sent to a dedicated observation unit or home based on their condition. These patients exit the system after the triage process. When all available ED beds are occupied, patients enter a queue for an available ED bed, which is referred to as ED waiting.

Patients occupy staffed ED beds until their treatment is complete before being moved to an inpatient unit. The patients may encounter one of the following two situations: IU staffed bed is available and IU staffed bed is not available. The simulation logic is shown in Figure 4.
If all inpatient beds are being utilized, patients continue to hold the ED bed until an inpatient bed becomes free. The time spent waiting for an available bed is computed as ED boarding. The process logic for inpatient treatment can be seen in Figure 4.

![Figure 4: Simulation logic for inpatient treatment](image)

First, if a staffed inpatient bed is available, then this patient is moved to the IU to initiate treatment there. Once a patient occupies an IU staffed bed, they will remain in the bed for at least 24 hours. It was assumed that any patient requiring less than 24 hours’ worth of treatment did not need to occupy an inpatient bed.

Second, if all staffed inpatient beds are occupied, the patient continues to occupy the ED bed until an inpatient staffed bed is available, or ED boarding.

The patient occupies the inpatient bed until they are deemed medically-ready to be discharged. Medically ready, for the static policy, is calculated as when the probability of readmission is at or below the average rate of readmission for the assigned medical class (see Table 3 in Section 4.1). The probability of readmission is calculated based on the patient’s rate of decline (ROD). The ROD is a linear approximation of the
relationship between probability of readmission and inpatient LOS. For more details on how the ROD was derived, see Section 4.1.

An ambulance diversion policy is included in the model. The diversion status is triggered by the number of patients waiting in the ED for a staffed ED bed. For this model, ambulance diversion is triggered when the number of patients in queue for an ED bed is 50% or more than the number of total ED staffed beds. Figure 5 below illustrates how we use a separate entity to set the trigger on or off based on the number of patients waiting in the ED. Whenever the diversion status is on it is assumed that patients who are scheduled to arrive by ambulance do not enter the system; a phenomenon similar to balking in queuing system. The system remains on diversion for 1 hour and then the trigger threshold is checked again. The system goes off of diversion when the number waiting in the ED is below the trigger point.

![Simulation logic for ambulance diversion](image)

Patients who leave without receiving treatment (LWOTs) are also modeled. For LWOTs, each patient is different in terms of their tolerance level of how long they are willing to wait for treatment. This is very difficult to model. Therefore, any patient who has waited a set time limit of 12 hours for an available ED bed is disposed from the system and considered to have LWOT, similar to Ramirez et al. (2009).
3.2.2 Modeling Dynamic Discharge Policies

Two dynamic discharge policies were developed to identify their impacts on the performance measures. These policies follow the same overall model logic as displayed in Figure 3 with the exception of the discharge process.

Figure 6: Simulation logic for inpatient treatment for the dynamic discharge policies

For the two dynamic policies, when the ED begins to crowd (based on a trigger condition), then patients occupying inpatient beds with less than pre-specified readmission probabilities are discharged. That is, patients are discharged, starting from patients with the lowest risk, and then continue to check the trigger up until we reach patients with an upper bound on the readmission risk (40%). If the trigger is set off in the intermediate, say at patients with 20% risk of readmission, no further patients are
discharged. If the trigger is still on once all patients with 40% or lower readmission risk are discharged, the discharge process then stops. This may mean that the ED may continue to crowd leading to ambulance diversion. This logic can be seen in Figure 6.

The dynamic policies differ in the trigger point to initiate patient discharges. Dynamic Policy 1 (DP-W) discharges patients more aggressively when a specific threshold is met for the queue of patients waiting for an ED bed. Dynamic Policy 2 (DP-B) discharges patients more aggressively when a specific threshold is met for the queue of patients waiting for an inpatient bed, or the number of ED boarding patients. We used readmission probability strata/bands of 0-20%, 21-30%, and 31-40%. Discharging patients with > 40% readmission risk seemed too aggressive from a quality of care standpoint. Patients then can either leave the system or reenter as a readmission patient based on their probability of readmission at the time of discharge.

We now describe the results of our preliminary experiments to compare the static and two dynamic policies.
4 ANALYSIS AND RESULTS

In this section, the input data and respective sources used for model building and validation are discussed in detail. This section also reports the results obtained from multiple scenarios using various bed capacities, discharge triggers, and arrival volumes.

4.1 Input Data

Multiple data sources were used to model and validate a generic ACH. The arrival distribution for emergency patients was obtained through a local ACH for the year 2010. The emergency patient arrival varied substantially by time-of-day, day-of-week, and month-of-year (see Figure 7). A non-stationary Poisson process was used to model the arrivals, where the expected arrival rate by hour, day, and month were identified. The average hour-of-day rates across the entire year were obtained. Scaling factors were then used to identify the number of ED arrivals for each day-of-week and month-of-year; see Figure 8. Among the arriving patients, 15% of them arrived via ambulance, while 15.6% of all arrivals resulted in admission to the inpatient units (CDC, 2008).
Figure 7: Actual arrival of emergency patients in 2010 at a large U.S. hospital

Figure 8: Monthly scale factors to account for seasonal variability
The medical class assignment for each patient in the inpatient units was based on the classes defined in The National Hospital Discharge Survey: 2007 Summary (CDC, 2010). This summary defined 17 medical diagnostic groups based on ICD-9 codes. Only 15 of the 17 medical diagnostic groups were included in this study; ICD-9 codes that fell under mental disorders (290-319), complications of pregnancy, childbirth, and the puerperium (630-677), and certain conditions originating in the prenatal period (760-779) were excluded from the study because patients who have these diagnoses follow a different path throughout the ED and ACH.

To identify the proportion of patients who belong to each medical class, the AHRQ data set for the state of Washington (2006) was analyzed. The data came from 114 hospitals located in Washington. This data set was cleaned to exclude patients who died during treatment or were transferred during their visit. This left 370,354 patients to be included in the analysis. Additionally, only the primary discharge diagnosis was used to assign medical classes. The medical class descriptions and distributions can be seen in Table 1.
Table 1: Data corresponding to admission distribution

<table>
<thead>
<tr>
<th>Medical Class</th>
<th>Diagnostic Groupings</th>
<th>ICD-9-CM code</th>
<th>% of Patients Admitted</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Infectious and parasitic diseases</td>
<td>001-139</td>
<td>0.6</td>
</tr>
<tr>
<td>2</td>
<td>Neoplasms</td>
<td>140-239</td>
<td>6.3</td>
</tr>
<tr>
<td>3</td>
<td>Endocrine, nutritional and metabolic diseases, and immunity disorders</td>
<td>240-279</td>
<td>2.8</td>
</tr>
<tr>
<td>4</td>
<td>Diseases of the blood and blood-forming organs</td>
<td>280-289</td>
<td>0.8</td>
</tr>
<tr>
<td>5</td>
<td>Diseases of the nervous system and sense organs</td>
<td>320-389</td>
<td>2.6</td>
</tr>
<tr>
<td>6</td>
<td>Diseases of the circulatory system</td>
<td>390-459</td>
<td>14.3</td>
</tr>
<tr>
<td>7</td>
<td>Diseases of the respiratory system</td>
<td>460-519</td>
<td>7.9</td>
</tr>
<tr>
<td>8</td>
<td>Diseases of the digestive system</td>
<td>520-579</td>
<td>10.7</td>
</tr>
<tr>
<td>9</td>
<td>Diseases of the genitourinary system</td>
<td>580-629</td>
<td>6.0</td>
</tr>
<tr>
<td>10</td>
<td>Diseases of the skin and subcutaneous tissue</td>
<td>680-709</td>
<td>2.1</td>
</tr>
<tr>
<td>11</td>
<td>Diseases of the musculoskeletal system and connective tissue</td>
<td>710-739</td>
<td>9.2</td>
</tr>
<tr>
<td>12</td>
<td>Congenital anomalies</td>
<td>740-759</td>
<td>0.5</td>
</tr>
<tr>
<td>13</td>
<td>Symptoms, signs, and ill-defined conditions</td>
<td>780-799</td>
<td>4.3</td>
</tr>
<tr>
<td>14</td>
<td>Injury and poisoning</td>
<td>800-999</td>
<td>9.3</td>
</tr>
<tr>
<td>15</td>
<td>Supplementary classifications</td>
<td>V01-V86</td>
<td>22.7</td>
</tr>
</tbody>
</table>

The state of Washington (2006) data set was also used to extract the average and standard deviation of length of stay for inpatient stay for each medical class; see Table 2. The LOS reflects the amount of time that the patient spends in the inpatient unit. The inpatient LOS for each medical class was assumed to follow a LogNormal distribution, LN(μ, σ²), similar to (Atienza et al., 2008, Faddy et al., 2008, Sastry and Sinha, 2010). JMP 9.0 was then used to find the LogNormal parameters. Since the LogNormal distribution is right skewed, the LOS was obtained so that 95% of all patients were included. The additional 5% were redistributed to each day of the LOS distribution. Two assumptions were made concerning patient LOS: 1) No patient experienced a LOS of less
than one day, and 2) LOS is recorded as a discrete value (e.g. patients could not stay in the hospital for 1.5 days). The LogNormal parameter values for LOS can be seen in Table 2.

Table 2: Data corresponding to inpatient length of stay distributions

<table>
<thead>
<tr>
<th>Med Class</th>
<th>Diagnostic Groupings</th>
<th>ICD-9-CM codes</th>
<th>LOS Lognormal (µ, σ²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Infectious and parasitic diseases</td>
<td>001-139</td>
<td>(1.07, 0.83²)</td>
</tr>
<tr>
<td>2</td>
<td>Neoplasms</td>
<td>140-239</td>
<td>(1.22, 0.86²)</td>
</tr>
<tr>
<td>3</td>
<td>Endocrine, nutritional and metabolic diseases, and immunity disorders</td>
<td>240-279</td>
<td>(1.01, 0.76²)</td>
</tr>
<tr>
<td>4</td>
<td>Diseases of the blood and blood-forming organs</td>
<td>280-289</td>
<td>(1.10, 0.84²)</td>
</tr>
<tr>
<td>5</td>
<td>Diseases of the nervous system and sense organs</td>
<td>320-389</td>
<td>(1.48, 0.91²)</td>
</tr>
<tr>
<td>6</td>
<td>Diseases of the circulatory system</td>
<td>390-459</td>
<td>(1.07, 0.83²)</td>
</tr>
<tr>
<td>7</td>
<td>Diseases of the respiratory system</td>
<td>460-519</td>
<td>(1.26, 0.79²)</td>
</tr>
<tr>
<td>8</td>
<td>Diseases of the digestive system</td>
<td>520-579</td>
<td>(1.11, 0.82²)</td>
</tr>
<tr>
<td>9</td>
<td>Diseases of the genitourinary system</td>
<td>580-629</td>
<td>(0.88, 0.72²)</td>
</tr>
<tr>
<td>10</td>
<td>Diseases of the skin and subcutaneous tissue</td>
<td>680-709</td>
<td>(1.22, 0.72²)</td>
</tr>
<tr>
<td>11</td>
<td>Diseases of the musculoskeletal system and connective tissue</td>
<td>710-739</td>
<td>(0.99, 0.68²)</td>
</tr>
<tr>
<td>12</td>
<td>Congenital anomalies</td>
<td>740-759</td>
<td>(1.13, 1.02²)</td>
</tr>
<tr>
<td>13</td>
<td>Symptoms, signs, and ill-defined conditions</td>
<td>780-799</td>
<td>(0.72, 0.73²)</td>
</tr>
<tr>
<td>14</td>
<td>Injury and poisoning</td>
<td>800-999</td>
<td>(1.20, 0.84²)</td>
</tr>
<tr>
<td>15</td>
<td>Supplementary classifications</td>
<td>V01-V86</td>
<td>(0.81, 0.88²)</td>
</tr>
</tbody>
</table>

The state of Washington (2006) data set was also used to calculate the average 30-day readmission rates for each medical class (see Table 3). An approach similar to Thakar et al. (2012) was used to identify patients readmitted within 30-days of discharge. An index discharge was identified and any subsequent hospitalization that was within 30 days of the index discharge was flagged to be included in the calculation.
Each patient was assigned a rate of decline (ROD) value based on the average readmission rate and LOS distribution for their respective medical class. The ROD is a linear approximation of the relationship between probability of readmission and inpatient LOS (see Equation 1). The ROD value is used to assess the patient’s current risk of readmission and if they can be discharged based on the policy in place. Figure 9 depicts 5 of 11 different ROD values that could be assigned to a patient diagnosed with diseases of the circulatory system. Based on the LOS distribution, some patients may experience a quicker reduction in the risk of readmission as opposed to others.

\[
ROD = \frac{Average \ Readmission \ Rate - 100}{LOS}
\]  

(1)
As mentioned previously, the criteria for ambulance diversion is based on a pre-specified number of patients waiting in the ED for a staffed ED bed. This value, often times is a certain fraction of the total number of ED beds (Ramirez et al., 2009). A local hospital uses 50% as this fraction; i.e., if there are 40-staffed ED beds, then the ambulances are diverted when there are 20 or more patients waiting in the ED for an ED bed. Additionally, when the ED diverts ambulances, they do so for a specified period of time, typically between 1 and 4 hours (Local Hospital, Ramirez et al., 2009). Based on this information, the diversion policy used in all discharge models was a 50% trigger point and a time period of 1 hour.

Resource capacity plays an integral role in the model. During the triage process, only one resource (triage nurse) is used. To analyze the effects of the bed capacity for the

Figure 9: ROD calculation for Medical Class 6 (diseases of the circulatory system)
ED and inpatient unit, various ED to inpatient bed ratios were analyzed. Table 4 shows the resource combinations used for each of the discharge policies.

Table 4: Capacity and resource combinations for sensitivity analysis

<table>
<thead>
<tr>
<th>ED Beds</th>
<th>IP Beds</th>
<th>Triage Nurse</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>200</td>
<td>1</td>
</tr>
<tr>
<td>30</td>
<td>225</td>
<td>1</td>
</tr>
<tr>
<td>40</td>
<td>200</td>
<td>1</td>
</tr>
<tr>
<td>40</td>
<td>225</td>
<td>1</td>
</tr>
</tbody>
</table>

Processing times were assumed to follow a triangular distribution since the distribution of each process was unknown. Table 5 displays the processing times relating to Triage, ED treatment and the delay in readmission. These processes and times are consistent across all models.

Table 5: Processing time distributions

<table>
<thead>
<tr>
<th>Activity</th>
<th>Processing Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Triage</td>
<td>TRI(0.01, 0.015, 0.02) hours</td>
</tr>
<tr>
<td>ED Treatment</td>
<td>TRI(2, 4, 6) hours</td>
</tr>
<tr>
<td>Delay in Readmission</td>
<td>TRI(3, 15, 30) days</td>
</tr>
</tbody>
</table>

4.2 Results

4.2.1 Model Validation

The main performance measures considered are time patients spend waiting in the ED waiting for an ED bed (ED waiting) and waiting for an inpatient bed (ED boarding), total hours per year the facility spent on diversion, the percentage of patients who left without treatment, and the number of patients readmitted within 30-days of discharge for
the simulated year. These performance measures were considered due to their impact on quality of care and healthcare costs.

The arrival data as well as the medical diagnosis data consisted of one year’s worth of data. Therefore, to validate the simulation model, the model was run for 1 year and 3 months, where the first 3 months were used as a warm-up period. The warm-up period was necessary as to not start with an empty and idle system. To validate model results, average and ranges of the performance measures were gathered from recent literature and national medical surveys. These values were compared against 95% confidence intervals about the mean that were recorded from 100 replications of the baseline model. The baseline model with 30 ED staffed beds and 225 IU staffed beds was used for model validation. The results can be seen in Table 6.

Table 6: Comparison of observed and simulated values for the various performance measures for the BL policy with ED and IP staffed beds of 30 and 225, respectively

<table>
<thead>
<tr>
<th>Performance Measure</th>
<th>Simulated Mean</th>
<th>Observed Mean</th>
<th>Range</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>ED wait (hr)</td>
<td>1.16 ± 0.03 hr</td>
<td>~1 hr</td>
<td>0.25 – 4 hr</td>
<td>(Expert, Bair et al., 2010)</td>
</tr>
<tr>
<td>ED board (hr)</td>
<td>6.28 ± 0.09 hr</td>
<td>5.55 hr</td>
<td>2.9 – 8.4 hr</td>
<td>(Bair et al. 2010, Hoot et al., 2006)</td>
</tr>
<tr>
<td>Ambulance diversion (hr)</td>
<td>228.6 ± 6.8 hr</td>
<td>220 hr</td>
<td>133.2 – 700 hr</td>
<td>(McConville and Lee 2008, Expert)</td>
</tr>
<tr>
<td>LWOT (%)</td>
<td>1.3 ± 0.1%</td>
<td>–</td>
<td>1 – 5%</td>
<td>(Khare et al., 2009)</td>
</tr>
</tbody>
</table>

The results in the above table show that the simulated values are reasonably close to the values reported in literature or expert opinion. The slight differences in values are likely because of the multiple input data sources, non-standard protocols followed by EDs in the nation when diverting ambulances, and the effect of non-clinical factors (such
as adherence to medication) on readmission rates. However, given that the 95% CIs either capture the national averages or overlap the range of observed values, it can be concluded that the simulation model reasonably captures the complex dynamics between the ED and inpatient units.

### 4.2.2 Experimental Design

Using the validated simulation model, we first obtained the performance measures for various bed capacity values for ED and IP, (ED, IP), as (30,200), (30,225), (40,200), and (40,225) or C1, C2, C3, and C4, respectively. The results can be seen in Table 7.

To analyze which of the two dynamic policies is better, we conducted sensitivity analysis on the behavior of these policies with respect to the trigger points. This trigger point ranged from the number of patients either waiting for an ED bed or boarding in the ED to be 25%, 33%, or 40% of the number of ED staffed beds. Tables 8 and 9 show the effect of the trigger values on performance measures; the %-LWOT was nearly 0 in all the instances, so not shown.
Table 7: Comparison of performance measures for BL, DP-W, and DP-B for various ED to IU bed capacities

<table>
<thead>
<tr>
<th></th>
<th>(ED, IU)= (30, 200)</th>
<th>(ED, IU)= (30, 225)</th>
<th>(ED, IU)= (40, 200)</th>
<th>(ED, IU)= (40, 225)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BL</td>
<td>DP-W</td>
<td>DP-B</td>
<td>BL</td>
</tr>
<tr>
<td>ED wait (hrs.)</td>
<td>2.6</td>
<td>0.1</td>
<td>0</td>
<td>1.2</td>
</tr>
<tr>
<td>ED board (hrs.)</td>
<td>10.8</td>
<td>3.2</td>
<td>1.1</td>
<td>6.3</td>
</tr>
<tr>
<td>Amb div (hrs.)</td>
<td>717.8</td>
<td>61.3</td>
<td>38.6</td>
<td>228.6</td>
</tr>
<tr>
<td>Readmissions (#)</td>
<td>1520.3</td>
<td>3869.2</td>
<td>4480.6</td>
<td>1691.6</td>
</tr>
</tbody>
</table>

Table 8: Effect of different trigger points for DP-W on performance measures

<table>
<thead>
<tr>
<th>Trigger Point</th>
<th>ED Beds</th>
<th>IP Beds</th>
<th>ED Wait (hr)</th>
<th>ED board (hr)</th>
<th>Diversion (hr)</th>
<th>Annual Readmissions</th>
</tr>
</thead>
<tbody>
<tr>
<td>25%</td>
<td>30</td>
<td>200</td>
<td>0.08</td>
<td>3.15</td>
<td>61.30</td>
<td>3869.17</td>
</tr>
<tr>
<td></td>
<td>40</td>
<td>225</td>
<td>0.05</td>
<td>1.92</td>
<td>1.93</td>
<td>2788.16</td>
</tr>
<tr>
<td>33%</td>
<td>30</td>
<td>200</td>
<td>0.11</td>
<td>5.72</td>
<td>56.97</td>
<td>3614.21</td>
</tr>
<tr>
<td></td>
<td>40</td>
<td>225</td>
<td>0.06</td>
<td>3.62</td>
<td>1.66</td>
<td>2536.95</td>
</tr>
<tr>
<td>40%</td>
<td>30</td>
<td>200</td>
<td>0.13</td>
<td>3.46</td>
<td>75.95</td>
<td>3819.14</td>
</tr>
<tr>
<td></td>
<td>40</td>
<td>225</td>
<td>0.08</td>
<td>2.18</td>
<td>3.19</td>
<td>2752.85</td>
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<tr>
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<td>3459.43</td>
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<td>4.30</td>
<td>4.12</td>
<td>2476.49</td>
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<td>3.19</td>
<td>2752.85</td>
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<td>3.74</td>
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<tr>
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<td>225</td>
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</tr>
<tr>
<td></td>
<td>40</td>
<td>0.32</td>
<td>6.85</td>
<td>101.19</td>
<td>3333.63</td>
<td></td>
</tr>
<tr>
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<td>225</td>
<td>0.17</td>
<td>4.54</td>
<td>7.21</td>
<td>2420.27</td>
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</tr>
</tbody>
</table>
Table 9: Effect of different trigger points for DP-B on the performance measures

<table>
<thead>
<tr>
<th>Trigger Point</th>
<th>ED Beds</th>
<th>IP Beds</th>
<th>ED Wait (hr)</th>
<th>ED board (hr)</th>
<th>Diversion (hr)</th>
<th>Annual Readmissions</th>
</tr>
</thead>
<tbody>
<tr>
<td>25%</td>
<td>30</td>
<td>200</td>
<td>0.01</td>
<td>1.07</td>
<td>38.64</td>
<td>4480.63</td>
</tr>
<tr>
<td></td>
<td>225</td>
<td></td>
<td>0.0002</td>
<td>0.19</td>
<td>0.38</td>
<td>3468.04</td>
</tr>
<tr>
<td></td>
<td>200</td>
<td></td>
<td>0.004</td>
<td>1.48</td>
<td>10.16</td>
<td>4450.35</td>
</tr>
<tr>
<td></td>
<td>225</td>
<td></td>
<td>0.00</td>
<td>0.28</td>
<td>0.00</td>
<td>3370.14</td>
</tr>
<tr>
<td>33%</td>
<td>30</td>
<td>200</td>
<td>0.01</td>
<td>1.13</td>
<td>39.48</td>
<td>4399.50</td>
</tr>
<tr>
<td></td>
<td>225</td>
<td></td>
<td>0.0002</td>
<td>0.27</td>
<td>0.35</td>
<td>3358.74</td>
</tr>
<tr>
<td></td>
<td>200</td>
<td></td>
<td>0.004</td>
<td>1.64</td>
<td>11.18</td>
<td>4331.67</td>
</tr>
<tr>
<td></td>
<td>225</td>
<td></td>
<td>0.00</td>
<td>0.50</td>
<td>0.02</td>
<td>3221.52</td>
</tr>
<tr>
<td>40%</td>
<td>30</td>
<td>200</td>
<td>0.01</td>
<td>1.23</td>
<td>40.27</td>
<td>4345.16</td>
</tr>
<tr>
<td></td>
<td>225</td>
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<td>0.0003</td>
<td>0.38</td>
<td>0.53</td>
<td>3283.28</td>
</tr>
<tr>
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<td>200</td>
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<td>0.004</td>
<td>1.74</td>
<td>9.94</td>
<td>4250.14</td>
</tr>
<tr>
<td></td>
<td>225</td>
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<td>0.00</td>
<td>0.64</td>
<td>0.01</td>
<td>3142.62</td>
</tr>
</tbody>
</table>

It can be seen from the tables that the dynamic policies DP-W and DP-B reduce the amount of time patients spend waiting for an ED bed and ED boarding as well as ambulance diversion considerably compared to the BL policy. This is because these two policies proactively discharge patients from the IU when the ED begins to crowd. However, the number of readmissions increases with these dynamic policies since patients are discharged sooner rather than later when the ED is in a crowded state. This can be seen clearly in Figure 10, which displays the average values across all runs for each policy.
Figure 10: Comparison of average values of performance measures for BL, DP-W, and DP-B policies with ED and IP staffed beds of 30 and 225, respectively.

ED waiting and boarding times are compared in Figure 11, where the four capacity instances are clustered for each of the three policies (static and two dynamic). Clearly, both ED waiting and boarding times are substantially high in the static case (the cluster with high values for both), while they are low for DP-W and nearly zero for DP-B policies (the two small clusters close to zero).

Figure 12 shows how the diversion hours and readmission numbers varied for the same four capacity scenarios. The diversion hours were observed to be close to 0 in both the dynamic policies compared to the static policy. This is evident because, as the name suggests, the dynamic policies are triggered when the ED begins to crowd. The negative consequence is that the readmission numbers are relatively high for both these policies.
So there is clearly a tradeoff between these two measures, unlike the clear benefits on the ED wait and board times.

Figure 11: Comparison of ED measures with static and dynamic policies

Figure 12: Comparison of diversion hours and readmission numbers for static and dynamic policies
Additionally, it was observed that adding beds to the IU compared to the ED might have a pronounced effect on the performance measures. More ED beds means that more arriving patients can be handled by the ED. However, if the number of IU beds is unchanged, then there is still a limited flow of patients between ED and IU, resulting in higher waiting and boarding times in the ED.

4.2.3 Sensitivity Analysis

In addition to the sensitivity analysis performed on the resource capacity, a sensitivity analysis was performed on the arrival pattern of patients to the ED. These results can be seen in Tables 10, 11, and 12 for the BL, DP-W, and DP-B policies respectively.

Table 10: Effect of different arrival volumes for the Baseline Policy on the performance measures

<table>
<thead>
<tr>
<th>Scale</th>
<th>ED Wait (hr)</th>
<th>ED board (hr)</th>
<th>Diversion (hr)</th>
<th>Annual Readmissions</th>
<th>LWOT (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.8</td>
<td>0</td>
<td>0.04</td>
<td>0.01</td>
<td>1420.38</td>
<td>0</td>
</tr>
<tr>
<td>0.9</td>
<td>0.15</td>
<td>1.80</td>
<td>15.82</td>
<td>1597.91</td>
<td>0.12</td>
</tr>
<tr>
<td>1</td>
<td>1.16</td>
<td>6.28</td>
<td>228.61</td>
<td>1691.60</td>
<td>1.00</td>
</tr>
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<td>1.1</td>
<td>2.34</td>
<td>8.87</td>
<td>697.01</td>
<td>1712.64</td>
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</tr>
<tr>
<td>1.2</td>
<td>3.07</td>
<td>9.66</td>
<td>1175.28</td>
<td>1714.96</td>
<td>5.31</td>
</tr>
</tbody>
</table>

It can be seen from these tables that the dynamic discharge policies have a much greater impact when the volume of arrivals increases.
Table 11: Effect of different arrival volumes for DP-W on the performance measures

<table>
<thead>
<tr>
<th>Trigger Point</th>
<th>Scale</th>
<th>ED wait (hrs.)</th>
<th>ED board (hrs.)</th>
<th>Diversion (hrs.)</th>
<th>Annual Readmissions</th>
<th>LWOT (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25%</td>
<td>0.8</td>
<td>0</td>
<td>0.02</td>
<td>0</td>
<td>1367.69</td>
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</tr>
<tr>
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<td>0.9</td>
<td>0.01</td>
<td>0.78</td>
<td>0.04</td>
<td>1663.15</td>
<td>0</td>
</tr>
<tr>
<td></td>
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<td>0.05</td>
<td>1.92</td>
<td>1.93</td>
<td>2788.16</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>1.1</td>
<td>0.07</td>
<td>2.34</td>
<td>38.32</td>
<td>4204.91</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>1.2</td>
<td>0.05</td>
<td>2.72</td>
<td>210.93</td>
<td>5144.76</td>
<td>0.21</td>
</tr>
<tr>
<td>33%</td>
<td>0.8</td>
<td>0</td>
<td>0.02</td>
<td>0</td>
<td>1356.31</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>0.9</td>
<td>0.01</td>
<td>0.85</td>
<td>0.04</td>
<td>1639.92</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0.08</td>
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<td>3.19</td>
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</tr>
<tr>
<td></td>
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<td>0.11</td>
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</tr>
<tr>
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<td>2.91</td>
<td>220.15</td>
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</tr>
<tr>
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<tr>
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<td>3.11</td>
<td>244.67</td>
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</table>

Table 12: Effect of different arrival volumes for DP-B on the performance measures

<table>
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<th>Trigger Point</th>
<th>Scale</th>
<th>ED wait (hrs.)</th>
<th>ED board (hrs.)</th>
<th>Diversion (hrs.)</th>
<th>Annual Readmissions</th>
<th>LWOT (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25%</td>
<td>0.8</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1382.18</td>
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</tr>
<tr>
<td></td>
<td>1</td>
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</tr>
<tr>
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<td>0.70</td>
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</tr>
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</tr>
<tr>
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</tr>
<tr>
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</table>
5 CONCLUSIONS AND FUTURE RESEARCH

The impact of various discharge policies, both static and dynamic, on various ED performance measures, such as time patients spend waiting and boarding in the ED, ambulance diversion hours, and readmission within 30-days of discharge, at an acute care hospital were analyzed. A discrete-event simulation model of a generic acute care hospital was developed. Using this model, the complex interdependencies between the operations of an ED and IUs were captured.

The simulation model helped in analyzing the benefits and limitations of two novel dynamic discharge timing policies compared to the typically employed static discharge policy. The results showed a tradeoff between reducing ED measures and the number of 30-day readmissions. The DP-W policy gave a reasonable compromise between low ED waiting and boarding times and low hours spent on ambulance diversion compared to the static policy, while having low readmission numbers compared to DP-B policy.

The implementation of the Affordable Care Act in 2013, which will penalize hospitals for high readmission rates for certain medical conditions, has placed a considerable burden on care providers to reduce readmission rates. Note that readmission may occur due to either or both clinical and non-clinical factors. The latter includes ineffective follow-up, patient compliance to medication, social support, etc., and is very
difficult to model. However, several processes have been proposed and implemented at various hospitals to control readmissions. Jack et al. (2009) showed that individualizing the discharge process and arranging follow-up appointments reduced hospital utilization within 30-days of discharged patients. Additionally, Hernandez et al. (2010) showed through an observational analysis that follow-ups within 7 days of hospital discharge for patients hospitalized with heart failure reduced the likelihood of readmission within 30-days of hospitalization for patients over the age of 65. If readmissions can be controlled using these methods, then either one of the two dynamic policies would become very attractive, especially the DP-B policy.

For this work, data for other patient pathways, such as elective or surgical admissions, was very difficult to obtain. Elective patient schedules, especially in the operating rooms, may affect ED boarding (Wong et al., 2009). In the future, when data does become available, the model can be expanded to capture these patient pathways.

Our work modeled medical conditions based on patient discharge diagnoses. However, a patient may receive various diagnoses throughout treatment at an ACH. First, he/she is assigned an ESI level based on his/her symptoms upon entering the ED. Once a patient is admitted, he/she is assigned an admission diagnosis. Upon discharge, a patient is assigned a primary discharge diagnosis based on the actual underlying medical condition during hospital stay and the subsequent treatment that they received. These diagnosis decisions that occur at different times during treatment may be similar or different. It may be worth exploring the relationships between these diagnosis stages in the future.
Additionally, only one ambulance diversion policy was modeled (50%, 1 hr). It would be interesting to see how the results are affected, for other possible policies proposed in Ramirez (2009). Finally, we have observed that many ACHs, when the occupancy levels are high, add capacity to their subsystems, ED and IP units, by doubling the occupancy in rooms, putting beds in the lobby, or opening specially staffed units. In so doing, the effects of ED crowding may be mitigated. We have not modeled such scenarios in this study; however it is not difficult to include such scenarios in our simulation model for a more comprehensive analysis.

This study was both exploratory and confirmatory. Through a generic model of an acute care hospital, two novel dynamic discharge-timing policies were compared with a static policy. Results showed that both these policies have substantial merit. Previous findings that the inpatient occupancy level has a direct impact on ED crowding were confirmed. The results also suggested that dynamically varying the inpatient occupancy level via appropriately timed discharges could reduce ED crowding. The tradeoff between ED measures and readmissions needs further investigation, especially if optimal policies are to be derived. The inclusion of other patient pathways and capacity planning are worth future investigation as to capture additional aspects of the complex ACH system.
6 REFERENCES


