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Prioritizing Patients for Emergency Evacuation From a Healthcare Facility

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Prioritizing Patients for Emergency Evacuation From a Healthcare Facility

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Abstract

The success of a healthcare facility evacuation depends on communication and decision-making at all levels of the organization, from the coordinators at incident command to the clinical staff who actually carry out the evacuation. One key decision is the order in which each patient is chosen for evacuation. While the typical planning assumption is that all patients are to be evacuated, there may not always be adequate time or resources available to move all patients. In these cases, prioritizing or ordering patients for evacuation becomes an extremely difficult decision to make. These decisions should be based on the current state of the facility, but without knowledge of the current patient roster or available resources, these decisions may not be as beneficial as possible.

Healthcare facilities usually consider evacuation a last-resort measure, and there are often system redundancies in place to protect against having to completely evacuate all patients from a facility. Perhaps this is why there is not a great deal of research dedicated to improving patient transfers. In addition, the question of patient prioritization is a highly ethical one.

Based on a literature review of 1) suggested patient prioritization strategies for evacuation planning as well as 2) the actual priorities given in actual facility evacuations indicates there is a lack of consensus as to whether critical or non-critical care patients should be moved away from a facility first in the event of a complete emergency evacuation. In addition, these policies are "all-or-nothing" policies, implying that once a patient group is given priority, this entire group will be completely evacuated before any patients from the other group are transferred. That is, if critical care patients are given priority, all critical care patients will be transferred away from the facility before any

non-critical care patient.

The goal of this research is to develop a decision framework for prioritizing patient evacuations, where unique classifications of patient health, rates of evacuation, and survivability all impact the choice. First, I provide several scenarios (both in terms of physical processing estimates as well as competing, ethically-motivated objectives) and offer insights and observations into the creation of a prioritization policy via dynamic programming. Dynamic programming is a problem-solving technique to recursively optimize a series of decisions. The results of the dynamic programming provide optimal prioritization policies, and these are tested with simulation analysis to observe system performance under many of the same scenarios. Because the dynamic programming decisions are based on the state of the system, simulation also allows the testing of time-based decisions. The results from the dynamic programming and simulation, as well as the structural properties of the simulation are used to create assumptions about how evacuations could be improved.

The question is not whether patient priorities should be assigned - but how patient priorities should be assigned. Associated with assigning value to patients are a variety of ethical dilemmas. In this research, I attempt to address patient prioritization from an ethical perspective by discussing the basic principles and the potential dilemmas associated with such decisions.

The results indicate that an all-or-nothing, or a "greedy" policy as discussed in the literature may not always be optimal for patient evacuations. In some cases, a switching policy may occur. Switching policies begin by evacuating patients from one classification and then switch to begin evacuations from the second patient class. A switch can only be made once; after a switch is made, all remaining patients from the new group should be evacuated. When there are no more patients of that group remaining in the system, the remaining patients from the class that was initially given priority should be evacuated. In the case of critical and non-critical care patients, switching policies first give priority to non-critical care patients. When the costs of holding patients in the system are not included in the models — and the decisions are just based on maximizing the number of saved lives — the switching policies may perform as good or better than the greedy policies suggested in the literature. In addition, when holding costs are not included, it is easier to predict whether the optimal policy is a greedy policy or a switching policy.

Prioritization policies can change based on the utility achieved from evacuating individual patients from each class, as well as for other competing objective functions. This research examines a variety of scenarios — maximizing saved lives, minimizing costs, etc. — and provides insights on how the selection of an objective impacts the choice. Another insight of this research is how multiple evacuation teams should be allocated to patients. In the event that there is more than one evacuation team dedicated to moving a group of patients, the two teams should be allocated to the same patient group instead of being split between the multiple patient groups.

Dedication

This dissertation is dedicated to my mom, who when I was 16 years old, told me that women with multiple earrings could not be successful and to my sister who did not believe her but instead supported me.

In addition, it is my opinion — after years of research aimed at improving evacuations — that my Aunt Louise should be given priority if her healthcare facility is ever forced to evacuate.

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Chapter 1

Introduction

1.1 Background

Over the past few years, there has been an increase in research and literature related to emergency preparedness and response. Most of this research relates to the preparation for, or response to, mass casualty emergencies. In these events, a healthcare facility is expected to be a resource to the affected population, and the facility must make decisions associated with sudden, increased demands. There are a number of papers that focus on creating and maintaining "surge capacity" in hospitals or rationing scarce resources — including patient beds, operating rooms, ventilators, etc. — after a mass casualty event (see Chapter 2, Section 2.5). There is not a good deal of research, however, that considers decision making in healthcare when the *facility* itself is a victim of an emergency ([19], [108], [143]). Some emergency types may affect a healthcare facility's ability to function and may therefore force the need for a complete evacuation. Healthcare facility evacuations present a number of challenges for patients as well as clinical staff and administrators.

A healthcare facility may be the victim of an emergency if 1) its resources are overwhelmed with sudden and unexpected demands or 2) the emergency causes - or presents potential for - damage to the facility. Terrorist attacks, pandemic outbreaks, or some other type of *external emergency* may cause this first scenario. In these types of emergency situations, a hospital is expected to be a resource for response efforts. A fire, flood, bomb threat, or other *internal emergency*, may cause the second scenario. Hurricanes or other natural disasters may cause both. In order to meet the demands of new patients, or to continue to care for their existing patients, a healthcare facility may have to evacuate some or all of its occupants. Depending on the type of facility, less critical patients can be discharged early to decrease the number of patients that require coordinated evacuation efforts, but those that need continued care will have to be transferred to another facility. Every healthcare facility is required to have an evacuation plan in place ([13], [143], [156]), and although considered a last resort, it is almost certain that every healthcare facility has the potential for some sort of emergency that would require patient transfers. Based on their location, certain facilities will have varying levels of risk. For example, facilities on the East Coast are more likely to have to evacuate patients due to hurricanes. In addition, these types of emergencies are forecasted, and the facility may be able to make evacuation decisions in advance of the event and even execute a "preemptive" evacuation.

Evacuation is considered a last-resort measure by many healthcare facility operators, especially due to the cost and advanced care often required by the patients. Some will even go as far as saying "we will not evacuate" [64]. The facility would prefer not to shut down, and they often have system redundancies in place to protect against catastrophic failures. Perhaps this is why there is not a great deal of research aimed at improving policies and methods for healthcare facility evacuations. Experiences during recent hurricanes, however, identified many healthcare facilities having to perform last-minute, pre-storm evacuations, as well as some post-storm evacuations.

Healthcare facilities usually implement one of the following generalized coordination structures to address decision making: the Hospital Incident Command System (HICS) [7] or the National Incident Management System (NIMS) [8]. Both of these emergency management systems utilize a central Incident Command System (ICS) and can actually be used in conjunction with each other. The ICS is an all-hazard incident management system that defines the components and characteristics of the management structure during the entire incident.

It is difficult to create a complete and comprehensive evacuation plan that includes all emergency types and response options [151]. Therefore, healthcare facility evacuation plans tend to be high-level, generic documents. Some researchers suggest that evacuation plans are written just to satisfy the requirements of accrediting agencies and are rarely practiced ([108], [152]). Decision-making guidelines are usually nondescriptive, especially concerning the order in which patients will be selected for transfer. However, an evacuation plan that addresses the patient roster, staffing requirements, supplies, and equipment must be laid out in great detail in order for an evacuation to be implemented effectively [156].

1.2 Objectives of Research

The typical planning assumption of a complete, emergency evacuation is that all patients will be transferred away from the facility, so most evacuation plans do not discuss which patients to evacuate if there is inadequate time available to transfer all patients. Moreover, there is no documentation about which patient types should be transported first or if transporting a certain patient type actually adds more risk than sheltering that patient in place. When there are limited time and resources, a plan that includes a patient prioritization scheme could provide healthcare providers guidance in setting patient priorities for evacuation. To further support this, it has been noted that unclear lines of authority have contributed to a large number of response failures [45]. By specifying an authority structure clearly and providing decision-makers with the best information about patient priorities, the clinical staff may have an increased ability to respond to the right patients at the right time.

In addressing the issues outlined above, the following questions come to mind:

- What are the current policies for patient selection decisions during evacuations?
- If there are limited resources and time, which patients should be evacuated first?

- When is a greedy, all-or-nothing policy optimal?
- Can patients be classified based on certain characteristics?
- What are the underlying objectives of evacuation decisions?
- Can we provide patient priority guidelines based on the risks and rewards?
- What are the ethical implications of various evacuation policies?
- Can patient priority guidelines be included in evacuation plans?

This research proposes a two-phase modeling approach to determine the order in which patients should be chosen for evacuation. Unique classifications of patient health, rates of evacuation, and survivability all impact the choice. First, I consider several scenarios (both in terms of physical processing estimates as well as competing, ethically-motivated objectives) and offer insights and observations into the creation of a prioritization policy. Dynamic programming is used to model the system, run a variety of tests to observe the optimal policy, and observe properties of the optimal solutions. The results of the numeric tests from the dynamic program are used in simulation analysis to observe system performance under many of the same scenarios. In addition, I use simulation analysis for tests that complicate the dynamic program. These two tools can be used together to analyze an evacuation for any facility: 1) the dynamic program is used to develop a decision framework for prioritizing patient evacuations and determine properties of the optimal solutions, and 2) the simulation model measures the performance of the optimal evacuation policy or extends the modeling capabilities.

During an emergency, the ethical perspective is utilitarian: do the most good for the most amount of people (beneficence). Should this be interpreted as "get the most out"? Is there a better objective to incorporate fairness, a second principle of ethical healthcare? The prioritization policies that will be discussed in this research can be categorized in two ways: greedy and switching. A greedy policy chooses to evacuate one patient group entirely before starting to evacuate any other patient groups, and a switching policy begins evacuating a patient class and then switches to another based on the number of each type remaining in the system. As shown in Chapters 5, 6, and 7, the policies change with the choices for model inputs.

Is it ethical to enact a policy that requires all of a certain patient group to be evacuated before beginning to evacuate any other patient groups? For obvious reasons, and reasons that will be discussed in Chapter 3, it would be unlikely that a clinical staff would be comfortable with this decision, especially when their patients are not categorized as the first to be evacuated. Manipulating values, such as holding costs or rewards, encourages changes to the policies, such that other patient groups get attention more quickly, but is this ethical?

Finally, this research considers how the utilitarian views of evacuation conflict with the ethics of virtue that tend to guide healthcare practitioners. How will conflicting ethical perspectives of a clinical staff, whose work is based more on morals than consequences, affect an evacuation based on utility? These issues will be discussed in Chapter 3. How value is placed and modeled on transferring patients, patient deaths, and keeping patients in the system will also be examined and used in Chapter 5.

1.3 Outline

The dissertation is structured in the following manner. Chapter 2 introduces the relevant literature including lessons learned from previous evacuations, research directly related to healthcare facility evacuation, other emergency preparedness literature, and modeling. Chapter 3 includes a detailed discussion of the ethical dilemmas and perspectives related to this problem. In order to gain a baseline understanding of local evacuation plans, a survey was distributed to healthcare facilities across South Carolina. Chapter 4 discusses the survey results. In Chapter 5, the model assumptions and parameters are introduced, and a single-server model is introduced and tested with dynamic programming and simulation analysis. In Chapter 6, the dynamic programming optimality equation for the single server model is further examined including a sensitivity analysis and a discussion of the properties of the optimal solutions and implications for practitioners. Chapter 7 presents an overview of model extensions, and Chapter 8 contains conclusions and recommendations for future work.

1.4 Scope of Research

Healthcare facilities, like police stations, airports, and schools, are classified as *essential facilities* because they are facilities that the community depends on for support and/or resources. During an emergency event, the population looks to essential facilities, such as a hospital or even a nursing home, to provide medical care, and in some cases, even the most basic resources such as food, water, and shelter. In addition, the dependence of a healthcare facility's occupants on its staff leads to a second classification as a *vulnerable facility*. Falling into either of these categories - an essential facility or a vulnerable facility - requires specific considerations for evacuation decisions [152]. Since a healthcare facility falls into both, evacuation plans should include guidelines for how to handle both internal and external emergencies. If patient evacuations are forced by an external emergency, the facility may be faced with sudden, increased demands. If an evacuation is underway, it has already been determined that the facility cannot function fully or safely, and special considerations need to be given as to how to handle incoming patients. This research focuses on prioritizing the vulnerable or dependent population of a healthcare facility and does not consider the effects of the classification of an essential facility.

Every facility may be faced with an emergency situation that would require an evacuation. No-notice emergencies (such as fires) leave little to no time for decision making. Other emergencies may threaten in advance or cause damages afterwards, such as a hurricane. Depending on the location of the facility, external events such as hurricanes or floods give an advanced notice that an evacuation may be necessary. Manmade emergencies or the aftereffects of disasters (i.e. loss of power, water, or oxygen) could require an evacuation after an emergency. In either of these cases, the administrative and clinical staff would very likely have some sort of decision window to prepare for patient transfers. In such cases, an Incident Command Center may be established. Fires or other emergencies that cause immediate damage to the facility and danger to the patients require an immediate response. In these cases, the staff must act instantaneously, and there will be no time for Incident Command to delegate the staff's assignments. This research pertains to evacuations with short- or long-term notice though insights from the results may be beneficial when planning for evacuations due to fires and other no-notice emergencies. In addition, having knowledge of the guidelines will likely help the clinical staff know how to respond in real-time when there is no time for direction from management.

As previously mentioned, certain emergencies may only require a healthcare facility to evacuate some of its patients. These partial evacuations can occur when some type of external emergency has increased demands by causing a patient surge. Some patients may need to be transferred to other facilities so that there are enough beds available to accommodate these incoming patients. Other emergencies may require a small area of the facility to temporarily evacuate some of its patients to directly outside of the facility, but these patients can usually return to their beds or some other area within a reasonable amount of time.

In the case of a forecasted emergency, the staff would likely discharge as many patients as possible to decrease the number of patients for which the healthcare facility would be responsible for transport. For the remainder of the discussions, we assume that the patient population has already been reduced by early discharges and that all patients remaining in the facility will have to be transported. This research focuses on an emergency that would require a full evacuation where *all* patients in the facility are at risk due to some type of internal or external emergency; sheltering-in-place is not an option. The additional assumption is that there are not enough resources available to transport all patients away from the facility before the emergency occurs or some critical time window ends.

1.5 Need, Significance, and Potential for Research

There are a variety of papers that clearly indicate that methods for ethically prioritizing patients for evacuation would be a beneficial contribution.

- "The whole topic of the evacuation of institutionalized populations badly needs research for it seems to require inordinate attention and resources, and generates many problems when such withdrawal movements are required" *Hans and Sell, 1974 in* Evacuation Risks: A Tentative Approach for Quantification [68].

- "Because of the large number of health care facilities in the United States, their placement and geographical presence in the population, their centrality in developing an adequate community response to a disaster, and the huge level of risk to patients associated with evacuation, it is important for health care executives to make sound decisions concerning the process of facility evacuation... Most research has focused on disaster events or facility planning for disaster types and not the decision processes required for a specific response or outcome in disasters" *Kathlyn McGlown, in her 1999 dissertation* Determinants of the Evacuation of Health Care Facilities [108].

- "Explicit guidelines for decision making on residents' evacuation must be developed" *Insights from the "Hurricane Summit," funded by the John. A Hartford Foundation in 2006* [78].

- "Familiarity with and utilization of a framework for ethical decision-making may facilitate health care professionals in maneuvering through disaster-instigated ethical dilemmas" *"Disaster Ethics, Healthcare and Nursing: A Model Case Study to Facilitate the Decision Making Process" in the* Online Journal of Health Ethics [129].

- "The goals of triage in different environments and contexts can lead to divergent perspectives of what constitutes ethically sound decision making," and "a system that allows real-time classification of risks and benefits...would be a great advantage in ethical decision making" *in "Lifeboat Ethics: Considerations in the Discharge of Inpatients for the Creation of Hospital Surge Capacity"* [93].

- "Advance agreement is needed among key parties about which patients will be evacuated first. Several disputes developed over priorities in the days after Katrina. There was disagreement, for example, over whether the sickest patients or those more likely to survive should be evacuated first" *in "Hospitals in Hurricane Katrina: Challenges Facing Custodial Institutions in a Disaster"* [63].

- "Medical and social needs must be considered in trigging evacuees. The traditional medical model for triage in the U.S. is to treat the most critically injured first; in an overwhelming disaster situations, health care providers may shift to battlefield triage practices in which those with the highest probability of survival are treated first. Little is known about lay clinicians' abilities to shift paradigms during response" *from the AHRQ's "Recommendations for a National Mass Patient Evacuee Movement, Regulating, and Tracking System"* [51].

- "The ethical decisions inherent in triage decisions should not be first considered during a real event. Rather, they should be rehearsed and discussed long before they are needed" *from "Terrorism and the Ethics of Emergency Medical Care" in the* Annals of Emergency Medicine [126].

The goal of this research is to address these issues by developing patient prioritization guidelines to improve decision-making during an emergency evacuation from a healthcare facility. By modeling the system and decisions mathematically - and by considering the ethical dilemmas associated with these types of decisions - some of the decision responsibility can be taken out of the clinical staff's hands. This will allow them to focus on their primary task of safely performing patient transfers. This research will promote a safe and effective means for continuing patient care during a disaster and thereby improve the standards for the quality of care during an emergency.

There are two obvious benefits to this research: first, the insights from this research can help emergency planners evaluate and determine guidelines and policies for evacuations. Such guidelines are based on mathematical modeling and will be suggested in this research. These can be included within emergency plans and practiced by the staff. Second, the insights from the guidelines and policies can be used to assist a clinician when faced with real-time decision making dilemmas during situations that have not been planned.

Finally, it should be noted that this research is not intended to direct clinicians from a medical perspective. Real-time decision making obviously requires unique, medical information for each patient. This research assumes, however, that the outcomes of such decisions can be improved by supplementing medical expertise with the insights from the models.

Chapter 2

Review of the Literature

This chapter will discuss the relevant literature from a variety of disciplines including healthcare, engineering, and ethics. The purpose is to review similar work and research efforts as well as to develop a base understanding of healthcare evacuation decision making. In addition, this literature review sets the stage for the modeling efforts being introduced and explored in the subsequent chapters.

This chapter begins by reviewing papers that discuss actual healthcare facility evacuations (Section 2.1) and the lessons learned. Section 2.2 discusses the patient prioritization strategies for evacuation based on a review of actual patient transfers or suggested protocol.

The next section, Section 2.3, discusses a higher-level stream of research dedicated to how the general population responds to evacuations. This includes how decisions are made about whether to evacuate, when to evacuate, and how to evacuate (selection of routes).

Section 2.4 outlines the research that directly relates to improving healthcare facility evacuations. Most of the healthcare emergency preparedness literature focuses on the healthcare facility's role during an emergency - instead of directly discussing evacuations only - so this much larger stream of research - including surge capacity, triage, and altered standards of care - is explored in Section 2.5.

Section 2.6 focuses on modeling techniques for allocating resources to time-sensitive tasks. The focus is on two papers, Glazebrook et al. and Argon et al. that are directly related to this research. In addition, examples of the use of dynamic programming and simulation for healthcare policies or improvement are outlined. The modeling parameters that will be considered in future chapters are discussed in Section 2.7.

Section 2.9 presents literature related to the ethical considerations in this problem. A more detailed discussion of ethics, however, is presented in Chapter 3.

2.1 Healthcare Facility Evacuations and Lessons Learned

The following section details the lessons learned during actual healthcare facility evacuations. Each subsection outlines the lessons learned and needs for improvement for pre-disaster planning, decision making, patient care and transportation, staffing, record-keeping, and communication as identified in the papers. The following papers describe emergency events and are were used to summarize the lessons lessons learned in Sections 2.1.1 - 2.1.6.

- Sternberg et al. [152] investigated databases to make assumptions about the types of hazards that resulted in 275 hospital evacuations in the United States between 1971 and 1999. Over half of these healthcare facility evacuations could be primarily attributed to internal emergencies such as a fire or potential exposure to hazardous materials.

- Schultz et al. [143] created and issued a questionnaire to personnel at area hospitals that were on duty during the Northridge, California earthquake. The earthquake resulted in eight hospital evacuations: six were evacuated with 24 hours of the earthquake, one evacuated 3 days after the earthquake, and one evacuated 2 weeks after the earthquake. For the six hospitals that evacuated soon after the earthquake, the decision to evacuate was based on non-structural damage. The other two hospitals had to evacuate patients because of non-repairable structural damage.

- Cocanour et al. [31] described the "Lessons Learned From the Evacuation of an Urban Teaching Hospital" after Hurricane Allison caused flooding and forced the full evacuation of Memorial Hermann Hospital and Memorial Hermann Children's Hospital. The facilities were able to discharge 169 patients but still had to evacuate 406 patients. These patients were transferred to 29 other facilities within approximately 30 hours.

- Bowers et al. [19] described the lessons learned from the perspective of Texas Medical Center's entire hospital system after Hurricane Allison.

- Hyer et al. [77] documented the experiences of almost 300 nursing homes during the 2004 Hurricane Season. Approximately 16% of facilities had to evacuate at least once.

- Augustine and Schoettmer [11] described a complete evacuation forced by a bomb threat. The staff of Galion Community Hospital in Columbus, Ohio evacuated all 46 of its patients to a single, similar-sized facility located 20 miles from their hospital.

- Bovender and Carey [18] summarized the experiences and lessons learned from the evacuation of Tulane Hospital after Hurricane Katrina. When the decision to evacuate was made, there were approximately 1,300 people at Tulane Hospital. Only 121 were patients; the rest were staff members, medical students and faculty, family members of patients and staff, and "medically fragile" patients sent from the Superdome. There were also 71 pets.

- Lach et al. [95] reviewed the basic considerations for evacuating older patients based on evacuations during Hurricanes Katrina and Rita.

- Gray and Hebert [63] conducted interviews with hospital executives, public officials, and others in New Orleans-area hospitals to summarize the effects of evacuations conducted before and after Hurricane Katrina.

- Castro et al. [25] distributed surveys to assess the response of long-term care facilities during Hurricanes Katrina and Rita.

- Dosa et al. [36] interviewed twenty nursing home administrative directors about the evacuation decisions made during Hurricanes Katrina and Rita.

- Laditka et al. [96] described the care of nursing home evacuees after transport based on interviews with staff members in receiving facilities after Hurricane Katrina.

- Hyer et al. [78] described need for improvements as identified at the John A. Hartford Foundation's "Hurricane Summit" in 2006. This report pertains to the preparation for and response to emergencies at long-term acute care facilities.

- The U.S. Government Accountability Office's "Limitations in Federal Evacuation Assistance for Health Care Facilities Should be Addressed" [1] discussed the federal government's involvement in hospitals' and nursing homes' preparation for evacuation.

- A report from the Office of Inspector General evaluated "Nursing Home Emergency Preparedness and Response During Recent Hurricanes" [2] by analyzing survey and interview responses as well as emergency plans.

- Lewis [98] described the evacuation response and lessons learned after a tornado damaged a facility in Americus, Georgia in 2007. Before the tornado, all patients were moved to interior hallways. Fifty-three patients were evacuated to local hospitals in approximately 3 hours.

- Barnett et al. [13] described two healthcare facility evacuations in Southern California to avoid damage from the wildfires in 2008. A hospital and a skilled nursing facility evacuated 77 inpatients and 122 skilled nursing facility patients to 7 hospitals and 13 long-term care facilities within 7 hours.

2.1.1 Pre-disaster Planning

This section discusses issues identified during evacuations that can be categorized as pre-disaster planning. Many of the lessons learned in the papers listed above relate to areas that should have been (or were successfully) discussed and implemented well in advance of any of the disasters described above.

Some of the lessons learned pertain to architectural or design concerns and should therefore be considered when developing a new or renovating an existing facility. For example, services that are critical to continued patient care - pharmacy, nursing units, etc. - should not be placed in areas that may be affected by flooding ([31], [63]). When these essential services are unnecessarily damaged, an evacuation that might otherwise be avoidable may be required. During Hurricane Katrina, generators were damaged, and facilities were forced to evacuate. Gray and Herbert [63] suggested that, had they been placed in areas that were not subject to flooding, some of the post-storm conditions may not have been as dangerous at multiple facilities. Even when generators are used as a means of backup power, it is important for the staff to consider that power outages may not necessarily be temporary [31], and generators are not likely to support the requirements for a facility to operate ([63], [78]), and evacuations may be necessary.

As mentioned before, every facility is required to have an evacuation plan in place. These should be reviewed and updated on a regular basis [11]. Most hospital evacuations are caused by internal emergencies such as fires, utility failures, or exposure to hazardous materials, but hospitals should plan for multiple hazard types [152]. To be effective, receiving facilities - the facilities to which the patients will be transferred - should be identified prior to an emergency event ([63], [77], [78]). Planners must also consider that certain types of emergencies may affect multiple local hospitals ([11], [18], [152]). Therefore, local facilities should be identified to receive patients from facilities that are affected by an internal emergency, and non-regional facilities should be identified for external emergencies that may affect an entire community. In these cases, patients may have to travel longer distances to be relocated to safety. These types of regional emergencies may also cause demands at a hospital to increase. In addition, community-wide disasters will place increased demands on transportation resources ([1], [78]). During external emergencies, other local facilities may have to shut down, so plans must include guidelines for how to handle new, incoming patients ([1], [63]). Since a hospital is considered a resource in an emergency, plans should also include how to handle the non-patient population that arrives seeking basic needs such as food, water, or shelter ([18],

[63]).

Good relationships with community organizations - churches, nursing homes, or school systems - may provide an additional opportunity for resources [11] whether it be supplies, water, or transportation resources. Additional resources such as staff, transportation, and supplies should be identified prior to a disaster for use after an event [95].

Evacuation plans should include backup policies and devices to handle power losess ([18], [31], [78]). This includes generators as previously discussed and also batteries for flashlights, alternate methods for recording patient information, and alternatives for equipment such as ventilators and medication storage systems. In addition, backup plans for communication ([18], [31], [98]) and patient care ([13], [31], [63], [143]) are essential. In the more recent papers, some of the authors suggested that patients, staff, and equipment may need protection during or after the evacuation ([18], [63], [98]).

Facilities that may be at a higher risk for evacuation may benefit from planning at a much lower level. Creating unit-specific "evacuation packs" that include patient worksheets, important contact information, and the supplies necessary to take care of the patients will help save critical time when evacuation orders are given [11]. Medications, food, and other supplies should be prepared in advanced and made easily portable [95]. Whether this level of planning is appropriate for a facility depends on the how the management views the risks and benefits, which will be further discussed in the next section.

Finally, the majority of nursing homes surveyed after Hurricanes Katrina and Rita indicated that nursing home facilities need more considerations for preparations or response in public health emergencies planning ([25], [36], [78], and [96]).

2.1.2 Decision Making

Whether planning for a potential disaster or facing an actual emergency, decision-makers must balance the uncertainty, risks, costs, and the narrowing window for evacuations [63]. This includes deciding whether to evacuate in advance when an emergency is forecasted. If the risks of transporting patients are greater than sheltering-in-place, then it is likely that a facility will choose not to move the patients. If the nature of the emergency threatens to affect the facility's ability to provide care, the facility must decide if and when to evacuate. Obviously the probability of predicting where a hurricane will make landfall increases as the time until landfall decreases. If patients are moved too soon, the forecasted event may not affect the facility at all. "Unnecessary" evacuations put patients at otherwise avoidable risks, and they are expensive for the facility. An advanced evacuation, however, may allow the facility access to resources that may decrease in availability as the time window decreases. Making the decision not to evacuate in advance may lead to some of the well-publicized complications that are reviewed in the papers that discuss the aftermath of Hurricane Katrina ([18], [63]) though advanced evacuation still puts patients at a variety of risks. Dosa et al. [36] discussed the issues inherent in evacuating frail patients from nursing homes and how this may influence the decision to evacuate or not. As part of their call for additional research in this area, they pose a framework for assessing the risk based on three key elements - the individual patient, the facility, and the emergency event. Such an approach to quantifying risk could be used in deciding whether to evacuate or not, as well as in prioritizing patient transfers once a decision to evacuate has been made.

Once the decision has been made to evacuate patients, there are no established guidelines about how to prioritize patients for transfer. Typically, triage refers to allocating scarce medical resources to a surge of incoming patients after an emergency such as a mass casualty event. Patients are chosen for treatment by determining who will benefit the most. In the context of a healthcare facility evacuation, patients may be "triaged" to determine the best prioritization scheme. The Center for Bioterrorism Preparedness and Planning [115] suggested that the patients that require the most assistance should be transferred away from the facility first. Gray and Hebert [63] agreed with this strategy for advanced evacuations. The Association of periOperative Registered Nurses (AORN) [3] and the New York Centers for Terrorism Preparedness and Planning [131] suggested that patients should be prioritized from least to most critical. Schultz [143] suggested that the effectiveness of triage decisions depends on the situation. Triaging patients will be further discussed in Section 2.2. Regardless of the strategy chosen to move patients, a staff member with knowledge of the current patient roster is critical to patient "triage." There should be multiple staff capable of filling this role so that there is someone on site at all times [31].

2.1.3 Patient Care and Transportation

Facilities need to remember that vehicles other than ambulances can be used to move patients. If the emergency affects the availability of transportation resources or routes, other forms of alternate transportation may be required ([18], [19], [25], [31], [63], [77], [78]). Access to transportation resources has been identified as a major issue during evacuations, particulary for nursing homes [77]. Since multiple facilities may have contracts with the same transportation service providers, demands may exceed availability during community-wide emergencies.

Even though some long-term care facilities had planned arrangements for patient transfers to specific receiving facilities, so many other facilities were overwhelmed by Hurricanes Katrina and Rita. These facilities may have also been forced to evacuate or may have already reached capacity by accepting other evacuees; therefore, the intended receiving facilities were unavailable [77]. In addition, some healthcare facilities may not be prepared or willing to accept some of the more critical patients due to resource or staffing constraints. One third of the nursing homes surveyed indicated that they were unable to find a place to transfer their special needs residents, and they were required to shelter in place [77]. Transport may negatively impact a patient's health, particularly for nursing home patients ([36], [2]).

Depending on the type of emergency and the conditions at the receiving facilities, it may be easier for a facility to choose to send all of its patients to a single facility. In the case of the bomb threat as described in Augustine and Schoettmer [11], the patient population was small enough - and the capacity at a receiving facility large enough - so that all of the staff could move with their patients to continue care. This allowed for less planning and paperwork. When it is not possible to redistribute the staff for uninterrupted care, sending patients to multiple facilities helps to avoid overwhelming a single facility [31]. If a receiving facility cannot immediately accept patients, there must be a plan in place for continuing patient care outside of a healthcare facility ([13], [143]).

Patients' special requirements and limitations should be considered when preparing them for transport ([1], [18], [25], [63], [77], [95]), and coordinating patients in vehicles leads to better utilization of that resource [31]. Particulary for older patients, stretchers or other equipment for transporting patients may be difficult to use and time-consuming [78]. Charts ([11], [63]) and medications [11] should travel with the patient, and patients should have some sort of identification attached to them [63]. For longer travel, supplies for heating and cooling the patients, as well as food and water, will need to travel with the patients ([96], [2]). For older patients that may have problems communicating, identification, medical history, and medication information should travel with the patients [95]. Finally, family members and volunteers may either help ([31], [63]) or hinder ([63], [98]) the evacuation efforts. In some cases, family members can assist with patient transfers, but in other cases, they may add to the problem by seizing scarce resources or getting in the way of the clinical staff and hindering the evacuation efforts.

2.1.4 Staffing

There are not many lessons learned that discuss staffing plans, roles, or requirements though it seems intuitive that an evacuation is highly dependent on staff's participation and cooperation. Most of the papers stress the importance of having evacuation plans, and authors stress the importance of training the staff to understand the plan ([11], [19], [25]). Lach et al. [95] suggested that nurses should be educated about the various types of disasters and their potential consequences.

As mentioned above, certain patient types may be difficult to transport, and may require the coordination and use of many staff resources [77]. Most of the papers credit their staff for participation, teamwork, and response.

Whether patients are assigned to be transported to a single receiving facility or to multiple ones, some authors suggested that the staff should be reassigned to the new facilities to continue caring for patients ([19], [31]) though these authors do not make it clear how such arrangements should be made or managed.

Staff at long-term residential facilities must take special care when transporting long-term care patients. The patients may be confused or scared, and the staff must be "calm and reassuring, yet firm in their directions. It is important to move quickly and confidently, without causing panic and further disorientation [95]." Though most nursing homes indicated that they had sufficient staff to evacuate patients during the 2004 hurricanes, maintaining adequate staffing levels throughout the evacuations was difficult, and the administration had to enforce staff participation [77]. Allowing the staff to travel with their families - or allowing families to come into the facility - may improve staffing levels [25].

In addition to the papers listed in this section, Qureshi [134] examines the staff's "ability and willingness to report to duty during catastrophic disasters," and Chaffee [26] discussed the impact of disasters on nurses and the ethical dilemmas associated with reporting to work. Qureshi et al. [134] surveyed healthcare workers around New York City about a wide range of disaster types including mass casualty events, environmental disasters, and epidemics. The authors discussed the barriers that affect healthcare workers' ability and willingness to report to work. Chaffee [26] listed "what employeers can do," to plan for emergencies. These include developing an outline of what is expected from employees during an emergency, determining which employees would not be available due to special needs or other volunteer obligations, and identifying services that would be made available to those employees who do work during an emergency (child care, pet care, food, shelter, counseling, etc.).

2.1.5 Record-keeping

Once patient evacuations are underway, there should be systems in place for tracking the evacuees ([63], [78], [98]) as well as a system to monitor bed availability at area hospitals [78]. Because loss of electricity may be a potential result of the disaster, a hard copy list of patient transfers should be maintained [11] at both the transferring and receiving facilities [31]. In addition, equipment transfers should be monitored [31], and a system that tracks costs would be beneficial [11].

2.1.6 Communications

Clearly reliable communication and coordination are essential to patient transfers ([11], [18], [31]) and potentially the most important factor that contributes to a successful evacuation [18]. This includes having back-up plans in place as discussed in Section 2.1.1 . Though communication channels are described as contributing to the success of the Southern California evacuation, it was determined to be the area that needed the most improvement in the debriefing session [13]. The lessons learned from the nursing home evacuations during Hurricanes Katrina and Rita indicate that there should be improvements to communication between the staff and physicians or medical directors before moving patients [25]. Communication needs to flow within the facility and to the receiving facilities ([18], [31], [63]).

One less obvious communication-related consideration relates to the media's effect on the evacuation. Bowers et al. suggested that communication with the media is important [19]. Hospitals can utilize the media to communicate where patients have been transferred or if there is any damage that would prevent providing care to incoming patients. However, the media may broadcast inaccurate information. This should certainly not be a primary concern, but the planners should be aware that the media may be present and may have an effect on the public's perception of the event [18].

2.2 Prioritizing Patients for Evacuations

A literature review of 1) suggested patient prioritization strategies for evacuation planning as well as 2) the transport priorities as used in actual facility evacuations shows that there is a lack of consensus about whether non-critical or critical care patients should be moved away from a facility first in the event of a complete emergency evacuation. In this section, the actual and suggested patient prioritization strategies are discussed. Figure 2.2.2 at the end of the section summarizes the prioritization strategies presented in the literature.

2.2.1 Evacuation Plans

The Center for Bioterrorism Preparedness and Planning [115] suggested a complete evacuation should happen in two phases: first, patients should be moved to a staging area. Because ambulatory patients require the least assistance, the Center for Bioterrorism Preparedness and Planning suggested that these patients be moved to the staging area first and that the more critical care patients be moved to the staging area last because moving these patients will require many more resources. Once the patients have been staged, however, the patients that require the most assistance should be transferred away from the facility first. These procedures are based on the START triage strategy where the staging phase follows the reverse triage rules and the transportation phase follows the traditional START triage rules. Gray and Hebert [63] agree with this strategy for advanced, pre-emergency evacuations because of the level of difficulty and the resources associated with transporting these patients.

The New York Centers for Terrorism Preparedness and Planning [131] and the Association of peri-Operative Registered Nurses (AORN) [3] suggested that patients should be prioritized from least to most critical. It should be noted, however, that the New York Centers for Terrorism Preparedness and Planning's *Hospital Evacuation Protocol* [131]is obviously written with a sudden, unexpected event. The *AORN Guidance Statement: Mass Casualty, Triage, and Evacuation* outlines that all ambulatory patients be lead out of the facility first, and then non-ambulatory patients should be prioritized from least to most critical. It is difficult to determine for what type of even the AORN statement was developed. At times, it would seem that the procedures refer to an immediate emergency such as a fire. For example, "staff members should assemble ambulatory patients together and designate one or more staff members to lead patients to the designated safe area." However, the document outlines considerations for patient evacuations including patient assessment, weight, stability, and transportability as well as resource requirements and equipment such as ventilators, tanks, monitors, and medications; it seems that such assessments refer to advanced evacuation due to a forecasted event.

In a discussion of simulation modeling to evaluate risks, Johnson [83] supports this prioritization strategy by stating that "the implicit objective at each stage is to maximize the number of people who can be moved to safety in the shortest available period of time." By stages, he is referring to the same phases as the *AORN Guidance Statement*, where ambulatory patients are moved first and then non-ambulatory patients are moved in the priority of least to most critical.

Moskop and Iserson [111] propose that patient evacuations follow reverse logic of normal triage methods and that attention must first be paid to ambulatory patients before evacuating those that are dependent on higher levels of care. The authors also suggested that triage in order to evacuate a hospital may be more difficult than "out-of-hospital." Finally, though the authors do not cite the sources, Lach et al. [95] discussed the complexities of nursing home triage "because triage protocols call for helping those in the best condition and most likely to survive first."

The actual patient transfers after the Northridge, California earthquake will be discussed in the next section. In a paper that discussed the eight hospital evacuations after the earthquake, Schultz et al. [143] summarized what they believe to be the most effective prioritization strategies: when the threat to patients is immediate, patients should be prioritized from least to most critical. When the treat is not immediate, the most critical patients should be given priority in order to decrease the burden on the staff and other resources.

2.2.2 Actual Patient Transfers

The Northridge, California earthquake in 1994 caused six hospitals to completely evacuate all of their patients and two others to partially evacuate. Six of these facilities chose to evacuate immediately, and they all cited nonstructural damage (such as loss of power) as a primary reason for evacuation (one facility also cited structural damage as a reason for evacuation). Five of these six facilities did not feel that their patients were in immediate danger, so they chose to evacuate their most critical patients first. The sixth hospital, however, felt that the damage was significant enough to put their patients at a serious risk, so they chose to evacuate their non-critical care patients first. The hospital moved all 334 patients to outside of the facility within 2 hours by prioritizing least to most critical. The final patients to leave the building were those who had been trapped inside the facility due to the structural damage from the earthquake.

After Tropical Storm Allison, facilities with the Texas Medical Center lost power and evacuated both of their hospitals. Patients from the intensive care units were evacuated first [19]. These patients and their records were transferred to other facilities within the system up to 200 miles away.

Gray and Hebert [63] summarized the challenges at multiple hospitals during Hurricane Katrina. They discussed the experiences at Lindy Boggs Medical Center where doctors prioritized patients into one of three categories: ambulatory patients, patients that needed medical attention, and critical patients. According to the hospital's existing evacuation policy, the critical patients were to be evacuated first, but the rescue teams insisted that women, children, and ambulatory patients had to be evacuated first because of the conditions in New Orleans. At Charity Hospital, the most critical patients (excluding intensive care babies) were evacuated first. Two of these patients were prisoners, and there were conflicts among the staff members since these patients were evacuated before other patients. Though not completely clear, Gray and Hebert [63] imply that the Veterans Affairs hospital evacuated its critically care patients first. The authors do not provide any insight on the prioritization strategies used at Tulane University Hospital or Children's Hospital. In the "Lessons Learned" summary, Gray and Hebert [63] conclude that "advance agreement is needed about which patients will be evacuated first."

Hodge et al. [12] also review the prioritization protocols used during Hurricane Katrina: at Memorial Medical Center, the healthy patients were evacuated first. In her discussion of Dr. Ana Pou - the surgeon accused of euthanizing patients in the wake of Hurricane Katrina - Okie [13] clarifies Memorial Medical's approach for patient priorities. Initially, the most critical care patients were evacuated first, but when help was not immediately available, the least critical patients were chosen for evacuation because they had the greatest chance of surviving. As the evacuation continued, the most critical care patients remained at Memorial. Approximately 200 patients were evacuated, however, and these included ICU patients, bariatrics patients, and patients with "do not resuscitate" (DNR) orders.

A few months after Katrina, Hurricane Rita threatened the University of Texas Medical Branch at Galveston. Until 2005, the University of Texas Medical Branch at Galveston's evacuation plan was to discharge healthy patients and to shelter-in-place and care for the critical patients [14]. When Hurricane Rita threatened a few months after Katrina, the facility changed its plan and chose to evacuate the most critical patients first.

	Critical Care Patients First	Non-critical Care Patients First
Evacuation Plans and Guidelines	• Center for Bioterrorism Preparedness and Planning • Gray and Hebert • Protocol at Lindy Boggs Medical Center • Protocol at Memorial Medical Center	• AORN's Guidance Statement • New York Center for Terrorism Preparedness and Planning • Johnson – simulation of evacuation risks • Moskop and Iserson – discussion of triage • Lach et al – geriatric patient evacuation • Texas Medical's policy until 2005
Actual Facility Evacuations	• Facilities not in immediate danger after the Northridge, California earthquake • Texas Medical Center after Allison • Charity Hospital after Hurricane Katrina • Texas Medical during Hurricane Rita	• Facilities in immediate danger after the Northridge, California earthquake • Lindy Boggs Medical Center after Katrina • Memorial Medical Center after Katrina

Figure 2.1: Summary of prioritization strategies for critical and non-critical care patients.

2.2.3 Prioritization Discussion

The important purpose of this section is to highlight two main points. First, there are not general guidelines for patient prioritization during healthcare facility evacuations. In addition, there is a lack of consensus about which patient types - critical care or non-critical care - should be evacuated first. Second, the policies included in evacuation protocols and those chosen for patient selection decisions in actual evacuations - with the exception of the actual patient transfers at Memorial Medical Center after Hurricane Katrina - are "all-or-nothing" policies meaning that the examples in this section advise completely evacuating all of one patient type before beginning to evacuate any patients that fall into the other classification. At Memorial, the plan was to evacuate the most critical care patients first, so the evacuations started with these patients. Because of the conditions, however, the patient prioritization switched to choosing patients with the greatest probability of survival.

2.3 General Evacuation Research

The general evacuation research typically relates to how individuals respond and move away from danger, beginning with the seminal paper by Quarantelli [132]. This paper collects and analyzes information related to evacuation characteristics and presents the findings of the literature and research in an analytical model of evacuation behavior at the local community level. The model describes the relationship between the context, threat conditions, social processes, behavior patterns, and consequences. This and other research in this stream address human decision making and how the general public makes decisions about evacuation. Specific to hospitals and special needs populations, Vogt [167], [168] and McGlown [108], [109] analyze the decision making process prior to and during evacuations (see Section 2.4.3).

2.3.1 Deciding to Evacuate

Various researchers have attempted to model the factors that influence how a person responds to a threat of an emergency including when to evacuate or whether to leave at all (see, e.g., [46], [117], and [150]).

Fitzpatrick and Mileti [47] discussed the factors that affect the public's perception about an evacuation. The paper references a variety of leading evacuation researchers including Clifford [30], Drabek ([37], [38], [39]), Fritz ([54], [55]), Perry ([118], [119], [120], [121], [122], [123], [124], [125]) Quarantelli ([132], [133]), Sorensen ([148], [149]), and Turner ([160], [161], [162]). Fitzpatrick and Mileti summarized the factors that affect the risk perception and therefore evacuation behavior as:

- Source - the credibility of where information about the risk is coming from,
- Consistency - whether the evacuation warning information is consistent with other types of warnings,
- Accuracy - the level of detail within the evacuation warning,
- Clarity - how easily the warning is understood,
- Certainty - how believable the evacuation warning is,
- Sufficiency - the appropriate amount of information - not too little such that the warning is confusing and not too much that the warning message is overwhelming,
- Guidance - the level to which the solution is outlined,
- Frequency - how often the warnings are delivered for a particular emergency,
- Specificity - where is the actual danger,

- Channel - the method(s) by which the information was delivered,
- Cues - the number of physical cues,
- Social Setting - what is happening when the information is delivered and what others are doing in response to the warning,
- Social Ties - various connections to people and places,
- Social Structure - characteristics of those who receive the warning,
- Psychological Factors - personal traits that affect how the warning is received, and
- Pre-warning Perceptions - perception of the actual risks

Notice that the first ten of these relate to the way the information about the evacuation is presented. The last six relate to personal and public factors. These all work together to contribute to perception, and then motivation and perception lead to action.

2.3.2 Deciding When to Evacuate

Sorensen studies the factors that influence an evacuee's decision on when to leave [150]. His general model considers the variation in individual's response times to an evacuation warning. The model confirms that the most important factor that influences an individual's evacuation decision depends on when they were warned, and the time that an individual receives a warning varies with the warning channel. In addition, personalized warnings decrease the response time, but it is obvious that personalized warnings take longer to create and deliver.

These factors are different for healthcare facilities where the occupants face greater risks during transport. In addition, most occupants of a healthcare facility are a dependent population, and they rely on direction and assistance from the staff as well as the availability of transportation and other resources.

2.3.3 Selection of Evacuation Routes and Resources

There is an entire stream of literature focusing on moving general populations away from hazards using roadway/highway infrastructure. For research contributions in macro/meso-simulation and network-based methods to evaluate traffic flow (see e.g., [33], [72], [127], and [145]). More recently, the application of micro-simulation and dynamic optimization has increased (see, e.g., [27], [52], and [73]). Many of these researchers propose operational policies for mass evacuations. Sumalee [154] focus on traffic networks after a major disaster.

2.4 Research for Improving Healthcare Facility Evacuations

Emergency preparedness and response has been researched for decades. However, since the World Trade Center attacks on September 11, 2001 and several other large-scale disasters (Hurricane Katrina, wildfires, tsunamis, etc.), there has been an additional focus on the preparation for, or response to, mass casualty emergencies. In fact, several papers specifically address triaging incoming patients (to evaluate the need and benefit of medical resources) and/or creating surge capacity in hospitals after a mass casualty event. There is significantly less research that considers healthcare facilities as the victims of these emergencies ([19], [36], [108], and [143]).

In this section, the current engineering contributions related to healthcare facility evacuations are highlighted. There are a number of papers that focus on each of the topics addressed in the following sections - healthcare facility design, evacuation plans, making the decision to evacuate, pre-evacuation times, and the selection of evacuation routes and resources - but there are limited sources that address these with respect to evacuations. Such papers will be discussed in Section 2.3. The papers presented in this section focus specifically on research related to improving healthcare facilities. The following section, Section 2.5, briefly highlights some of the other healthcare emergency preparedness research streams.

2.4.1 Healthcare Facility Design

Ünlü et al. [112] present a space syntax model to consider the navigation issues during a hospital evacuation. The authors site the shape of the building and evacuation routes, ergonomics, and characteristics of the occupants as the main factors that influence circulation out of a hospital during an evacuation. The model can be used to test designs for new facilities and analyze weaknesses as related to patient evacuations.

Various risk assessment techniques can be used to identify potential hazards, but it is difficult to estimate how these risks may further complicate patient evacuations. For example, certain emergencies may affect exit routes, elevators, or equipment. Congestion in corridors or smoke in the air may slow evacuation times or alter routes. Instead of staging several drills to test the various complications, Johnson [83] created a simulation model of the evacuation of Glasgow Hospital and considered the various risks to estimate the average and worst-case evacuation times.

2.4.2 Evaluating Evacuation Plans

By examining more than 2,000 nursing home evacuation plans, Castle [24] determined the elements that were most often excluded: staffing procedures for the evacuation (44%), plans for coordination with the community (42%), reentry to the facility (40%), consideration of residents' medical and personal needs (37%), maintaining water supply (36%), consideration of residents' personal belongings (35%), and pre-identified evacuation routes and travel time estimates (31%).

In her dissertation, McGlown [108] suggested that hospital evacuations plans are usually only "production documents" that are written only to meet the standards set by accrediting agencies. Vogt [168] surveyed nursing home facilities and used Quarantelli's model to evaluate the threats, resources, social climate, and other extracommunity factors as they relate to the effectiveness of an evacuation. While many of the issues are common to general population evacuations, Vogt [168] identified the need for different evacuation strategies for dependent populations.

2.4.3 Deciding to Evacuate and Pre-evacuation Times

For a discussion for the general population, see Section 2.3.1.

McGlown's [108] main research focus is to consider the variables that contribute to a healthcare facility's decision to evacuate, and they fall into five categories: infrastructure impediments, event monitoring, time and risk factors, the internal environment, and the external environment. The study participants included those with the authority to make evacuation decisions including management from healthcare facilities and "prehospital agencies" (EMS and fire). She presents a conceptual model for "interpretation of variables relevant" to making a decision to evacuate based on these factors. Her method for analyzing the relationships of the variables was based on Quarantelli's framework [132], and the findings are similar. For example, the variables are related as shown in Table 2.1 below. *Note: the table was adapted from a figure in [108].*

Once the decision to evacuate has been made, it is important to note another difference in the evacuation of a healthcare facility. Gwynne et al. [66] studied the pre-evacuation time - the difference between the time the occupant started to evacuate and the time the evacuation order was given - at a university residence hall and at a hospital. In the hospital case study, the authors point out that the behavior of the staff directly affects the patients' response to - and activities during - an emergency. They suggested that any hospital evacuation model should include some element to represent pre-evacuation time, but the factors that affect pre-evacuation time need further research.

2.4.4 Selection of Evacuation Routes and Resources

In the event of an external, regional disaster, other healthcare facilities - as well as the general population - may also be evacuating, and the patients may have to compete for transportation resources including vehicles and routes. If an internal emergency forces a facility to evacuate, the

Table 2.1: Factors that Affect the Decision to Evacuate.

Quarantelli (General Population)	**McGlown (Healthcare)**
Threat	**Event Monitoring**
Situational Variables	Disaster type/severity
Agent variables	Imminent danger
Social-psychological variables	weather conditions
Resources	**Infrastructure Impediments**
Evacuation drills	Loss of [utilities]
Evacuation planning	Structural damage
Personnel	Fire/smoke, bomb treat or discovery
Physical/safety structures	
Social Climate	**Time and Risk**
Risk perception	Time factors
Hierarchy of decision making	Preparation
Complexity of organization	Level of risk and assessments
Ability to receive warnings	
Constraints on decision making	
Organizational Characteristics	**External Environment**
Regulations	Regulations or legal authorization
External resources	Community resources or services
Ability to predict hazard	Community infrastructure
Ability to win	
Definition of threat or risk	
Social Linkages	**Internal Environment**
Interorganizational linkages	Facility resources
Intraorganizational linkages	Facility census, acuity, staffing
Previous organization interaction	Alternatives or alternate facilities
Specially designated emergency units	Special needs

facility may have access to additional resources to help with an evacuation. Taaffe et al. [155] used simulation to evaluate various scenarios for evacuation time requirements. Tayfur and Taaffe [158] developed a model to determine the allocation of staffing and transportation resources during a pre-specified evacuation window that minimizes cost.

The Agency for Healthcare Research and Quality (AHRQ) provides a web-based evacuation planning tool for healthcare facilities. Based on the user's input assumptions including the number and types of available transportation resources as well as the number and types of patients to be evacuated, the model provides estimates for the times to evacuate patients and transportation resource utilization. Patients are classified by their transportation requirements, and the assumption is that this reflects their acuity. Patient relocation assignments are made such that the sickest patients are transferred to the closest facilities to reduce travel time [50].

Tayfur and Taaffe [157] used simulation to evaluate various scenarios for evacuation time requirements. Tayfur and Taaffe [158] developed a model to determine the allocation of staffing and transportation resources during a pre-specified evacuation window that minimizes cost. Though the authors do not incorporate traffic simulation, they instead include a traffic congestion factor to include additional delays in travel times.

Duanmu et al. [40] recognized the variety of emergency and evacuation planning at healthcare facilities but identified a need for research related to external disasters that force the general population and healthcare facilities to simultaneously evacuate. The authors create a traffic simulation model to analyze the interaction and the effects on evacuation time, delays, and routes. The model can be used to test various evacuation start times by estimating travel ties between the evacuating and receiving facilities. A case study of the Charleston, South Carolina metropolitan area indicated that in order to evacuate all patients from a large hospital prior to a hurricane's landfall, a hospital evacuation should begin no less than 12 hours prior to the community's mandatory evacuation orders or both can begin simultaneously if both the hospital and community evacuations begin 2 days prior to landfall.

2.5 Emergency Preparedness in Healthcare

This section briefly highlights the more researched emergency preparedness topics including surge capacity, triage, and rationing, and battlefield medicine. The ethical dilemmas associated with these will be further discussed in Chapter 3.

2.5.1 Surge Capacity

Surge capacity refers to a facility's ability to quickly make room for incoming patients when there is an unexpected increase in demand due to an emergency or disaster [85]. There are a variety of papers that discuss hospital surge capacity during emergencies (see e.g., [23], [44], [71], [85], [116], [142], and [144]). Hick [71] et al. and Kaji [85] et al. present conceptual models, but none of these use any mathematical modeling techniques for responding to increased demands. Both papers discuss the differences in normal daily volume surges with emergency surges.

Though presented in the context of surge capacity, I think the discussion of a successful surge response could also be applied to a discussion of the requirements for a successful evacuation. Hick et al. [71] cite the four most important factors that contribute to successful surge capacity as system, space, staff, and supplies. The authors describe classifications for these four components in terms of conventional, contingency, and crisis capacity levels. In order for these parameters to be effective, the following "underlying system components" must be in place:

- Command - an incident command system should be included in the emergency plan and practiced for application
- Control - the facility can control their building by managing the people and even the air that is allowed to enter the facilities

- Communication - internal and external communication links are required
- Coordination - particulary for emergencies that affect more than just the facility, incident command should coordinate with other healthcare facilities as well as public safety support
- Continuity of operations - to provide continued care
- Community infrastructure - support from local agencies may help provide assets. In addition, the facility has to be prepared to handle its existing and new, incoming patients.

Kanter and Morgan examined hospital occupancy rates in New York and found that there may not be enough capacity to handle demands after certain types of mass casualty events. In order to be able to meet the demands, the authors suggested that altered standards of care may be necessary [86]. See Section 2.5.3.

2.5.2 Triage and Rationing

Triage refers to the allocation decisions that must be made when the available resources cannot satisfy the available demands. It refers to prioritization of patients, and in some cases, "some [demands] may not be satisfied at all" [110]. The concept of triage is generally considered in terms of a response to an emergency situation - in what order should victims be treated - to increase chances of survival.

Rationing refers to "any implicit or explicit mechanisms that allow people to go without beneficial services" [164]. Rationing does not only refer to the allocation of medical supplies; physician bedside rationing refers to determining whether certain clinical interventions are necessary [76] .

Hurst [76] describes the three forms of rationing by clinical judgement: triage (a number of patients competing for limited resources), strained or fixed resources (actual patients are not competing, but candidates for a resource are compared to potential candidates), and by opinion of the gains (comparison of the costs to the benefits). Examples of triage rationing include dividing time between patients during rounds or admitting patients to an ICU. Deciding how to allocate limited blood supplies or vaccines is an example of comparing patients to other potential patients.

The papers listed in Table 2.2 are just a sample of those that discuss strategies for triage and rationing.

Table 2.2: Papers That Discuss Rationing in Healthcare.

Author	Topic
Cookson and Dolan [32]	Justice
Egol et al. [41]	ICU Admission
Ham and Coulter [67]	Determining coverage for the insured
Jacobs et al. [81]	Oregon Health Plan
Krízová and Simek [94]	Expensive care in a “transition country”
Roberts et al. [138]	Mass care with scarce resources
Sinuff et al. [147]	Critical care beds
Ubel and Goold [163]	Bedside rationing

2.5.3 Altered Standards of Care

In 2005, before Hurricanes Katrina and Rita, the Agency of Healthcare Research and Quality published the “Altered Standards of Care in Mass Casualty Events” [79]. Because of the terrorist attacks in 2001, it became obvious that the ability of providers to administer the usual levels of quality care may decrease during a mass casualty event. The usual levels of care are determined by [79]:

- “What - what types of interventions, clinical protocols, standing orders, and other specifications should be used in providing health and medical care?”
- “To whom - which individiuals should receive health and medical care according to their condition or likelihood of response?”
- “When - with what urgency should health and medical care be provided?”

- "By whom - which individuals are certified and/or licensed to provide care within a defined scope of practice and other regulations?"
- "Where - what facility and system standards (pre-hospital, hospital, alternate care site, etc.) should be in place for the provision of health and medical care?"

"The standard of care is often defined as the level at which average, prudent, similarly qualified providers in a given community would have managed the patient's care under the same or similar circumstances" [171]. Such definitions are necessary for liability, and therefore it is necessary to define the altered standards of care for situations in which those usually accepted levels are not possible.

As mentioned above, Hick et al. [71] discussed the four elements of surge capacity in terms of conventional, contingency, and crisis capacities. When at "contingency capacity," the patient volumes are higher than the usual, "conventional" capacity, but the additional patient volumes have little to no impact on patient care. "Crisis capacity," on the other hand refers to limited space, staff, or supplies that are inconsistent with the usual levels of care in a disaster setting. The goal in such a case is to "provide the best possible care to patients given the circumstances and resources available."

The Indiana State Department of Health [113] published a document regarding the altered standards of care with respect to pandemic influenza. Such decisions are not only regarding how patient care will change but also how the use of supplies and equipment (such as ventilators) will be managed and rationed if necessary.

2.6 Modeling Policy Decisions

2.6.1 Scheduling Impatient Jobs

Queuing theory has been applied to healthcare as a tool to examine utilization ([21], [146]), determine appropriate appointment or staff schedules ([65], [88]), model patient flow ([22], [91]), and assess waiting lists for services such as transplants ([9], [175]). Many researchers have also considered how to distribute resource-constrained service to jobs or customers that are "impatient." Bhattacharya and Ephremides [16] and Panwar et al. [114] consider jobs with deadlines and single servers and prove that scheduling the most time-critical jobs is the optimal policy when the objective is to minimize the number of tardy jobs. Bhattacharya and Ephremides [17] further their research and suggested state-dependent policies when considering a single server with two queues and minimizing average tardiness per job. Dalal and Jordan [34] consider scheduling impatient jobs and prove that the optimal policy to maximize reward chooses the job with the highest product of reward and service rate. Additional papers consider deadlines while assuming that all jobs are available immediately (see, e.g., [20], and [42], [128]).

In Glazebrook et al. [58], the authors propose models for determining single-server service allocation schedules where (1) service is preemptive or nonpreemptive, (2) jobs reside in one or more classes, and (3) jobs arrive randomly or are available immediately. When all jobs are waiting in the system at time zero, the objective is to maximize the rewards until no jobs remain in the system or to minimize the rewards lost through abandonment. The near-optimal policy is based on strictly ordered tasks and therefore chooses tasks with small service times and large reward-rate loss. For a multi-class problem, each customer classification is associated with a unique abandonment time as well as a unique reward for successful completion of service. The resulting index policy approaches decisions based on the maximum available reward rate [58].

The work of Argon, Ziya, and Righter [10] pertains to scheduling impatient jobs in the context of emergency triage. Where our research addresses the evacuation of a hospital due to an emergency, Argon et al. [10] consider a surge on a hospital's operating rooms due to a mass casualty emergency. Their mode could also be used to determine patient priorities for allocating scarce resources in response to an emergency event. Their triage system is modeled as a single-server clearing system where patients are classified by two distributions - one to represent how long the patient has to live and another to represent their service times. These jobs or patients already exist in the system (no consideration of arrivals) and abandon the system if they 1) are selected for service or 2) if they are not selected for service within their lifetime.

The problem discussed in this dissertation is similar to the one presented by Argon et al. [10] in that there are a finite number of patients waiting for service and that new patients will not arrive to the system. Key differences include:

- In this research, we examine a two-server model in addition to the single server model;
- In [10], once a patient is chosen for service, it does not abandon the system. In the models presented in this paper, there is a probability of successful a successful evacuation (service) to represent the fact that patients may not survive the evacuation conditions;
- The model in Argon et al. [10] does not consider holding costs;
- The goal of the model in [10] is to maximize the number of patients chosen for service. For this research, the models were created to examine multiple objectives including maximizing saved lives and minimizing cost; and
- In some of the models developed for this research, patient transitions between classes are allowed.

Argon et al. [10] show that when the order of jobs based on service times is identical to the indexed order of lifetimes, then the job with the shortest service/lifetime is treated first. However, the least severe cases typically do not require the longest service times. Argon et al. [10] propose a dynamic program to determine server allocation when maximizing the total number of patients taken into service, and they show that when the number of jobs is high, the servers should be allocated to the “less time-critical patients with shorter treatment times.” As the total number in the system becomes infinitely large, the “shortest expected process time first” rule becomes the optimal policy. For the case when time-critical jobs have long service times (as is to be expected), the authors develop two heuristic approaches and provide numerical results on the performance of the resulting policies. Argon et al. [10] acknowledge that decisions to admit patients into an operating room would require much more system knowledge and human interaction, and therefore their work is not to suggest policies, but to provide insights on triage decision making.

Note: Argon et al. [10] refer to their evacuation system as a “clearing system.” In the 1970’s, Shaler Stidham, Jr. ([139], [140]) classified certain stochastic processes as clearing systems. These systems accumulate queues and are intermittently and instantaneously cleared. For example, consider the arrivals of passengers at a bus stop. When the bus arrives, the queue is instantly emptied. Though their model aims to clear a group of incoming patients through triage, the system is not actually a clearing system.

In Glazebrook et al. [58] and Argon et al. [10] (as well as many others), the $c\mu$ rule plays a key role in their results. The $c\mu$ rule minimizes cost by giving priority to the job with the highest value of $c_i\mu_i$ where c_i is the cost of keeping job i in the system and μ_i is the service rate for job type i (see, e.g., Iravani and Kolfal [80] and Van Mieghem [165]).

The work of Glazebrook et al. [58] and Argon et al. [10] has connection to our proposed research, but there are some fundamental differences in our approach. One major difference in our system is that our parameters are not necessarily stationary over time. For example, only a small percentage of patients should have expiring lifetimes during the evacuation period (die waiting for evacuation). Once the evacuation period is over and the disaster occurs, depending on the nature of the disaster, all patients lifetimes may expire instantaneously. Another difference is the decision horizon. In the case of a patient surge on an emergency room, there is no time limit, and the decisions will be made until all patients have been triaged. In our research, there is a limited time window between the decision to evacuate and the impending disaster. As the disaster approaches, we also believe it is important to consider how the standard level of care changes, and how that will impact service or evacuation times, as well as patient selection decisions. For these reasons, we strongly believe this is a rich area of research, where advancements in modeling (via tools such as dynamic programming and simulation) will be abundant.

2.6.2 Healthcare Policy Decisions with Dynamic Programming and Simulation

This section discusses the application of dynamic programming and simulation in healthcare. Dynamic programming consists of a variety of techniques used to determine the optimal solution for problems where decisions are required within a sequence of events [14]. This problem-solving approach can apply to a wide range of problems including both deterministic and stochastic problems. Dynamic programming can be used to numerically solve problems as well as develop conclusions about the structural properties of the optimal policy. Most dynamic programs are solved by backwards induction, so therefore the optimal policy consists of the optimal policies for a series of subproblems.

When the routine performance of a system is represented, simulation can be used to test "what if" scenarios without requiring the initial investment and actual implementation of each scenario. This allows an opportunity to analyze how changes to various inputs, resources, or time requirements affect the entire system. Simulation is used often in healthcare as teaching opportunities for the clinical staff. These simulations are usually in the form of physical models of the system. For example, simulation labs are used to create scenarios for mock patients, and even evacuations or other emergency events can be simulated. Computer simulation is obviously preferred when actual simulations would be too expensive, complicated, intrusive, or impossible.

2.6.2.1 Dynamic Programming in Healthcare

The following are examples of applications of dynamic programming to policy decisions in healthcare:

- As early as 1969, dynamic programming was used to model healthcare decisions. Esogbue [43] modeled the operating rooms in hospitals.

- Fries and Marathe [53] used dynamic programming to examine appointment systems in ambulatory care clinics.

- Weiss [172] modeled an operating room as a single machine job shop where the operations are jobs that are either 1) already scheduled or 2) used to determine the optimal order. In both cases, the estimated start times of the procedures depend on the two costs considered in the problem (idle cost and surgeon's waiting cost).

- In order to estimate price expectations of over-the-counter pain relievers, Gönül [60] developed a dynamic program to examine brand choice.

- Claxton and Thompson used dynamic programming to optimize the design clinical trials [29] including sample size, allocation, and the "societal payoff to proposed research."

- Maxwell et al. [105] used approximate dynamic programming to determine re-deployment strategies for minimizing the time it takes an emergency medical service (EMS) crew to respond to a call.

2.6.2.2 Simulation in Healthcare

Jun et al. [84] and Gnal et al. [59] two of the most recent papers that review the use of discrete-event simulation in healthcare. The following are examples of applications of discrete-event simulation in healthcare with respect to policy making:

- Hupert et al. demonstrated the usefulness of discrete event simulation modeling improving response to emergency events. The authors created a model to design antibiotic distribution centers after a bioterrorism attack [75]

- Giachetti et al. [57] developed a simulation model to evaluate scheduling policies in an outpatient clinic.

- Fletcher et al. [48] discussed a simulation model used to evaluate patient visits to England's Accident & Emergency departments in accordance with the national policy of completing 98% of patient visits within 4 hours of their arrival.

- As described in Section 2.4.4, Taaffe et al. [155], Tayfur and Taaffe ([158], [157]) and Duanmu et al. [40] used simulation to examine the resources and routes associated with evacuating healthcare facilities.

- Ramwadhdoebe et al. [136] developed a discrete-event simulation model to determine a policy for testing infants for developmental dysplasia in the Netherlands.

- Werker et al. [173] examined waiting times for radiation therapy at the British Columbia Cancer Agency and tested a variety of scenarios to shorten waiting times.

- Konganakorn et al. [92] used discrete-event simulation to test the economic benefit of two different treatments for pneumonia.

2.7 Evacuation and Transportation Data

The models in Chapters 5, 6, and Chapter 7 will consider the following input parameters: patient evacuation rates, probabilities of successful evacuations, and patient death rates while waiting for evacuation. To our knowledge, there are no papers that estimate these parameters. This section will examine any relevant data points from the papers discussed in this chapter.

Løvås [103] studies the complex system that results when a building is evacuated. Though not healthcare facility-specific, the performance measures of interest apply: number of deaths, number of safe evacuees, and the time needed to evacuate a given number of people. In addition, Løvås provides an excellent discussion on how to measure evacuation systems based on these key outcomes or objectives. These suggestions of past researchers clearly identify the need for improved decision making during healthcare emergencies.

2.7.1 Time to Evacuate

The time it takes a person to evacuate a building depends on his or her response time to the emergency and how long it takes to physically move to an exit. Evacuation time estimates have been studied in the context of nuclear power plants [73], communities [27], and traffic [100]. In the case of a healthcare facility, the building's occupants cannot immediately leave the facility. Most patients must rely on the decisions of the clinical staff, and the clinical staff must remain in the building to carry out the evacuation. For the models described in the following sections, most of the evacuation time parameters are based on our observations of a mock evacuation.

In his summary of a simulation created for a London hospital, Johnson [83] reminds modelers about the delays associated with moving patients. He estimates the minimum and maximum delays associated with the preparation for the helping the patient evacuate. For "mobile patients able to move on their own," the minimum delay is 30 seconds, and the maximum delay is 90 seconds. For "immobile patients who could be moved with relative ease," the minimum delay is 1 minute, and the maximum delay is 3 minutes. For other immobile patients, the minimum delay is 3 minutes, and the maximum delay is 15 minutes. These times, however, are only associated with preparing the patient for physical movement; there is no discussion of locating and preparing medications, charts, and other equipment that may have to travel with the patient. Johnson [83] also estimates the time required for a nurse to transport a patient. He gives "fast," "medium," and "slow" estimates. The time required for a nurse to push a patient in a bed is estimated to be 20, 25, or 35 seconds per 10 meters. For a nurse to push a patient in a wheelchair, the times are between 12, 16, and 20 seconds per 10 meters. Finally, for a nurse to walk alone with a patient, the travel times per 10 meters are estimated to be between 8, 12, and 16 seconds.

Table 2.3 was adapted from Schultz et al. [143] to provide insight on the time required to complete an evacuation. These time requirements are for both partial and complete evacuations, and the time required was measured from the beginning of the evacuation to the moment that the last patient was transported away from the facility.

Table 2.3: Time Required to Evacuate Patients.

Number of Patients Evacuated	Time Required for Evacuation [hours]	Average Time per Patient [minutes]
25	13	31.2
2	1	30
320	9	1.69
125	19	9.12
270	9	2
202	10	2.97
46	12	15.65
76	13	10.26

There is no direct discussion in [143] of why the average time per patient is so different. Note that the least amount of time per patient is associated with the facility that moved their patients to a staging area directly outside of the facility. It is easy to understand that the differences in resource requirements, patient volumes, and transportation distances can cause such differences in the average evacuation time per patient, but it is difficult to understand exactly how a patient can be evacuated in less than 2 minutes.

2.7.2 Transportation Risk

According to a study conducted in 2005 that analyzed the vital signs of critically ill patients transferred to the intensive care unit of a tertiary referral center, 37% of these patients exhibited a vitals increase beyond predefined thresholds after transport. Either a nurse or physician was present in 80% of the transports, and the distance of transport did not correlate with the condition on arrival [99]. The data collected from this study shows there is a definite increase in risk associated with a transfer. Among those parameters that differed after arrival were oxygen saturation, heart rate, temperature, and glucose level.

A patient's age will also affect the likelihood of mortality or increased complications during transfer. Patients 75 years or older account for 1.8 million trauma-related visits per year. Over 40% of these visits require ambulatory assistance. Patients in younger age groups are not as likely to be admitted into a hospital with ambulatory assistance [49]. These patients who are 85 years or older have a mortality rate 2 times those under 85 years old [153]. Often transfers for continued medical care were more common among younger patients while older patients more frequently fell into the categories of emergency and urgent admissions, indicating a natural increase in risk when transferred (see, e.g., [35] and [170]). Inter-hospital transfers also present an increase in risk to the patient. In an analysis performed by the National Institute of Health in 2006, the risk of in-hospital mortality was 2.25 times higher among those transferred compared with those who were not transferred. However, the study concluded that the risks differed with the experience of the attending physician at the receiving hospital [170].

The following are related to patient complications during actual evacuations:

- One patient experienced complications related to evacuation after evacuating Galion Community Hospital in response to a bomb threat [11].
- There were no deaths reported from the eight hospital evacuations after the Northridge, California earthquake [143].
- After Hurricane Katrina, none of patients from Tulane University Hospital died during the evacuation, but two patients from Charity Hospital that had been transported to Tulane died during the evacuation [63].
- St. Charles Parish Hospital did not evacuate until after Hurricane Katrina, and there were no deaths reported [63]. There were 8 patient deaths at Charity Hospital, 19 at Lindy Boggs, and 45 at Memorial Hospital.
- There were no deaths reported in the summary of lessons learned from the evacuation of Texas Medical Center during Tropical Storm Allison [31].

2.8 Goals

The following discuss the goals or objectives of evacuation, triage, and allocation decisions.

- With respect to evacuation and surge capacity at Robert Wood Johnson University Hospital, the goal is to "maximally reduce the number of casualties" [82].
- The goal of allocation decisions should be "maximizing the survival rate" [87].
- Based on Texas Medical Center's experiences during Tropical Storm Allison, receiving facilities should be chosen that avoid "overwhelming a facility with too many patients arriving at once" [31].
- According to a draft published by the Massachusetts Department of Public Health and the Harvard School of Public Health [4], "priority for limited medical resources and [altered standard of care clinical] protocols will be based upon the allocation of scarce resources to maximize the number of lives saved."
- "The goal of a ... response [is] to maximize the number of lives saved" [79].
- White et al. discuss ethical decision making in the context of allocating ventilators to hospitalized patients during an pandemic influenza outbreak [174]. The authors point out that many allocation decision criteria are based on maximizing the number of people that survive until hospital discharge.

2.9 Ethical Considerations

Hardin [69] introduced the concept of lifeboat ethics: there is only room in the limited supply of lifeboats for some percentage of the population, and the rest of the population are left to swim on their own. There are a number of decision criterion that can be used to make decisions about how to "fill the lifeboats." In a healthcare context, Kraus et al. [93] consider a hospital as a lifeboat for a community during a disaster. With a patient surge, the authors suggested that triage decisions should balance the basic medical ethical principles: autonomy (respect for patients as decision makers), beneficence (maximizing benefits and minimizing injury), nonmaleficence (avoiding harm), and justice (fairness). Patient triage during disaster events typically takes on a utilitarian view: do the most amount of good for the most amount of people. In order to do this, the public accepts that the standard quality of care may decrease, and thus "sufficient" care becomes acceptable. This leads to a key question in our research: how do ethical decision making and acceptable level of care impact the selection of the next patient for evacuation?

Most triage decisions are made by the patient roster, and clinical staff does not necessarily have access to information about the available resources, risks, and rewards. Kraus et al. [93] further suggested that "a system that allows real-time classification of risks and benefits...would be a great advantage in ethical decision making."

An ethical dilemma, according to Rushworth Kidder [89], is a problem where more than one "right" option conflict. These can generally be categorized into one or more of the following categories: individual versus community, short-term versus long-term, truth versus loyalty, and justice versus mercy [89]. Once the evacuation orders are underway, other potential ethical dilemmas include [97], but are not limited to

- Determining when to evacuate,
- Prioritizing patients for evacuation,
- Deciding which staff members should report to work,
- Allocating and distributing scarce resources,
- Maintaining privacy and granting patient autonomy,
- Identifying authority and managing teamwork, power, and roles,
- Determining how to best use non-clinical staff such as family members and volunteers,

- Determining acceptable levels of care,
- Deciding the best plan for patients that will inevitably die, and
- Handling admissions and emergent patients from outside of the facility

Note: Ethical dilemmas are not categorized in [89] or [97]; Larkin [97] suggested some potential dilemmas and Kidder [89] suggests the categories. The ethical dilemmas will be further discussed in Chapter 3 along with a discussion of the four main ethical frameworks.

Chapter 3

Ethics and Objectives

This chapter discusses the ethical dilemmas associated with healthcare facility evacuations. It must be noted that there are a number of stakeholders in healthcare ethical dilemmas, and each has a shared objective: patients' health. These stakeholders, however, also have additional - and sometimes competing - objectives. Consider the following in Table 3.1.

Table 3.1: Internal Stakeholders in a Healthcare Facility.

Stakeholder	Goal
Patients	Health
Patients' Family and Friends	Health of the patient
Patients' Employer	Want employee to return to work
Nurses	Deliver quality care
Physicians	Diagnose and deliver quality care
Facility administrators	Maximize revenue; deliver quality care
Third party payers	Maximize revenue; develop cost-effective treatment plans

It is an assumption that the patients should always be at the center of the "moral universe" (a term used in [89]) for healthcare decisions. Including additional stakeholders into ethical decision making compounds and increases the complexity of ethical dilemmas. My opinion of the moral universe with respect to evacuations, or at least how I would like it to be, is represented in Figure 3.1, though there are no papers to support this idea.

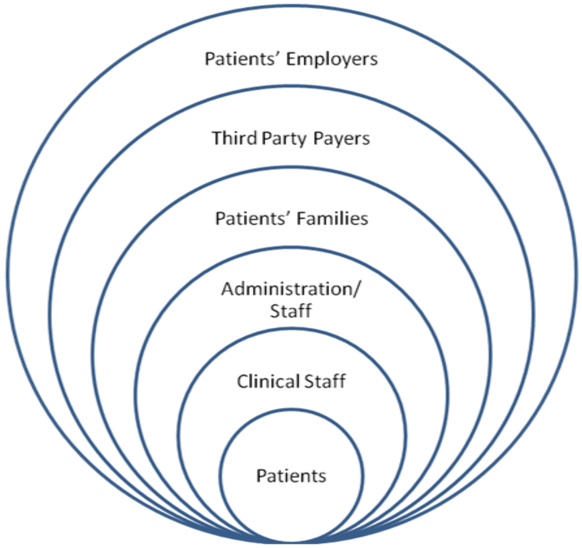


Figure 3.1: Example of the moral universe for healthcare facility evacuations.

An ethical dilemma, according to Rushworth Kidder [89], is a problem where more than one "right" option conflict. These can generally be categorized into one or more of the following categories: individual versus community, short-term versus long-term, truth versus loyalty, and justice versus mercy [89]. There are a variety of ethical dilemmas associated with healthcare facility evacuations [97], and these are listed in Table 3.2. Note the list is not classified in [97] as in the table.

The ethical dilemma at the focus of this chapter is determining the order in which patients should be transported. According to Bernard Gert [56], "a person acts irrationally when (s)he acts in a way that (s)he knows (justifiably believes), or should know, will significantly increase the probability that (s)he, or those (s)he cares for, will suffer death, pain, disability, loss of freedom, or loss of pleasure: and (s)he does not have an adequate reason for acting so." Patients are a dependent population, and in order for most to get to safety, they will require the assistance of the clinical staff. When the choice to transport one patient causes another to be left behind, this may directly cause harm. In the case of an emergency evacuation with limited time for transport, there actually is the potential for "death, pain disability, loss of freedom, or loss of pleasure." The caveat at the end of Gert's definition of rationality "justifies" causing harm as proper prioritization policies will lessen the harm for the entire system.

Table 3.2: Breakdown of Healthcare Evacuation Dilemmas by Type.

Dilemma	Individual vs. Community	Short-term vs. Long-term	Truth vs. Loyalty	Justice vs. Mercy
Determining when to evacuate	X			
Prioritizing patients for evacuation	X		X	X
Clinical staff reporting to work	X		X	
Duty to patients versus family	X			
Distributing scarce resources	X		X	X
Maintaining privacy		X	X	
Granting patient autonomy	X	X	X	
Identifying authority	X	X	X	
Teamwork, power, and roles	X	X	X	
Use of non-clinical staff, volunteers	X	X		
Determining acceptable levels of care	X	X	X	
What to do when a patient will inevitably die?		X	X	X
How to handle admissions, emergent patients		X	X	
Receiving facilities:resource distribution	X		X	X

3.1 Ethical Perspectives

"Morality is, at the very least, the effort to guide one's conduct by reason" [135], and Ethics is "the obedience to the unenforceable" [89]. There are four, main ethical perspectives that guide such decision making: utilitarian, deontological, care-based, and virtue-based ethics. Care-based ethics will not be discussed as it is not a good model for policy making or occupational behavior; however, it is interesting to consider that those carrying out an evacuation are in care-giving roles.

3.1.1 Utilitarianism and Evacuations

"Utilitarian theories assign people responsibility for producing certain results, leaving the individuals concerned broad discretion in how to achieve those results" [62]. As compared to the other ethical perspectives, utilitarianism is the best guide for public policy, and its concepts can help evaluate options for the proper objective functions for evacuations. Using a utilitarian framework, right and wrong are evaluated based on consequences alone, and these consequences - or utility - are the most important. The goals of a Utilitarian are to do the greatest good for the greatest amount. We assume that each person is the best judge of their preferences and interests except in the case when they are the only ones to suffer from potential consequences. The "greatest good" was originally considered to be "happiness" by Jeremy Bentham, one of the philosophers originally credited with Utilitarianism [135]. In Utilitarianism, each person's happiness should be given equal consideration: "each counts for one and no one counts for more than one" [62]. Finally, "it is legitimate for the collectivity to impose sanctions upon individuals in pursuit of [a] goal" [62].

During an emergency, the public generally accepts Utilitarian decision making [93]. Therefore, it is fair to assume the "public health model" as a standard; "the patient is the public, and the mission is to promote the public's health" [169].

"The greatest good for the greatest amount" presents the most challenging aspect of our research. How should the greatest good be quantified: number of evacuees, profit, number of life years? In addition, there are some limitations to using utilitarian principles to improve evacuations. First, it is hard to foresee consequences. Our models only look at the immediate consequences: life or death. However, there are so many different stakeholders, and the potential effects of an evacuation grow exponentially as more people are included and the costs, happiness, time, etc. are considered. That being said, there is no way to represent what is the "greatest good" for individuals, and it is hard to know what to include in trying to quantify this for a community. Further, "there is no obvious place within utilitarian theories for people's idiosyncratic perspectives, histories, attachments, loyalties or personal commitments" [62]. We cannot assume that those carrying out an evacuation would not have some sort of personal relationship with the patients that they would be responsible for evacuating.

This leads us to our discussion of responsibilities and Deontological ethics. However, before I transition from utilitarianism to Kantian ethics, it is important to consider the middle-ground or "rule utilitarianism" as it directly applies to decision making in evacuations. Once determining the set of rules that it optimal, "we do not have to invoke the principle again to determine the rightness of particular actions" [135]. That is, once the set of optimal policies that "does the most good for the most amount" has been determined, it is not necessary to reconsider each individual decision-epoch from a utilitarian perspective.

3.1.2 Deontological Ethics and Evacuations

The major concepts in Deontological, or Kantian, ethics include duty and respect for persons. The ethical rules are absolute, and the morality of a particular action depends on the intent and purpose, not the final consequences. In order to determine if an action is ethical from a Kantian perspective, consider if it would be acceptable as a universal law. The consequences of the action do not matter; the duty is what is important.

In a Kantian framework, people should not be treated as a means to an end, and patient autonomy should be respected. As noted before, it is easier to grant patient autonomy in cases where the outcomes only affect the patient or a small group. Kantian ethics does not focus on outcomes, so it is important to remember that evacuation is a utilitarian concept. During an evacuation though, the staff have a duty to keep their patients safe. They also have other duties that may be competing. In the event of a community-wide emergency, a staff member may have family obligations. Even when someone from the clinical staff assists with evacuations, there could be different motives for fulfilling this duty. Are they helping only because it is their job? It is fair to assume that those in the business of care-giving have virtuous traits. It is a combination of their virtues and duties that motivates them to assist with evacuations. In the case of an emergency evacuation, however, duties may conflict. In the event that duties as identified by a utilitarian policy diverge, a virtue-based approach to ethics may help identify solutions.

3.1.3 Virtue-Based Ethics and Evacuations

As stated before, utilitarianism is the best guide for policy making. Therefore, the hope is that we can outline the most ethical procedures for prioritizing patients based on the greatest good. There will, however, likely be unplanned events that require immediate decisions. Such decisions will be ethical decisions, and will test the "ethical fitness" [89] of those carrying out the evacuation. Coincidentally, health care professionals are known for their virtuous traits. The ethical codes for nurses and physicians center on moral values and require compassion, respect, commitment, responsibility, accountability, integrity, dedication, and truthfulness [5], [6].

Larkin and Arnold identified the virtues for healthcare workers during an emergency: "prudence, courage, justice, stewardship, resilience, vigilance, and charity" [97]. "Virtue-based ethics are more adaptable to the multiplicity of rapidly changing disaster circumstances than mere principles, rules and protocols, particularly since the scope, magnitude, and dynamics of a particular challenge cannot be determined in advance [97]".

Priel and Dolev [130] and Kraus et. al [93] suggest that medical decisions must balance beneficence, nonmaleficence, autonomy, and justice. Priel and Dolev [130] extend Larkin and Aronld's [97] list, and include "compassion, trustworthiness, discernment, and integrity" as the four virtues essential to medical practitioners and suggest these "be manifested in mass casualty situations."

3.2 Ethics and Public Policy

According to Goodin, "utilitarianism can be a good normative guide to public affairs without necessarily being the best practical guide to personal conduct. But special circumstances confound the direct application of utilitarianism to personal affairs, and in such circumstances utilitarianism itself recommends that people's conduct be guided by more indirectly utilitarian mechanisms - obeying rules of conduct or developing traits of character" [62]. The middle ground between Utilitarianism and Kantian is rule-based utilitarianism where the consequences guide the formulation of a set of rules. The utilitarian concepts determine the policies, these guidelines define roles and responsibilities, and virtues contribute to the success of an evacuation.

The optimal policies vary with the choice of objectives, and the purpose of this research is to investigate the options for objectives and determine the one(s) that best balance the basic ethical principles.

Current evacuations operate based on beneficence (maximize benefit and minimize harm). In conversations with healthcare officials, the typical opinion is that non-critical care patients should be evacuated first. Will this produce justice and equity to all patient classes? We address this issue in Chapter 5 by incorporating ethical considerations into the modeling objective.

3.3 Ethical Perspectives in Healthcare Emergency Preparedness

During an emergency, when allocation decisions are to be made, the accepted perspective is Utilitarian: do the most good for the most amount ([93], [70], [107], and [126]).

In collecting papers regarding ethical decision making for emergency events in healthcare, it is almost always easy to predict how the arguments for ethical behavior will be framed. If the author is a doctor or a nurse, the arguments will most likely focus on values and virtues. Lawyers and those in public health tend to argue for the greatest good (utility). Robert Veatch, Ph.D. agrees that there are two major, moral principles for triage; one is to choose to care for victims that would benefit the most from care (utility), and the other is to care for those in the greatest need (justice) [166].

The purpose of this section is to suggest a potential conflict in the ethical perspectives. Because this research focuses on the utilitarian concept of doing the most good for the most number, it is important to consider that those actually carrying out the utilitarian policies may not agree with the decision.

- "Many [medical professionals] are simply not prepared to modify their intransigent principle of unwavering duty to their patients' individual interest" [104]
- "Nursing is a discipline rich in values" [137]
- "Public health ethics differs from clinical ethics by giving priority to promoting the common good over protecting the individual autonomy.... Public health policies, which focus primarily on population-level health outcomes, may subordinate the interests and rights of indviduals to the common good.... The notion that public health measures could shape life-or-death choices for all ... patients is foreign to most clinicians and patients" [174]

The papers outlined in the following subsections address ethical concerns during emergency events with an emphasis on virtues, values, and morals.

3.3.1 Values and Virtues

In their discussion of triage in healthcare, Moskop and Iserson [111] suggest that it is "important that triage officers understand the triage system they employ and the moral values and principles upon which it is based" [111]. "To begin an ethical analysis of triage," the authors "first consider how triage fosters the values of human life, health, efficient use of resources and fairness." "Triage and Values" is their first major section, and the authors discuss the values inherent and foreign to triage [111]. Though there is a lengthy discussion of utility, it is in a subsection of "Triage and Principles of Distributive Justice" that comes after the discussion. Moskop is a Professor of Medical Humanities at East Carolina University and Kenneth Iserson is an M.D. and Professor of Emergency Medicine.

Larkin and Arnold [97] present the ethical dilemmas that may be associated with a terrorist attack, and discuss virtue-based ethics as the best approach for "emergency planning, preparedness, and response to acts of terrorism." Larkin and Arnold are both M.D.s. In fact, they support the hypothesis that M.D.s may be predisposed to think of ethics in terms of virtue rather than utility by stating "we espouse the notion that virtue-based ethics are more adaptable to the multiplicity of rapidly changing disaster circumstances than mere principles, rules and protocols."

The ethical framework presented in [159] for decision making in pandemic influenza preparedness is based on the following. First, the ethical decision making process should include the following values: accountability, inclusiveness, openness and transparency, reasonableness, and responsiveness. Decisions should be made based on: duty to provide care, equity, individual liberty, privacy, protection of the public from harm, reciprocity, solidarity, stewardship, and trust. Notice that the Utilitarian concept of stewardship is included as a value. Thompson et al. [159] state that "decision makers have a responsibility to avoid and/or reduce collateral damage that may result from resource allocation decisions; maximize benefits when allocating resources; protect and develop resources where possible;" and "consider good outcomes (i.e. benefits to the public good) and equity (i.e., fair distribution of benefits and burdens)."

The following papers also examine ethical dilemmas with a virtue-based framework:

- Linda Good, R.N. [61], also discusses disaster ethics in terms of virtue. "The same fundamental virtue-based ethics that have guided health care decisions ... provide the moral foundation to carry out the challenging task of triage."
- G. Richard Holt, M.D., reviews literature to summarize the ethical challenges and perspectives of medical care during mass casualty events [74]. He concludes that "it is necessary to... formulate a virtue-based, yet practical, ethical approach to medical care under such extreme conditions."
- Nora Bell [15] challenges the utilitarian-based triage system: "the 'more is better' principle lacks the status of a universal moral obligation and leads to an impersonal view of the valuing of life."

3.3.2 Duties

In addition to utilitarian- and virtue-based ethics, there is another framework, Deontological or duty-based ethics, that is based on rules and obligations. In her discussion of whether nurses should report to work during an emergency situation, Chaffee's [26] arguments appeal to "duty," "responsibility," and "obligation." It could be argued, however, that whether a nurse decides to report to work as a function of such commitments could be a reflection of his or her personal virtues.

In the Indiana State Department of Health's [113] report on altered standards of care, the following ethical framework is suggested for determining how breathing equipment should be allocated during pandemic influenza: "duty to care, duty to steward resources, duty to plan, distributive justice, and transparency." "Duty to steward resources" refers to utilitarian principles in that allocation decisions must be made based on the saving the most lives.

3.3.3 Utilitarian Approach

The following papers discuss triage and other allocation decisions from a Utilitarian perspective:

- "Lifeboat Ethics: Considerations in the Discharge of Inpatients for the Creation of Hospital Surge Capacity" was written by Kraus (M.P.H), Levy (M.D, J.D), and Kelen (M.D.) [93].
- Ken Kipnis, a professor of Philosophy, does not appeal to the values and virtues behind triage decisions but instead says that triage decisions are to "produce the best outcome" [90].
- Rhonda Hartman, a lawyer, argues that "the rationale for triage is utilitarianism" [70].
- Linzer et al. [101] agree that "triage is largely utilitarian in nature," and suggest that social workers rely on Utilitarian and Deontological ethics to make decisions. The authors are professors with degrees in social work.

In summary, the discussion in this chapter was to illustrate that there may be some conflicting and competing ethical perspectives during a healthcare facility evacuation. When doctors and nurses, who are driven by virtues and values, are asked to carry out policies that are based on utilitarian principles, ethical dilemmas beyond those already inherent in the evacuation process may further complicate the decision making process.

Chapter 4

Evacuation Survey

In research funded by South Carolina State University's James E. Clyburn University Transportation Center, we developed and distributed an evacuation survey to hospitals and nursing homes across the state. Approximately 30 surveys were mailed to contacts, but only 7 were returned. Despite the low response rate, the information helped set a baseline for our understanding of healthcare facility evacuation plans across our state. It is important to note that *none of the facilities reported having a prioritization plan or instructions on who to evacuate if only a limited number of patients could be moved.* In addition, we received nine evacuation plans to review and compare with the survey results.

4.1 Survey Creation

In 2005, Schultz et al. [141] noted the lack of standardized data collection for hospital evacuations. The team created a survey tool for systematically collecting data on the actual emergency, hospital demographics, existing emergency plans, incident command, patient transfers, and "hospital recovery."

The survey distributed for this research used, amended, and supplemented questions from [141]. A copy of the survey informational letter and the actual survey can be found in Appendix 4. Sample questions included:

- With regard to evacuation, are there strategies used to determine transfer/movement priority in the evacuation plan? If so, please describe.
- Does your evacuation plan address patient evacuation out of the facility?
- Does the plan include an estimate for the time required for a full evacuation?
- Does the evacuation plan address what to do if there is a limited time window for evacuation (not enough time to get all patients out of the facility)?
- What transportation resources are available to actually move patients?
- Which patient group would you most likely transport first?
- Which patient age group do you think have priority in transporting to safety?

This survey was created and distributed in the beginning phases of this entire body of research. The purpose was to determine whether any prioritization guidelines were currently being included in emergency planning.

4.2 Survey Responses

Seven surveys were returned from various sized hospitals including a 53-bed facility, a 54-bed facility, a 56-bed facility, a 145-bed facility, a 296-bed facility, a 588-bed facility, and an 845-bed facility. The number of staffed beds in these facilities ranged from 28-850 beds. These facilities were 2-, 1-, 3-, 5-, 7-, 8-, and 6-stories tall, respectively.

With respect to transportation priority, two facilities indicated that ambulatory patients would be evacuated first. Two of the facilities indicated that their evacuation plans addressed which patients should be chosen for transport in the event that there was not enough time to get all of the patients out, though such guidelines could not be identified in the evacuation plans that they provided to us. The other 5 facilities indicated that there were no guidelines for patient selection if there was not enough time available to move patients. The two largest facilities estimated it would take “24 hours” and between “36-48 hours” to evacuate. The smaller hospital replied “yes,” there is an estimate for how long a complete evacuation would take, but no estimate was given. Another of the smaller facilities is a nursing home, and they estimate that a complete patient evacuation would take between 3-4 hours to complete.

The following tables represent the responses to the prioritization questions. Table 4.1 represents patient groups, and Table 4.2 represents age groups.

Table 4.1: Which patient group would you most likely transport first?

Facility No.	Hospice	Acutely Ill	Chronically Ill	Immediate Care	Other
1			X		
2		X			
3					skilled nursing
4		X	X		
5		X			
6	X	X	X	X	

Facility 7 did not check any of the options listed in Table 4.1 but instead answered: “ethical question; answer determined by event type (pan flu event vs. mass casualty event for best likelihood of survival/best good for most/etc. or whatever ethics model is for event type.” There was however, no mention of ethics models in the evacuation plans.

Table 4.2: Which patient age group do you think has priority in transporting to safety?

Facility No.	Infants	Children	21-35	35-65	66+
1	X				X
2					
3					X
4	X	X	X	X	X
5		X			
6	X				

Facility 7 did not respond to the age prioritization question.

As expected, all facilities indicated that their disaster plans specified transferring medical records, medication, and equipment with patients. Four of the facilities (including the smallest and the largest hospitals) indicated that the nearest facility to shelter its patients was within 5 miles. The 296-bed facility indicated that the closest facility was within 5 miles, but if there was no room for their patients at this receiving facility, patients would have to be transferred out of the state.

The survey included questions about the types of transportation vehicles available. All would have access to ambulances for an evacuation. Public busses, personal and facility-owned vehicles, and helicopters would also be available to some of the facilities. The two largest hospitals - along with one other facility - indicated that they had resources that would allow them to move more than 10 people at a time. Two other facilities estimated that they would be capable of moving between 20 and 25 people at a time. Only two facilities indicated that they could only move up to 5 and 6 patients at a time.

Each of the facilities require annual evacuation training for their personnel. Six of the six responses to this question indicated that nurses were required to be trained annually, but only 3 of the 6 indicated that doctors were required to be trained annually.

4.3 Survey Conclusions

The limited response to the survey was disappointing but helpful, and it indicated and foreshadowed the limited focus in this research area. The survey, however, provided us with a baseline knowledge of facility sizes and helped us identify points of contact with an interest in our work. Over the next two years, discussions with clinicians and presentations at healthcare conferences continued to confirm that patient prioritization during facility evacuations are rarely discussed - likely because of the associated highly ethical decisions and liabilities - but most everyone we presented the research idea to confirmed the potential research benefits.

Chapter 5

Markov Decision Process Model, Dynamic Programming, and Simulation

This chapter presents a basic, single server model used for determining priorities for evacuation selection decisions. The basic model is discussed and tested with dynamic programming and simulation. Most of the information within this chapter is based on a paper that was selected for publication in the Transportation Research Record [28].

First, the model parameters and assumptions are introduced. Next, the dynamic programming model is described and tested with six scenarios. Then, the optimal policies from the dynamic program are analyzed with discrete-event simulation. An additional simulation discussion follows where patient selection decisions are based on the time remaining in the evacuation window (as opposed to state-dependent policies resulting from the dynamic program).

5.1 Model Introduction

A complete evacuation from a healthcare facility would very likely be accomplished by multiple unit-, department-, or floor-level evacuations occurring simultaneously. Within each evacuation, an evacuation team - or multiple evacuation teams - would be responsible for moving the patients to safety, and these evacuation teams would likely consist of some subset of the clinicians who usually staff that area. The model presented in this chapter will be used to examine policies and create assumptions for evacuation guidelines. The model is designed to prioritize patients within floors or units instead of choosing patients from the entire set of patients throughout the facility as teams are unlikely to leave their patients.

Consider a system in which there are N jobs (patients) to be serviced (evacuated). After each evacuation, there are (N - 1) patients remaining in the system. In addition, a patient death also reduces the number of patients remaining in the system. Assuming that the evacuation and death transition rates are exponentially distributed, the system can be modeled as a Markov chain. If the N jobs are divided into groups that are classified by their transition rates (i.e., $N_1 + N_2 = N$), the state of the system can be represented by the number of both types of patients awaiting evacuation. When there are rewards and costs associated with decisions and transitions from each state, the system can be modeled as a Markov decision process. Therefore, there is an optimal sequence of selecting jobs for service. In this work, the optimal sequence of patient evacuations will maximize the overall expected reward.

In the case of a healthcare facility evacuation, patients abandon the system if they 1) are successfully transferred to another facility, 2) die waiting for evacuation, or 3) die during the evacuation. In the case of a forecasted emergency that requires an evacuation (i.e., hurricane), it is likely that the facility will discharge as many patients as possible to reduce the number of patient evacuations.

5.2 Model Parameters and Assumptions

During an evacuation, the staff must decide where they will allocate their resources for evacuating the next patient. The following parameters are used to determine how resources should be allocated. Let λ_i denote the rate of evacuating type i patients. The evacuation rate represents the time needed for the team to complete a patient transfer before starting a new patient. This rate can be interpreted differently and updated according to the role of the evacuation team. For example,

- Some evacuation teams may only be in charge of prepping patients for transfer, and separate teams of facility workers or emergency medical services (EMS) crews may transport patients from their rooms. Remember in Chapter 2, the minimum and maximum times to prepare a patient for transport were presented based on estimates from Johnson [83];
- An evacuation team could prep a patient in his room and then take him to a designated staging point for transport. Johnson [83] also presented estimates for the walking speeds to transport patients alone, in a wheelchair, or in a bed;
- An evacuation team may travel with a patient to the receiving facility and then return to the evacuating facility. In this case, λ_i is the time required for a round trip.

This rate may also include the time required to order and prepare medications, collect the medical record and any equipment, and physically prepare the patient for transportation.

During the evacuation process, there is a risk of mortality based on the patient's medical condition or the transportation conditions. Assume that a type i patient can be successfully evacuated with probability p_i (and, likewise, a patient will die during evacuation or transport with probability $(1 - p_i)$). Based on these parameters, the effective rate of a successful evacuations is $\lambda_i p_i$ for patient type i. During the evacuation process, the classification status of patients can also change as they wait for medical staff to move them to safety. Such transitions could occur because of a change in the patient's health status or because of his relative location to the emergency (i.e. non-critical care patients that are located close to a fire or exposed to a chemical or toxin could take longer to evacuate and have an increased death rate). Therefore, assume that a patient transitions to the other patient class at rate β_i. Such a transition would decrease the number of type i patients ($X_i - 1$) and increase the number of type j patients ($X_j + 1$). Finally, patients may perish as they wait for evacuation, and we denote the rate at which type i patients die as α_i. This can be thought of as the usual mortality rate of the patients though the rate may be increased due to the nature of the emergency. For example, exposure to a hazardous chemical could increase the patient death rates. In summary,

- X_i - denotes the number of type i patients in the system;
- λ_i - denotes the rate of evacuating type i patients;
- p_i - denotes the probability of a successful evacuation of a type i patient;
- β_i - represents the rate at which a type i patient becomes the other type; and
- α_i - denotes the death rate for type i patients while waiting for evacuations.

Each successful evacuation is associated with a reward, l_i^e, and each death is associated with a cost, l_i^d. These are assigned at the time a patient leaves the system. There could also be costs associated with holding type i patients in the system, so let h_i denote the cost of holding a type i. The holding rates are charged after every transition based on the number remaining to be evacuate. In summary,

- l_i^e - denotes the reward for a patient i evacuation;
- l_i^d - denotes the cost for a patient i death; and
- h_i - denotes the cost of holding a type i patient in the system.

5.3 Basic Two-Class Model

The dynamic programming and simulation models in this section consider evacuations where patients can be classified into one of two patient classes, usually assumed to be critical and non-critical care patients. It is fair to assume that certain scenarios, however, will alter these assumptions, and these will be discussed as they are presented.

In addition, the numeric tests described in this chapter will assume that there are 20 critical care patients and 20 non-critical care patients to be evacuated. Some of the values of the parameters listed in the previous section will be based on observations from two local mock evacuations since there is not data available for the models otherwise (see Appendix B for a discussion of data collected at mock evacuations). Most tests will assume that between 1 - 4 critical care patients can be evacuated per hour and between 2 - 6 non-critical care patients can be evacuated per hour. Because few of the papers described in Chapter 2 discuss any transportation-related deaths, the probability of a successful evacuation is assumed to be high.

The objectives of the models are to maximize a value. This can be thought of as a profit when holding costs are included for patients in the system. Without holding costs, the objective can be considered as maximizing reward where every successful evacuation contributes to the overall reward and every death costs.

Assume that there are N patients in the system that require service, and that these patients belong to either classification group, so there are N_1 Type 1 patients and N_2 Type 2 patients to be evacuated where $N_1 + N_2 = N$. The continuous-time state description of such a system can be defined by $(X_1(t), X_2(t))$, where $X_1(t)$ denotes the number of Type 1 patients remaining in the system ($X_1(t) \in \{0, 1, \ldots, N_1\}$) at time t, and $X_2(t)$ denotes the number of Type 2 patients remaining in the system ($X_2(t) \in \{0, 1, \ldots, N_2\}$) at time t.

5.3.1 Model Description

As previously mentioned, transitions can occur at any point in time t, so the state description includes continuous-time parameters. With uniformization techniques, the problem can be converted to an equivalent discrete-time problem. First used by Lippman in 1975 [102], all of the transition rates are scaled by the maximum rate of transition (refereed to as γ in this research). After uniformization is applied, "fictitious" transitions may be introduced, and all transitions happen at the same rate. If it was not time for the system to transition, the state will remain unchanged based on the fictitious transition. The state of the system for the discrete-time problem is (X_1, X_2) where X_i denotes the number of type i patients remaining in the system.

Let the policy π describe how to allocate resources for evacuating the next patient, based on the current state. Policy π is therefore a sequence of decisions $\pi = \{a_1, a_2, \ldots\}$, where a_k is a vector of actions to be taken based on the current state. Let Π be the set of all such policies. For the discrete time problem, let (X_1, X_2) represent the state of the system at time n and a_k denote the actions taken at time k under policy π. The resulting n-stage expected reward is given by

$$v_n(X_1, X_2) = E^{\pi}_{(X_1,X_2)}\left[\sum_{k=0}^{n-1} r(x_{1k}, x_{2k}, a_k(x_{1k}, x_{2k}))\right], \tag{5.1}$$

where $r()$ denotes the reward achieved at stage or time k. This leads to the optimal n-stage expected reward of

$$v^*_n(X_1, X_2) = \sup_{\pi\in\Pi} v^{\pi}_n(X_1, X_2). \tag{5.2}$$

For the evacuation prioritization decision making problem, the evacuation teams can choose from which patient class to evacuate the next patient. This leads to the following decision at any epoch:

$$\pi = \begin{cases} (\lambda_1, 0) & \text{evacuate type 1 next - Policy 1} \\ (0, \lambda_2) & \text{evacuate type 2 next - Policy 2} \end{cases}, \tag{5.3}$$

where λ_i denotes the selected evacuation rate and implies selection of a type i patient. Figure 5.1

below represents the state transition diagram if Policy 1 is applied at all decision points for a single server evacuation. For the purpose of the figure, assume that each patient class has 20 patients to be evacuated. The dashed lines represent the fictitious transitions used in uniformization. For this problem, the maximum rate of transition, $\gamma = \lambda_1 + \lambda_2 + N_1\alpha_1 + N_2\alpha_2$, is used to scale the rates in the Equation (5.3.1). Remember that N_i represents the total number of type i patients to be evacuated, and X_i represents the number of type i patients remaining in the system. Therefore, the fictitious transition rate - shown as a dashed line in Figure 5.1 - is $(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + \lambda_2$ when Policy 1 is chosen and $(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + \lambda_1$ when Policy 2 is chosen (not shown in a transition diagram).

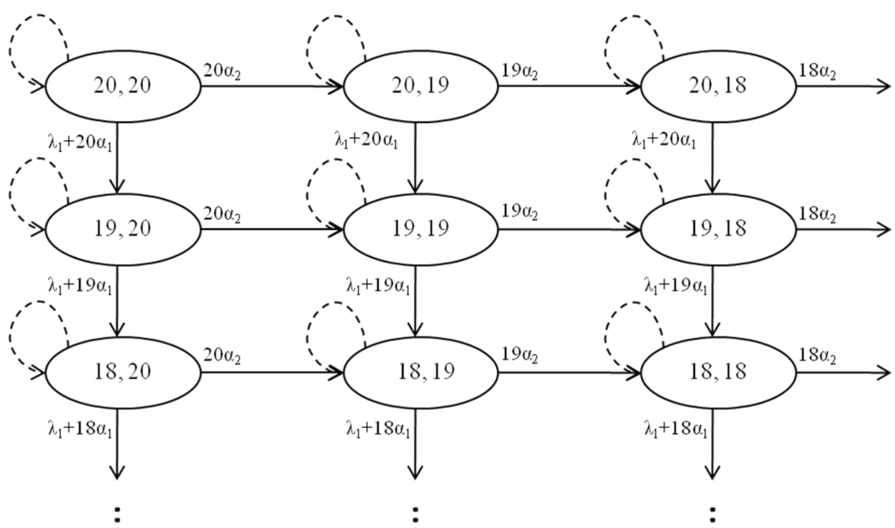


Figure 5.1: Transition diagram for the single server model when Policy 1 is chosen.

The optimality equation for the single server finite horizon evacuation decision problem shown below in Equation (5.3.1).

$$
\begin{aligned}
\nu(X_1, X_2) &= X_1\alpha_1\left[\nu(X_1 - 1, X_2) - l_1^d\right] + X_2\alpha_2\left[\nu(X_1, X_2 - 1) - l_2^d\right] - h_1X_1 - h_2X_2 \\
&+ \max\begin{cases} \lambda_1 p_1\left[\nu(X_1 - 1, X_2) + l_1^e\right] + \lambda_1(1 - p_1)\left[\nu(X_1 - 1, X_2) - l_1^d\right] + [(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + \lambda_2]\nu(X_1, X_2) \\ \lambda_2 p_2\left[\nu(X_1, X_2 - 1) + l_2^e\right] + \lambda_2(1 - p_2)\left[\nu(X_1, X_2 - 1) - l_2^d\right] + [(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + \lambda_1]\nu(X_1, X_2) \end{cases}
\end{aligned}
$$

The first two terms in Equation (5.3.1) represent patient deaths while waiting for evacuation. Based on the number of patients remaining in the system, a patient death - unrelated to the evacuation decision but dependent on the normal operations of the facility or the emergency type - will occur. When a patient death occurs, the number of patients waiting in the system is reduced and a penalty is assigned. The next two terms represent the costs of holding each patient type in the system. The final term represents the choice: either evacuate a Type 1 patient or a Type 2 patient. With both choices, there is a chance of an unsuccessful evacuation, so the number of patients in the system will be reduced, and either a reward or penalty will be assigned based on the probability of a successful evacuation. In addition, each decision is associated with a fictitious transition rate that is used for uniformization.

5.4 Numeric Tests and Initial Patient Selection Decisions

A dynamic program was created based on the work of Mayorga et al. [106]. The program reads the input parameters from a text file and returns the value of Policy 1 at each combination of (X_1, X_2), the value of executing Policy 2 at each combination of (X_1, X_2), the value of the optimality equation at each combination of (X_1, X_2), and the optimal sequence of decisions based on those parameters. See Appendix C for an example of the input and output files as well as discussion of the dynamic programming code.

For the purpose of continuity, assume that the floor, unit, or department has 20 critical care patients and 20 non-critical care patients to be evacuated. Within the following sections, the optimal patient selection policy is shown in a diagram. These diagrams indicate which patient should be evacuated (Type 1 or Type 2) for any combination of (X_1,X_2) which represents the number of Type 1 and Type 2 patients remaining in the system at that point in time. For these tests, values for (X_1,X_2) can range from (0,0) to (20,20). It is assumed, however, that a floor-, unit-, or department-level evacuation would not consist of 40 patients. Because dynamic programming works by solving problems recursively, the policy diagrams still apply for any subset of patients.

It is fair to assume that non-critical care patients have quicker evacuation rates, higher probabilities of successful evacuations, and slower death rates than critical care patients. Table 5.1 below summarizes the test parameters that will be used for the initial tests described in the remainder of this chapter.

Table 5.1: Summary of Test Parameters.

Parameter	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6
λ_1	2.5/hour	2.5/hour	2.5/hour	2.5/hour	2.5/hour	2.5/hour
λ_2	4/hour	4/hour	4/hour	4/hour	4/hour	4/hour
p_1	0.99	0.99	0.99	0.99	0.99	0.99
p_2	0.999	0.999	0.999	0.999	0.999	0.999
α_1	0.055	0.1	0.1	0.1	0.1	0.1
α_2	0.055	0.055	0.055	0.055	0.055	0.055
h_1	0	0	0.02	0.035	0.035	0.035
h_2	0	0	0.02	0.02	0.02	0.02
l_1^e	1	1	1	1	0	1
l_1^d	1	1	1	1	0	2
l_2^e	1	1	1	1	0	1
l_2^d	1	1	1	1	0	2

5.4.1 Maximizing Saved Lives

Let us first consider a case where the objective is to maximize the number of lives. In this case, the reward for a saved life is the same for both patient classes, and it is equal to the cost of a patient death for both patient classes ($l_i^e = l_i^d = 1$ for $i = 1, 2$). Assume that there is no cost for holding either type of patient in the system ($h_i = 0$ for $i = 1, 2$) and that patients will never transition to the other type of patient ($\beta_i = 0$ for $i = 1, 2$). In most evacuation settings, it is logical to assume that patient transfer times are lower for the less critical patients, and that this group of patients is less likely to die during transport (have higher probabilities of successful evacuation). However, assume the unlikely case that these patients also have a quicker rate of death while waiting for evacuation. Therefore, assume that

- The rate of a successful evacuation rate is higher for Type 2 patients than it is for Type 1 patients, and

- Type 2 patients die at a quicker rate while waiting for evacuation than Type 1 patients.

These observations lead to the following property:

Property 1. *For a 2-class system as shown in Equation (5.3.1), $\lambda_i p_i \geq \lambda_j p_j$ and $\alpha_i \geq \alpha_j$ implies priority should always be given to type i patients.*

Though this property has not yet been proven, intuitively, however, it makes sense that removing such patients first would maximize the objective function. Consider the parameters given for Test 1 in which the conditions of Property 1 are satisfied. Priority should be given to all Type 2 patients first. This means that all Type 2 patients should be evacuated first before beginning to evacuate any Type 1 patients. Figure 5.2 shows the optimal policy diagram for this “greedy” policy. In a greedy policy, the choice is to completely evacuate all of one patient type before beginning to evacuate any from the other.

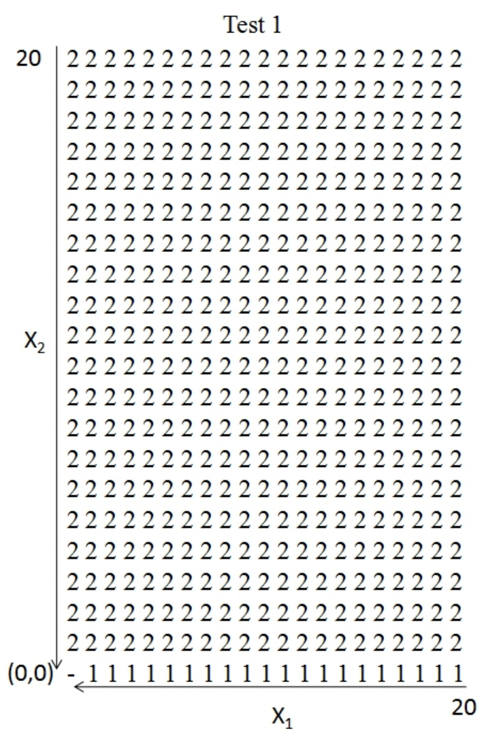


Figure 5.2: Initial observations - Test 1 policy decisions.

To illustrate Property 1, we have assumed that Type 1 and Type 2 patients die at the same rate for Test 1. While this could occur based on the type of threat and the location of the patients in a facility, $\alpha_1 = \alpha_2$ is not the typical case. Instead, it is fair to assume that critical care patients would die at a faster rate than non-critical care patients. To examine this more typical case, assume the Test 2 parameters. Now, assume $\alpha_1 > \alpha_2$, and all other conditions are the same as described above for Test 1. The objective is still to maximize the number of evacuees that leave the system. The policy structure for this case is shown in Figure 5.3. Notice how the optimal sequence of decisions chooses non-critical care patients when there are larger numbers of both patient classes still in the system waiting to be evacuated. As we transfer the non-critical care patients - and patients from both groups die while waiting to be evacuated - there will be a point at which priority should switch to the critical care patients. All critical care patients remaining in the system would be evacuated before returning attention to non-critical care patients.

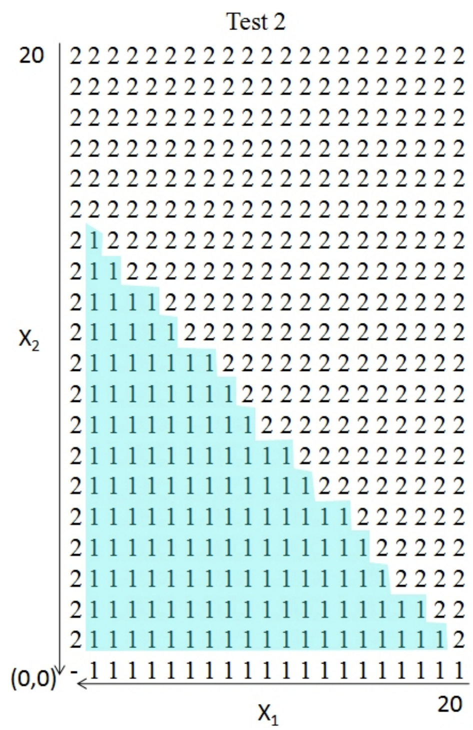


Figure 5.3: Initial observations - Test 2 policy decisions.

5.4.1.1 Including Holding Costs

In Section 5.4.1, the objective was to maximize the number of lives saved (where $l_1^e = l_1^d = l_2^e = l_2^d = 1$), with no consideration for how long each patient waits in the system for evacuation. By including non-zero holding costs ($h_i \neq 0$) in Equation (5.3.1), the model now considers the speed at which patients are leaving the system to avoid penalties from holding them in the system. As mentioned before, holding rates are charged after every transition based on the number still in the system, while rewards and penalties are assigned when a patient leaves the system. Now, the model is driven by getting the most number of evacuees out as quickly as possible.

Using the same parameter values for Test 2, we now include $h_1 = h_2 = 0.02$ for Test 3 (please refer back to Table 5.1 for parameter values). In this case the policy is greedy and recommends evacuating all patient non-critical patients first (the policy diagram is not shown as it is the same as Test 1, shown in Figure 5.2). Recall that the optimal policy in Test 2 requires switching between choosing Type 2 and Type 1 depending on how many patients remain in the system. By including holding costs, we now choose to evacuate all non-critical care patients first (i.e., the policy is greedy and is optimal for both Tests 1 and 3). Since these patients have a higher evacuation rate, we can add more value to the objective function by getting more patients out quickly.

Note that "equal holding costs" does not imply that the group that can be evacuated more quickly will always be chosen for transport first. The resulting policy depends on the other input parameters discussed in this section, but it has been shown that the addition of holding costs can change a switching policy to a greedy policy. As a comparison, the following test sets unequal holding costs for the critical and non-critical care patients. Assuming that it costs more to hold a critical care patient in the system ($h_1 = 0.035$ and $h_2 = 0.02$), Test 4 is discussed again in the following section, and Figure 5.4 contains the optimal policy structure for selecting patients for evacuation.

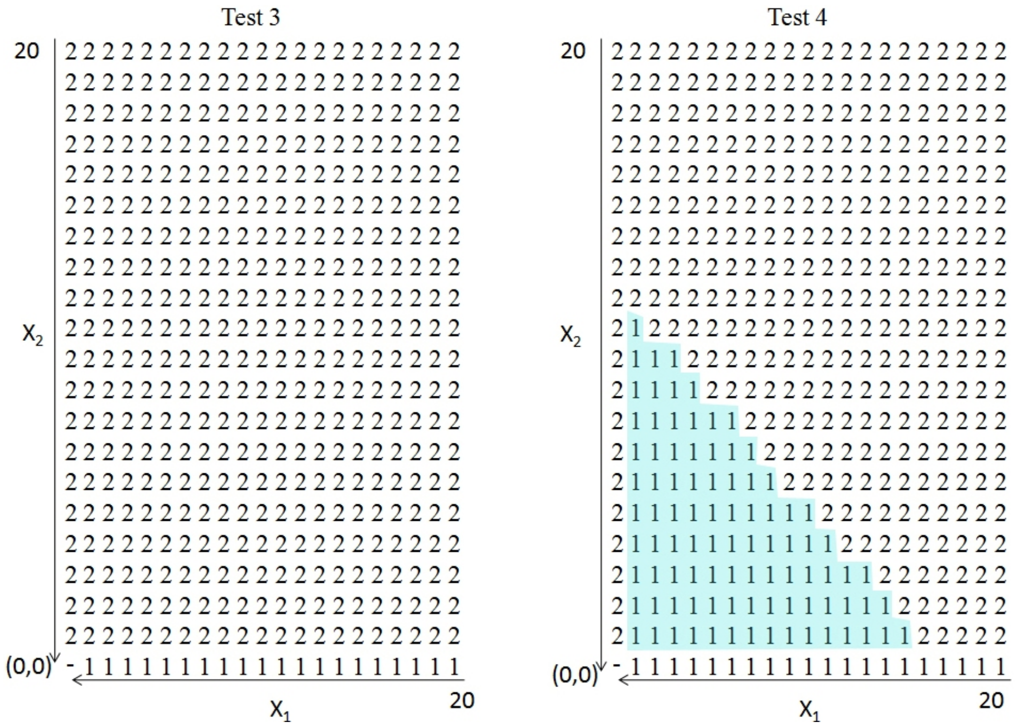


Figure 5.4: Initial observations - Tests 3 and 4 policy decisions.

5.4.2 Initial Ethical Observations

One of the more interesting pieces of this research is determining the objective that best balances the ethical principles. This involves considering the information available in the medical record, estimating costs and rewards, and determining the best way to incorporate these into the model. In this section, consider how we place and model value on transferring patients, patient deaths, and keeping patients in the system. As shown in the previous sections, the optimal policies can change with the addition of and choices for evacuation rewards, death penalties, and holding costs.

In Figure 5.5, we compare three scenarios for how rewards and costs are weighed into the objective function. Beginning with Test 4 ($h_1 = 0.035 > h_2 = 0.02$) as discussed in the previous section, the optimal policy varies between selecting a critical care or non-critical care patient next based on the remaining number in each class. In Test 5, we then consider a case that places no value on saved or lost lives (i.e., only holding costs are used). Since this objective focuses on the cost of those patients not evacuated yet, we would more often want to evacuate non-critical patients as opposed to critical patients. This is observed by the slight shift in the threshold for when the policy switches between Type 1 and 2. Finally, Test 6 compares making a death twice as costly as the saving of a life (as opposed to Test 4 where the cost and reward are the same). All other input parameters are identical for the tests. Now, we observe that critical care patients have more of an increased priority than in Test 4 (i.e., the shaded region of 1s is larger).

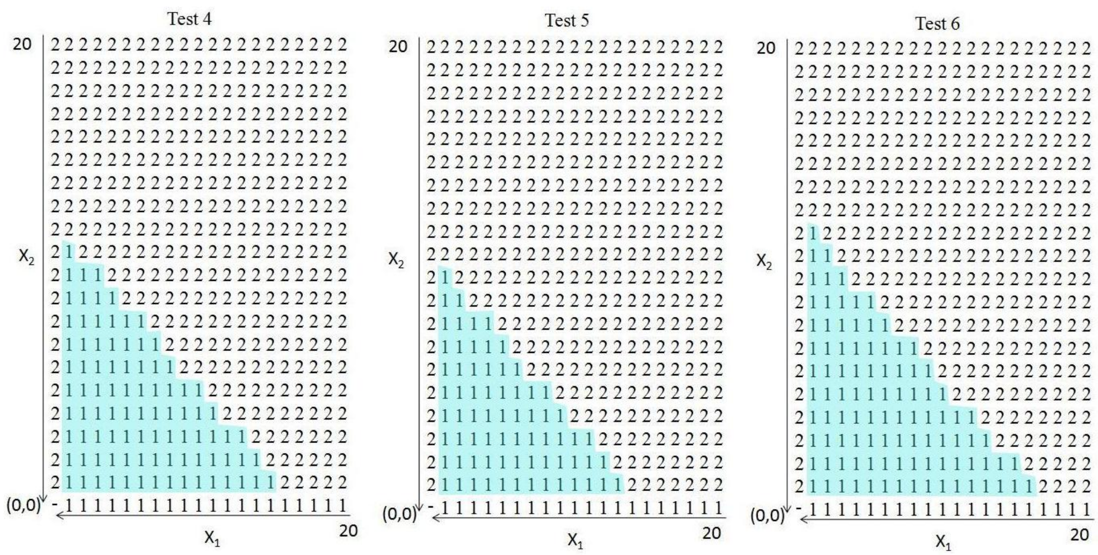


Figure 5.5: Initial observations - Tests 4, 5, and 6 policy decisions.

5.4.3 Additional Dynamic Programming Observations

First, note that when the optimal policy is a switching policy, the Type 1 regions form triangles. In their research, Argon et al. [10] show that the "triangle heuristic" os a good representation of the optimal policy.

While we can make several valuable observations concerning which patient class to transfer at various time epochs, we can also discern evacuation performance by modeling these policies using simulation. Note that the above analysis assumes an infinite horizon. In reality, there is likely some finite time available for decisions to be made. In some situations, patients may be left behind. An impending threat could mean that every patient dies when the disaster occurs. In other situations, patients may not die, but the availability of quality healthcare would decrease and therefore their death rates would likely increase. Now, such situations can be described and modeled using simulation.

5.5 Patient Selection Decisions with Simulation

This section describes a simulation model that was created to 1) test the policies generated by the dynamic program and 2) examine other scenarios that complicate a dynamic programming model. For a discussion of how the simulation model works, please see Appendix D.

Again, each test considers a population of 40 (N_1= 20 critical care patients and N_2 = 20 non-critical care patients). The tests in the following sections, Sections 5.5.1, 5.5.2, and 5.5.3 are for 250 replications each. This resulted in extremely small confidence intervals on the true mean of each performance measure recorded (typically, the half-width value for the number of evacuees was less than 0.3 and less than 0.2 for deaths and evacuation times).

5.5.1 Simulating Dynamic Programming Policies

The dynamic program generates a policy structure but does not return any statistics that represent the performance of that policy. Therefore, the suggested patient selection decisions are embedded into the simulation to determine the number of evacuees and deaths as well as the time to complete the evacuation process. Based on the input values including the number of patients in each class to be evacuated, the evacuation rates, the death rates, and the probability of a successful evacuation; the evacuation window; and the prioritization strategy (see Appendix D), the simulation returns the following statistics:

- The percentage of incomplete evacuations based on the given evacuation window;
- The total number of Type 1 and Type 2 evacuees;

- The total number of Type 1 and Type 2 deaths; and
- The average completion time (the time taken to completely clear the system of all patients).

Table 5.2 summarizes the performance measures of the policies suggested for Tests 1 - 6 in the previous section. We run each test as if there are two evacuation windows: 8 and 16 hours. In some cases, there may not be enough time to completely evacuate, and this is reflected in the table as well under the "*Complete*" column. This column indicates the percentage of completed evacuations - or the percentage of runs in which the system was completely cleared during the given evacuation window.

Table 5.2: Average Performance Measures of Dynamic Programming Policies.

Evacuation Window	Test No.	Complete (%)	Total Type 1 Evacuees	Total Type 2 Evacuees	Total Type 1 Deaths	Total Type 2 Deaths	Number of Lives Saved	Average Completion Time (hours)
8 hours	1	31.6	9.272	16.18	7.548	3.82	14.084	7.7843
8 hours	2	55.2	9.5680	14.232	9.828	4.804	9.168	7.3556
8 hours	3	60.8	7.924	16.216	10.808	3.784	9.548	7.2988
8 hours	4	57.6	8.372	15.092	10.488	4.492	8.484	7.2947
8 hours	5	54.4	7.5720	15.608	10.7	4.236	8.244	7.3771
8 hours	6	60	8.656	14.908	10.412	4.592	8.56	7.287
16 hours	1	100	12.008	16.18	7.992	3.82	16.378	8.8993
16 hours	2	100	10.0960	15.128	9.904	4.872	10.448	7.8266
16 hours	3	100	8.98	16.216	11.02	3.784	10.392	7.7652
16 hours	4	100	9.328	15.484	10.672	4.516	9.6124	7.7775
16 hours	5	100	8.984	15.756	11.016	4.244	9.48	8.0304
16 hours	6	100	9.456	15.368	10.544	4.632	9.648	7.7539

Tests 1 and 3 are greedy policies and are run by evacuating all non-critical patients before starting to evacuate critical patients. The input parameters are the same for both tests except α_1. For Test 2 and each test after, the death rate increases to almost twice the rate for critical care patients. Notice that Tests 1 and 2 have the highest percentage of incomplete evacuations in an 8-hour evacuation window; these are the only two tests that do not consider holding costs.

Tests 2, 4, 5, and 6 have similar switching curves, so their performance is very similar. It is interesting, however, to note the effect of the objective on the results. For example, the only difference in the parameters of Tests 2 and 3 is that holding costs are introduced in Test 3. We see that doing this actually saves fewer lives (10.392 versus 10.448 for a 16-hour window), but the objective is weighted to reduce the total number waiting, not simply the total number evacuated as in Test 2. Figure 5.7 graphically depicts the simulation results from Test 2. It shows the number of evacuees of each patient type for evacuation windows between 1 and 16 hours as well as the percentage of incomplete evacuations in a given time window (over 250 replications).

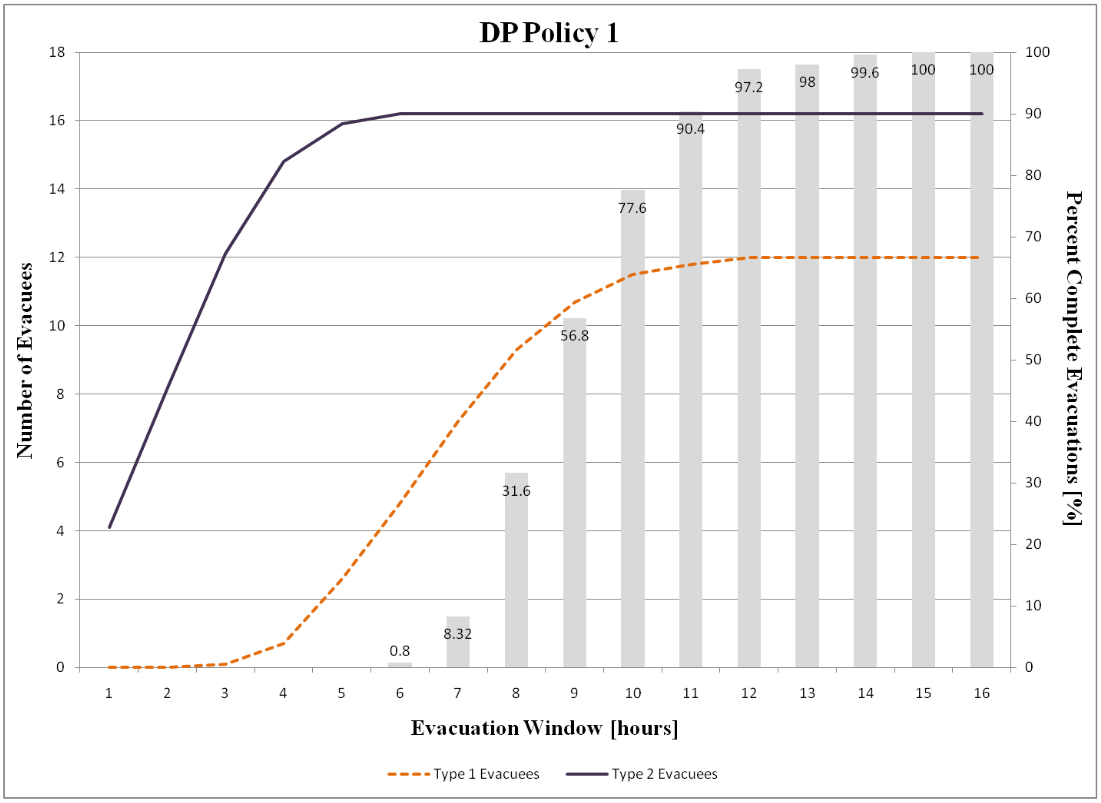


Figure 5.6: Simulation results for DP policy - Test 1.

Tests 3 and 4 have the same input parameters except it is more expensive to hold Type 1 patients in Test 4. This changes the policy from a greedy policy (Test 3) to another switching policy where it is better to evacuate non-critical care patients when there are greater numbers of both types of patients in the system and evacuate critical patients when the number of patients remaining in both classes is low.

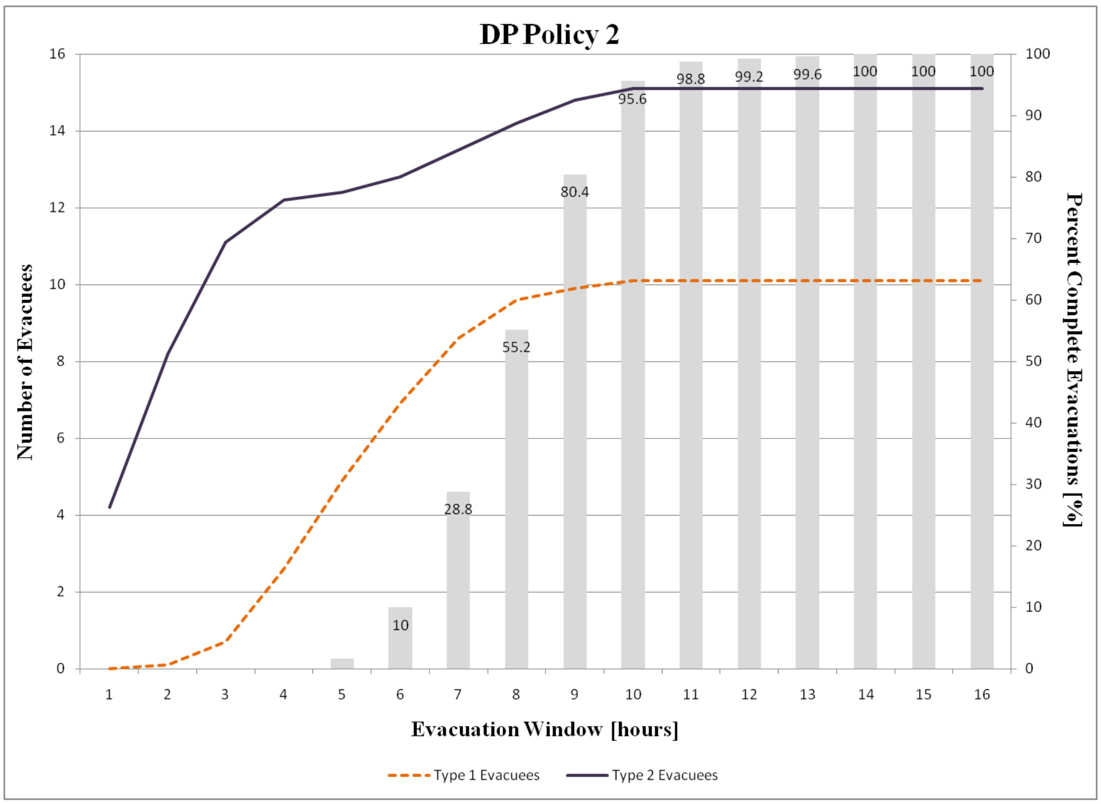


Figure 5.7: Simulation results for DP policy - Test 2.

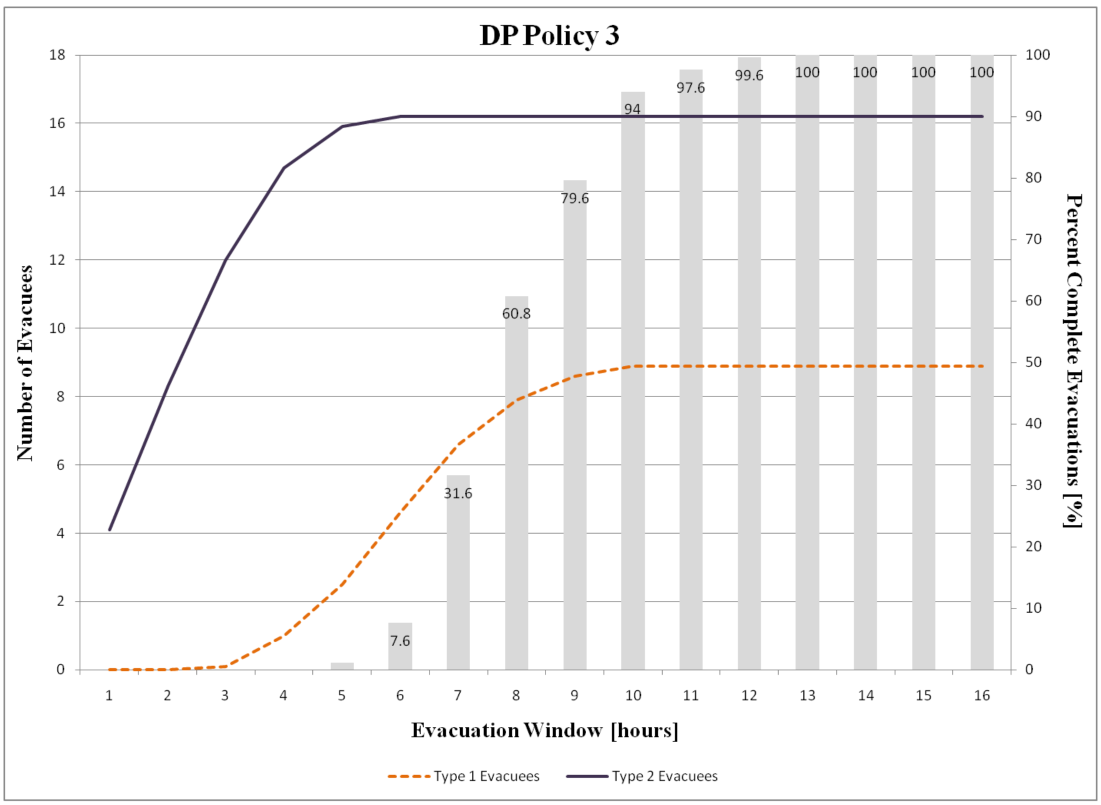


Figure 5.8: Simulation results for DP policy - Test 3.

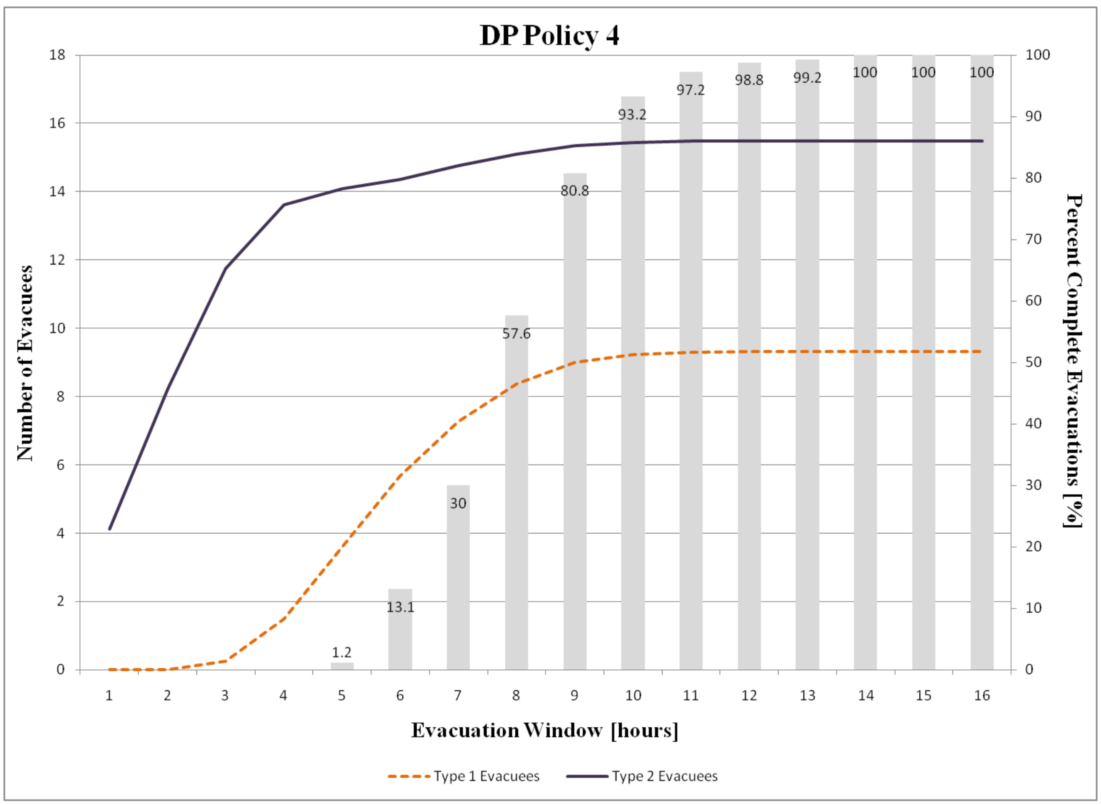


Figure 5.9: Simulation results for DP policy - Test 4.

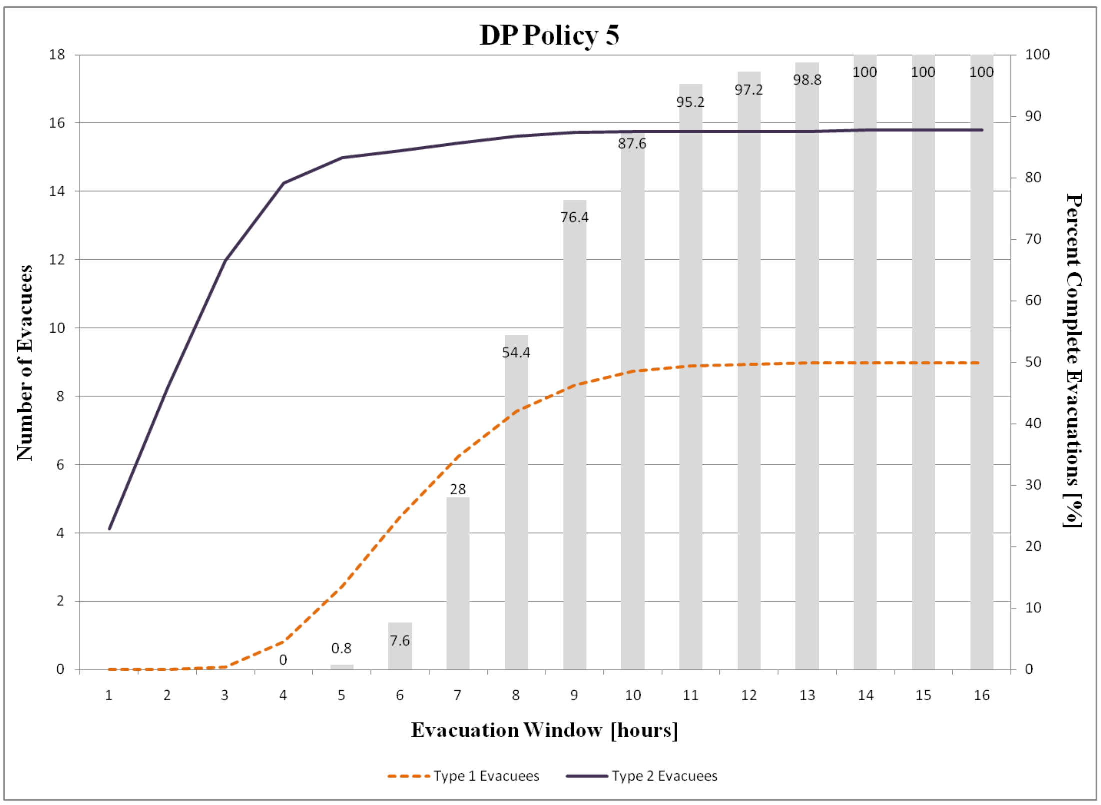


Figure 5.10: Simulation results for DP policy - Test 5.

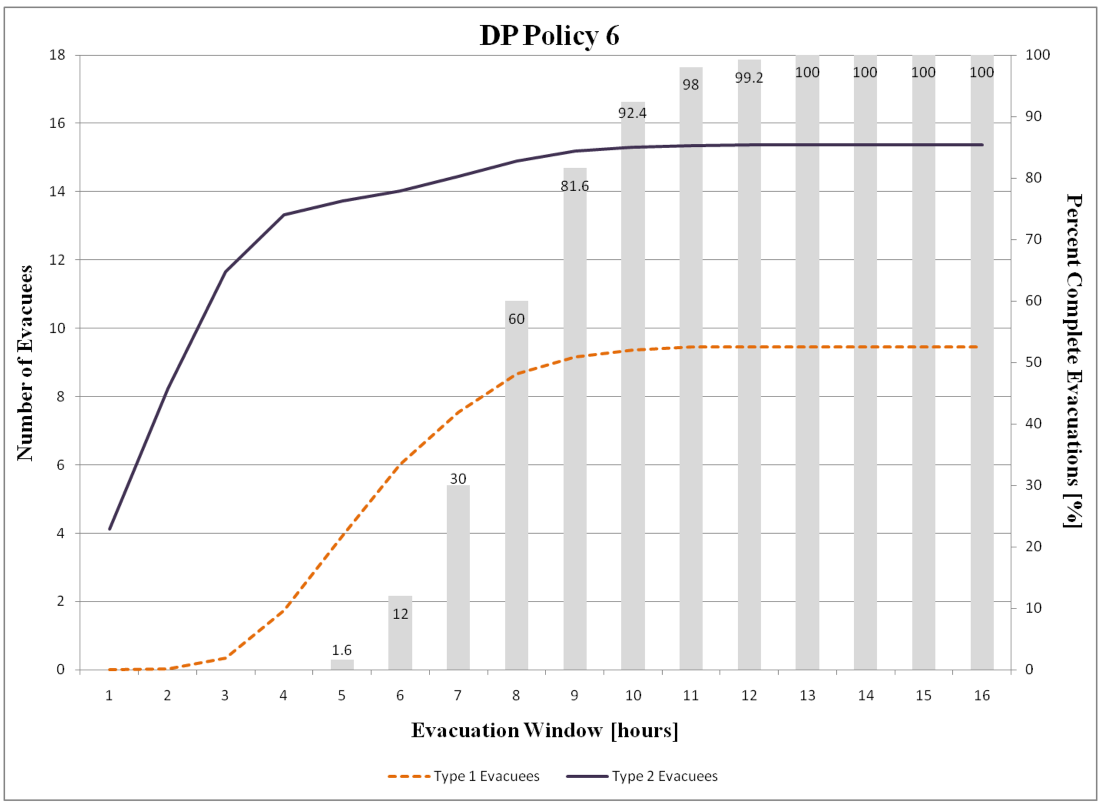


Figure 5.11: Simulation results for DP policy - Test 6.

5.5.2 Policy Comparisons with Simulation

In this section, the performance of the dynamic programming policies, including the number of evacuees, deaths, and saved lives, as well as the average evacuation completion time (as shown in Table 5.2 above), is compared to the performance of the all-or-nothing, greedy policies that suggested in the literature or used in practice. For each combination of parameters, there are two additional simulation runs to compare to the optimal policy: all Type 1 patients are evacuated first and all Type 2 patients are evacuated first. Table 5.3 represents an 8-hour evacuation window, and Table 5.4 represents a 16-hour window. The simulation only uses the rates of evacuation and death, as well as the probabilities of successful evacuation as input parameters. Because the only difference in Tests 2 - 6 were the rewards and costs, the simulation output for a greedy Type 1 policy is the same for Tests 2 - 6, and the simulation output for a greedy Type 2 policy is the same. However, they are listed in the table to compare to the results of simulation of the dynamic programming policies.

Table 5.3: Comparison of the Optimal Policies with Greedy Policies - 8 Hours.

Evacuation Window	Test No.	Complete (%)	Total Type 1 Evacuees	Total Type 2 Evacuees	Total Type 1 Deaths	Total Type 2 Deaths	Number of Lives Saved	Average Completion Time (hours)
Type 1	1	28.4	14.78	7.696	5.076	7.604	9.796	7.7829
DP	1	31.6	9.272	16.18	7.548	3.82	14.084	7.7843
Type 2	1	31.6	9.272	16.18	7.548	3.82	14.084	7.7843
Type 1	2	45.6	12.96	9.42	7.004	7.484	7.892	7.5874
DP	2	55.2	9.5680	14.232	9.828	4.804	9.168	7.3556
Type 2	2	60.8	7.924	16.216	10.808	3.784	9.548	7.2988
Type 1	3	45.6	12.96	9.42	7.004	7.484	7.892	7.5874
DP	3	60.8	7.924	16.216	10.808	3.784	9.548	7.2988
Type 2	3	60.8	7.924	16.216	10.808	3.784	9.548	7.2988
Type 1	4	45.6	12.96	9.42	7.004	7.484	7.892	7.5874
DP	4	57.6	8.372	15.092	10.488	4.492	8.484	7.2947
Type 2	4	60.8	7.924	16.216	10.808	3.784	9.548	7.2988
Type 1	5	45.6	12.96	9.42	7.004	7.484	7.892	7.5874
DP	5	54.4	7.5720	15.608	10.7	4.236	8.244	7.3771
Type 2	5	60.8	7.924	16.216	10.808	3.784	9.548	7.2988
Type 1	6	45.6	12.96	9.42	7.004	7.484	7.892	7.5874
DP	6	60	8.656	14.908	10.412	4.592	8.56	7.287
Type 2	6	60.8	7.924	16.216	10.808	3.784	9.548	7.2988

First, notice that a 16-hour window was enough to completely evacuate all patients at the input

Table 5.4: Comparison of the Optimal Policies with Greedy Policies - 16 Hours.

Evacuation Window	Test No.	Complete (%)	Total Type 1 Evacuees	Total Type 2 Evacuees	Total Type 1 Deaths	Total Type 2 Deaths	Number of Lives Saved	Average Completion Time (hours)
Type 1	1	100	14.912	11.944	5.088	8.056	13.712	8.9077
DP	1	100	12.008	16.18	7.992	3.82	16.376	8.8993
Type 2	1	100	12.008	16.18	7.992	3.82	16.376	8.8993
Type 1	2	100	12.992	12.192	7.008	7.808	10.363	8.3098
DP	2	100	10.0960	15.128	9.904	4.872	10.4448	7.8266
Type 2	2	100	8.98	16.216	11.02	3.784	10.392	7.7652
Type 1	3	100	12.992	12.192	7.008	7.808	10.363	8.3098
DP	3	100	8.98	16.216	11.02	3.784	10.392	7.7652
Type 2	3	100	8.98	16.216	11.02	3.784	10.392	7.7652
Type 1	4	100	12.992	12.192	7.008	7.808	10.363	8.3098
DP	4	100	9.328	15.484	10.672	4.516	9.6124	7.7775
Type 2	4	100	8.98	16.216	11.02	3.784	10.392	7.7652
Type 1	5	100	12.992	12.192	7.008	7.808	10.363	8.3098
DP	5	100	8.984	15.756	11.016	4.244	9.48	8.0304
Type 2	5	100	8.98	16.216	11.02	3.784	10.392	7.7652
Type 1	6	100	12.992	12.192	7.008	7.808	10.363	8.3098
DP	6	100	9.456	15.368	10.544	4.632	9.648	7.7539
Type 2	6	100	8.98	16.216	11.02	3.784	10.392	7.7652

value settings chosen for these simulation runs. Therefore, examine Table 5.4 and notice that the number of saved lives is as good as or greater than the number of saved lives when one of the greedy policies is chosen for Tests 1 and 2. These are the only two tests that did not include holding costs. In Tests 3 - 6, holding costs were included so that the objective included more than just a reward for an evacuee and a penalty for a patient death (in Test 5, however, only holding costs are considered; remember that there was no reward for an evacuee or cost for a death). When the holding costs are introduced in the models, additional costs are incurred at every transition based on the number of patients remaining in the system.

The differences in the performance are at the heart of one of the issues surrounding this research: any policy decisions that maximize the number of saved lives would likely be preferred to those that include additional costs by most stakeholders, except for perhaps the administrators. The fact that the number of saved lives is similar for the greedy policies and the switching policies — and the time to complete an evacuation is similar — is likely due to the fact that the rates at which the two patient types are leaving the system are similar for the values chosen. For example, Type 1 patients are evacuated at a rate of 2.5/hour, and they die while waiting at a rate of 0.1 per hour;

and Type 2 patients are evacuated at a rate of 4/hour, and they die while waiting at a rate of 0.055 per hour (the probability of a successful evacuation was very high for both at 0.99 and 0.999 for Type 1 and Type 2 patients, respectively). These results prompt the need for further testing and comparisons.

5.5.3 Patient Selection with Simulation

For the following tests, consider now that the policy is based on the amount of time until the disaster occurs rather than the number of patients in the system. In order to test these policies, a switch time is imposed for stopping the evacuation of one group and beginning the evacuation of the other. That is, the evacuation begins by evacuating either type of patient. For example, assume that the evacuation begins with Type 2 patients. At the switch time, the simulation would switch to Type 1 patient evacuations and clear this group before completing any remaining Type 2 evacuations.

Each 15-minute increment of time between the start of the evacuation and the end of the evacuation window is evaluated as a possible switch time. Using Arena's OptQuest optimization package, the optimal switch time is determined to be the time that maximizes the number of evacuees minus the number of deaths.

First, two of the tests from the previous sections, Tests 1 and 2, were chosen for testing in order to compare the number of evacuees when the optimal policy decisions are based on the number of patients remaining in the system (Table 5.2) to a policy driven by time (see Table 5.5 below). Table 5.5 includes the new information on the switch time as well as the number of lives saved when the switch is made at that time. In addition, two new scenarios, Tests 7 and 8, are presented in which slower death and evacuation rates were used. In particular, the death rates are now set to between 0.004 deaths/hour and 0.01 deaths/hour and more accurately represent non-catastrophic emergency events and provide a sense of how frequently deaths could occur within a controlled, mass patient transfer or evacuation. As a result, the simulations also now require a 24-hour window since a full evacuation cannot be completed in 16 hours (patients do not perish as quickly and, therefore, must still be evacuated).

Table 5.5: Suggested Switching Times.

Test No.	λ_1	p_1	α_1	λ_2	p_2	α_2	Evacuation Window (hours)	Number of Saved Lives - Start with Type 1	Time to Switch From 1 - 2	Number of Saved Lives - Start with Type 2	Time to Switch From 2 - 1
1	2.5	0.99	0.055	4	0.999	0.055	8	13.9	0	13.0	3.25
1	2.5	0.99	0.055	4	0.999	0.055	16	16.3	0	16.0	3.25
2	2.5	0.99	0.1	4	0.999	0.055	8	10.3	0	9.3	2.0
2	2.5	0.99	0.1	4	0.999	0.055	16	11.3	1.0	11.3	0.25
7	1.33	0.99	0.01	3	0.999	0.004	8	16.6	0	15.2	6.0
7	1.33	0.99	0.01	3	0.999	0.004	16	26.5	0.5	23.5	4.25
7	1.33	0.99	0.01	3	0.999	0.004	24	29.5	7.0	29.4	0
8	2	0.99	0.006	2	0.999	0.006	8	12.7	0.75	12.7	5.0
8	2	0.99	0.006	2	0.999	0.006	16	26.7	2.25	26.6	2.25
8	2	0.99	0.006	2	0.999	0.006	24	30.4	2.0	30.5	0

Consider Test 1. If the plan is to start evacuating Type 1 patients, the simulation shows an optimal switch time at $t = 0$ which implies that we should start evacuating Type 2 patients first. Remember that the dynamic program suggested this greedy policy as well. For an 8-hour evacuation, the simulations show 13.8 lives saved (evacuees minus deaths) in Table 2 and 13.9 lives saved in Table 5.5. The times to switch from Type 2 to Type 1 are 3.25 hours for both evacuation windows as a full evacuation takes approximately 8 hours.

It is expected that the time to switch from Type 1 patients to Type 2 patients would increase and the time to switch from Type 2 patients to Type 1 patients would decrease as the available evacuation window increased when Type 1 patient die at a faster rate (Tests 7 and 8).

In Test 8, the patient types have the same parameters except for the probabilities for successful evacuation, and therefore the switch time is not as important and the number of lives saved is similar during each evacuation window.

5.6 Conclusions from the Single Server Model

This chapter presented and discussed the first dynamic programming and simulation tests for healthcare facility evacuations. Based on these tests, the following trends were observed:

- A policy can be categorized as either 1) a greedy, Type 1 policy; 2) a greedy, Type 2 policy; or 3) a switching policy.
- There is at most one switch.
- Any switching policy for critical and non-critical care patients starts by evacuating non-critical care patients and then switches to evacuate all remaining critical care patients.

The results presented in this chapter has limited ability for direct implementation by practitioners, and it would be unfair to assume that the clinical staff would have all of the suggested input parameters to run these models. Therefore, the aim of the following chapters is to identify generic policies or characteristics of the optimal policy that would improve decision making during an emergency evacuation.

Chapter 6

Properties of the Single Server Model

The purpose of this chapter is to further investigate the single server evacuation model (presented in the previous chapter) and determine properties of the optimal solutions that will in turn provide insights into patient selection decisions. Section 6.1 describes a sensitivity analysis for critical and non-critical care patients, and the trends and observations from these tests are discussed in Section 6.2. For the discussion in this chapter, it is assumed that the reward resulting from a complete patient evacuation is the same for both patient classes, and in addition, the value is equal in magnitude to the cost of a lost life from either of the patient classes. That is, $l_1^e = l_2^e = l_1^d = l_2^d = 1$. This assumption follows the utilitarian logic: every patient counts equally towards the greater good such that no patient is considered more valuable than another.

When patients are categorized as critical and non-critical care patients, it is assumed that

1. Non-critical patients can be evacuated more quickly than critical care patients.
   - $\lambda_1 < \lambda_2$
2. Non-critical patients have a higher probability of a successful evacuation.
   - $p_1 < p_2$
3. Critical care patients die while waiting at a quicker rate than non-critical patients.
   - $\alpha_1 > \alpha_2$

6.1 Sensitivity Analysis

In order to investigate how the input parameters affect the optimal policy, a sensitivity analysis was performed to examine the location of the switching curve in the optimal policy diagram (the switching curve may be so low or so high that a switch does not exist; therefore, the optimal policy is a greedy policy). Figures 6.1 and 6.2 illustrate the movement of the switching curve. Incremental changes to the input parameters can create small shifts in the location of the switching curve and therefore the size of the classification regions, and eventually the relationships may lead to greedy policies.

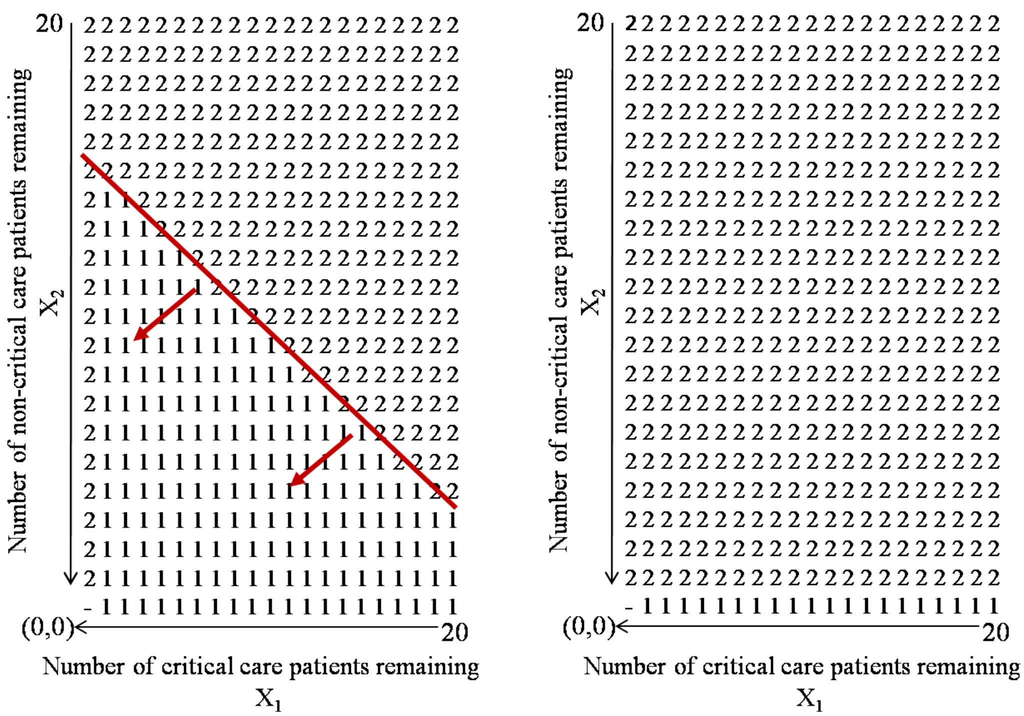


Figure 6.1: Optimal policy diagrams: Switching curve moving down.

A full factorial design of experiments (DOE) was created to study the effects of the input parameters. In order to decrease the number of runs, the ratios of the eight input parameters (λ_1/λ_2, p_1/p_2, α_1/α_2 and h_1/h_2) were selected as the adjustable factors. The parameters for the Type 2 patients were held constant while the parameters for the Type 1 patients were varied. With three

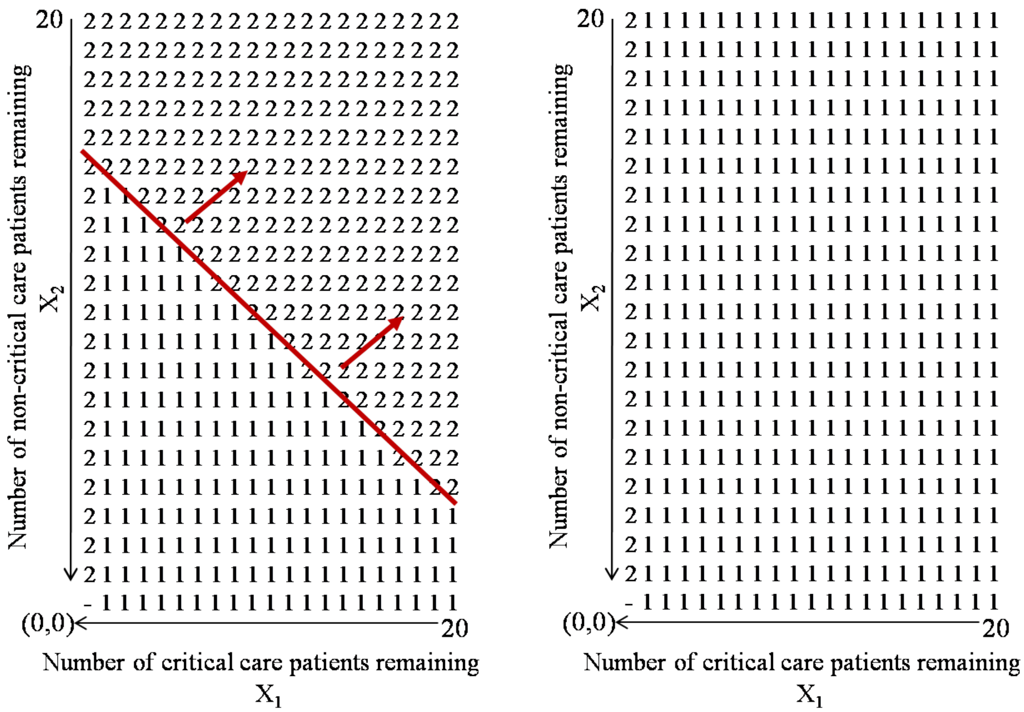


Figure 6.2: Optimal policy diagrams: Switching curve moving up.

levels for each of the ratios - low, medium, and high - required only 81 runs to account for ratio changes as opposed to 6,561 if all eight parameters were examined separately!

6.1.1 Sensitivity Analysis Setup and Output

The design of experiments tests are described below, and then a discussion of the additional analysis follows. The values chosen to remain constant for the Type 2 patients are shown in Table 6.1, and Table 6.2 includes the parameter settings chosen to be varied.

Table 6.1: Constant DOE Parameters for Sensitivity Analysis of the Single Server Model

λ_2	p_2	α_2	h_2
4 patients/hour	1.0	0.001 patients/hour	0.02

An example of the output for one run is shown here, and the output from the other runs has been submitted in the electronic appendices (please see the file "Sensitivity Analysis.xlsx"). The first

Table 6.2: Variable DOE Parameters for Sensitivity Analysis of the Single Server Model

Parameter	Low	Medium	High
λ_1	2	3	3.5
p_1	0.5	0.75	0.95
α_1	0.025	0.05	0.075
h_1	0.01	0.02	0.03

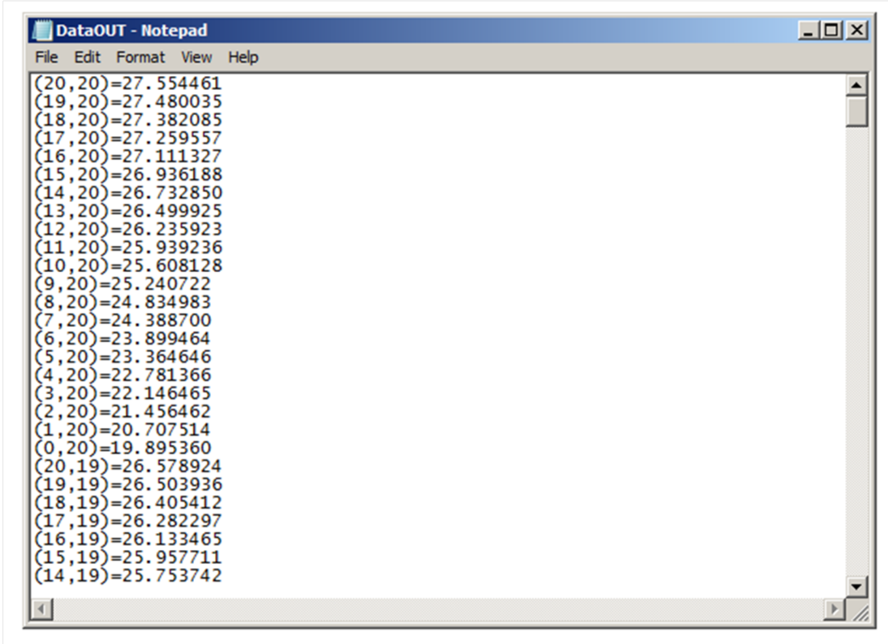
run (DOE #1) was chosen to be an example for the discussion of the steps taken in the sensitivity analysis. The parameter settings for DOE #1 were as shown in Table 6.3.

Table 6.3: Parameters Settings for DOE Test #1

Type	λ	p	α	h
1	2 patients/hour	0.5	0.05 patients/hour	0.02
2	4 patients/hour	1.0	0.001 patients/hour	0.02

The dynamic program generates multiple output files including a list of the resulting value function at each combination of (X_1, X_2) (see Figure 6.3). This value represents the expected average reward associated with starting to evacuate patients in that particular state. These values, for each (X_1, X_2) can be copied into Excel relatively quickly and arranged in a matrix of corresponding X_1 and X_2 rows and columns (see Figure 6.4). Though not labeled, the rows represent a fixed number of Type 1 patients, and the columns represent a fixed number of Type 2 patients. Therefore, the value circled in the figure represents the expected average reward of an evacuation starting with four Type 1 patients and nineteen Type 2 patients remaining in the system. This format is opposite of the method for displaying the optimal policy diagrams. In addition, the optimal policy diagrams reduce to $(0, 0)$ in the bottom, left corner, and the figure shows the value for $(0, 0)$ in the bottom, right corner.

In addition to the list of values, the dynamic program generates a text file with the optimal policy choice (1 or 2) for each (X_1, X_2). These values are copied into a template to create the optimal policy diagrams that were introduced in Chapter 5. In order to better visualize the trends, two graphs were created: one that shows the value function at fixed values of X_1 and another that



```
(20,20)=27.554461
(19,20)=27.480035
(18,20)=27.382085
(17,20)=27.259557
(16,20)=27.111327
(15,20)=26.936188
(14,20)=26.732850
(13,20)=26.499925
(12,20)=26.235923
(11,20)=25.939236
(10,20)=25.608128
(9,20)=25.240722
(8,20)=24.834983
(7,20)=24.388700
(6,20)=23.899464
(5,20)=23.364646
(4,20)=22.781366
(3,20)=22.146465
(2,20)=21.456462
(1,20)=20.707514
(0,20)=19.895360
(20,19)=26.578924
(19,19)=26.503936
(18,19)=26.405412
(17,19)=26.282297
(16,19)=26.133465
(15,19)=25.957711
(14,19)=25.753742
```


Figure 6.3: Sample output file: “DataOUT.txt” for DOE Run #1.

DOE1	20	19	18	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
20	-14.0546	-13.8162	-13.6081	-13.4302	-13.2827	-13.1654	-13.0784	-13.0216	-12.9951	-12.9987	-13.0326	-13.0967	-13.1909	-13.3153	-13.4698	-13.6545	-13.8694	-14.1143	-14.3894	-14.6946	-15.0298
19	-12.377	-12.158	-11.9693	-11.8111	-11.6833	-11.5858	-11.5187	-11.482	-11.4756	-11.4995	-11.5538	-11.6383	-11.7531	-11.8982	-12.0735	-12.2792	-12.515	-12.7811	-13.0773	-13.4038	-13.7605
18	-10.7296	-10.5305	-10.3619	-10.2238	-10.1163	-10.0393	-9.9927	-9.97661	-9.99098	-10.0358	-10.111	-10.2167	-10.3528	-10.5192	-10.716	-10.9432	-11.2008	-11.4886	-11.8068	-12.1554	-12.5342
17	-9.11327	-8.93465	-8.7867	-8.66941	-8.58276	-8.52675	-8.50134	-8.50655	-8.54233	-8.60869	-8.70561	-8.83307	-8.99106	-9.17956	-9.39857	-9.64806	-9.92803	-10.2385	-10.5793	-10.9506	-11.3524
16	-7.52887	-7.37136	-7.24466	-7.14877	-7.08366	-7.04932	-7.04573	-7.07289	-7.13077	-7.21936	-7.33865	-7.48862	-7.66926	-7.88055	-8.12248	-8.39503	-8.6982	-9.03195	-9.39629	-9.7912	-10.2167
15	-5.97737	-5.84161	-5.73681	-5.66296	-5.62005	-5.60806	-5.62698	-5.67679	-5.75748	-5.86902	-6.01142	-6.18465	-6.38869	-6.62354	-6.88917	-7.18558	-7.51274	-7.87064	-8.25927	-8.67862	-9.12866
14	-4.45976	-4.3464	-4.26417	-4.21305	-4.19304	-4.20411	-4.24626	-4.31946	-4.4237	-4.55896	-4.72523	-4.9225	-5.15074	-5.40995	-5.70011	-6.0212	-6.37321	-6.75612	-7.16992	-7.61459	-8.09012
13	-2.97705	-2.88679	-2.82784	-2.80018	-2.8038	-2.83868	-2.9048	-3.00216	-3.13073	-3.2905	-3.48146	-3.70359	-3.95687	-4.2413	-4.55684	-4.9035	-5.28124	-5.69007	-6.12996	-6.60089	-7.10286
12	-1.53034	-1.46391	-1.42898	-1.42552	-1.45354	-1.513	-1.6039	-1.72622	-1.87995	-2.06507	-2.28156	-2.52942	-2.80862	-3.11915	-3.461	-3.83414	-4.23857	-4.67427	-5.14122	-5.63941	-6.16882
11	-0.12075	-0.07891	-0.06877	-0.09031	-0.14353	-0.22839	-0.3449	-0.49304	-0.67279	-0.88413	-1.12706	-1.40155	-1.7076	-2.04519	-2.41429	-2.81491	-3.24702	-3.7106	-4.20564	-4.73213	-5.29005
10	1.25053	1.266981	1.251516	1.204149	1.124892	1.013759	0.870765	0.695922	0.489244	0.250747	-0.01956	-0.32165	-0.65553	-1.02116	-1.41854	-1.84766	-2.3085	-2.80103	-3.32526	-3.88116	-4.46872
9	2.582263	2.572488	2.530562	2.456499	2.350309	2.212007	2.041604	1.839114	1.604549	1.337922	1.039248	0.708538	0.345808	-0.04893	-0.47566	-0.93437	-1.42505	-1.94768	-2.50224	-3.08873	-3.70712
8	3.873145	3.836263	3.766979	3.665304	3.531248	3.364824	3.166042	2.934913	2.67145	2.375665	2.047569	1.687175	1.294495	0.869542	0.412328	-0.07713	-0.59883	-1.15275	-1.73887	-2.35719	-3.00769
7	5.121808	5.056894	4.959308	4.829058	4.666153	4.470602	4.242417	3.981605	3.688179	3.362147	3.00352	2.612309	2.188526	1.732179	1.243282	0.721845	0.16788	-0.4186	-1.03759	-1.68907	-2.37302
6	6.326814	6.232896	6.106013	5.946173	5.753382	5.527648	5.268979	4.977382	4.652865	4.295438	3.905107	3.481882	3.025771	2.536784	2.014929	1.460216	0.872655	0.252256	-0.40097	-1.08702	-1.80587
5	7.48665	7.362705	7.205477	7.014977	6.791208	6.534174	6.24388	5.920332	5.563536	5.173496	4.750218	4.29371	3.803976	3.281024	2.724859	2.13549	1.512923	0.857165	0.168223	-0.55389	-1.30918
4	8.599726	8.444669	8.255996	8.033708	7.777806	7.488292	7.165168	6.808437	6.418099	5.994159	5.536619	5.045481	4.520749	3.962425	3.370515	2.74502	2.085946	1.393295	0.667073	-0.09272	-0.88607
3	9.664362	9.477058	9.255772	9.000504	8.71125	8.388009	8.030778	7.639558	7.214344	6.755138	6.261937	5.734741	5.173548	4.578359	3.949173	3.285989	2.588808	1.85763	1.092454	0.293282	-0.53989
2	10.67879	10.45804	10.20291	9.913397	9.589501	9.231212	8.838524	8.41143	7.949924	7.454002	6.923656	6.358882	5.759674	5.126027	4.457936	3.755396	3.018401	2.246948	1.441031	0.600646	-0.27421
1	11.64114	11.38566	11.09539	10.77031	10.4104	10.01567	9.586086	9.12165	8.622348	8.088168	7.519099	6.915131	6.276251	5.602449	4.893715	4.150037	3.371404	2.557807	1.709235	0.825676	-0.09288
0	12.54944	12.2579	11.9311	11.56903	11.17167	10.739	10.27101	9.767668	9.22897	8.654892	8.045418	7.400531	6.720212	6.004444	5.253208	4.466489	3.644266	2.786524	1.893244	0.964409	0

Figure 6.4: Sample value function output: DOE Run #1.

shows the value function at fixed values of X_2. So that the graphs do not appear convoluted, only increments of 5 are displayed. Figures 6.5 and 6.6 illustrate sample plots for fixed values of X_1 and X_2 (X_i = 0, 5, 10, 15, and 20 for i = 1, 2).

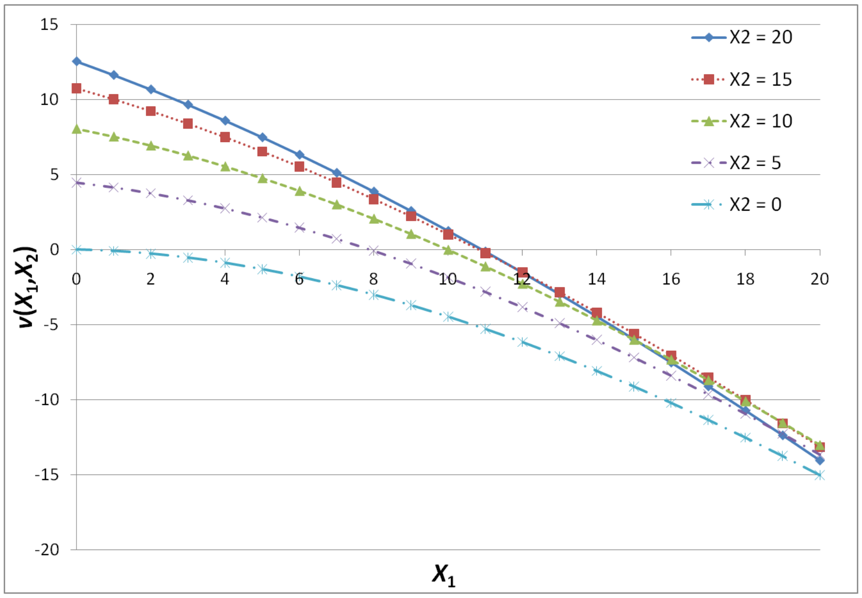


Figure 6.5: Property 1: Sample value functions for selected fixed values of X_1: DOE Run #1.

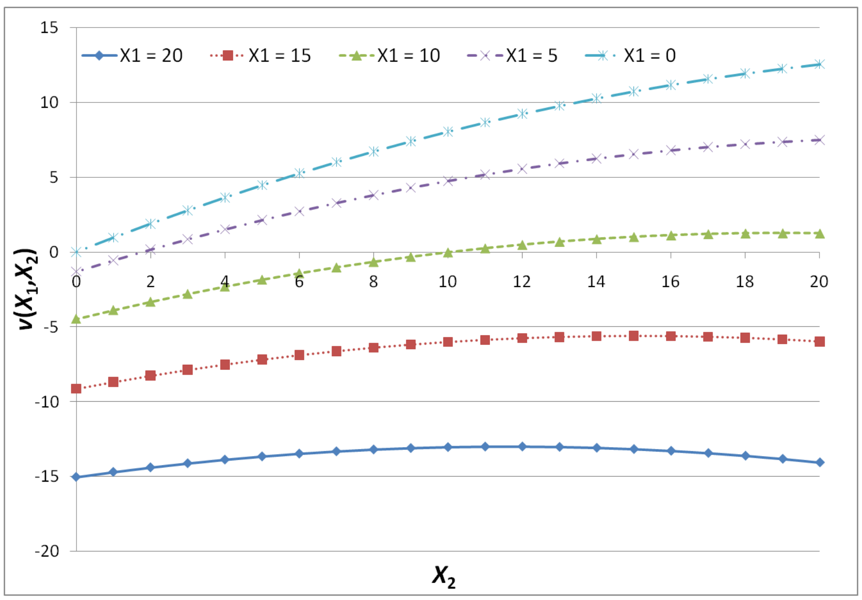


Figure 6.6: Property 1: Sample value functions for selected fixed values of X_2: DOE Run #1.

6.1.2 Sensitivity Analysis Results

The parameters used for each run as well as the optimal policy and resulting value function are shown in the tables below. A greedy policy is indicated by either "1" or "2."

Each set of tests shown in the tables represents a unique combination of parameters with only one parameter varied so that a low, medium, and high ratio is achieved. Each subgroup is listed so that the holding costs are varied; the lowest ratio is shown first, the medium ratio is shown second, and the highest ratio shown third. Notice that within each group, for the set of parameters chosen, a greedy Type 1 policy (denoted by “1”) is never optimal for the low ratio within each set.

In addition, within each group, if the policy changes, it changes along the order of “Type 2,” “Switch,” and then “Type 1.” This does not imply that a “Switch” policy always follows a “Type 2” policy, but it does imply that the switching curve is moving upwards as the ratios are increasing. For example, consider the set of parameters listed third to last in Figure 6.5 (Tests #73 - #75). Figure 6.7 illustrates the optimal policies for the low, medium, and high ratio settings (from left to right). Therefore if a “Switch” policy is optimal at the low settings, the only possibilities for the medium setting would be a second “Switch” policy (with a larger region associated with Type 1 patients than was observed in the low settings) or a “Type 1” policy. If a “Type 1” policy is shown to be the optimal policy for any of the levels, then the optimal policy at each subsequently higher level will also be “Type 1.”

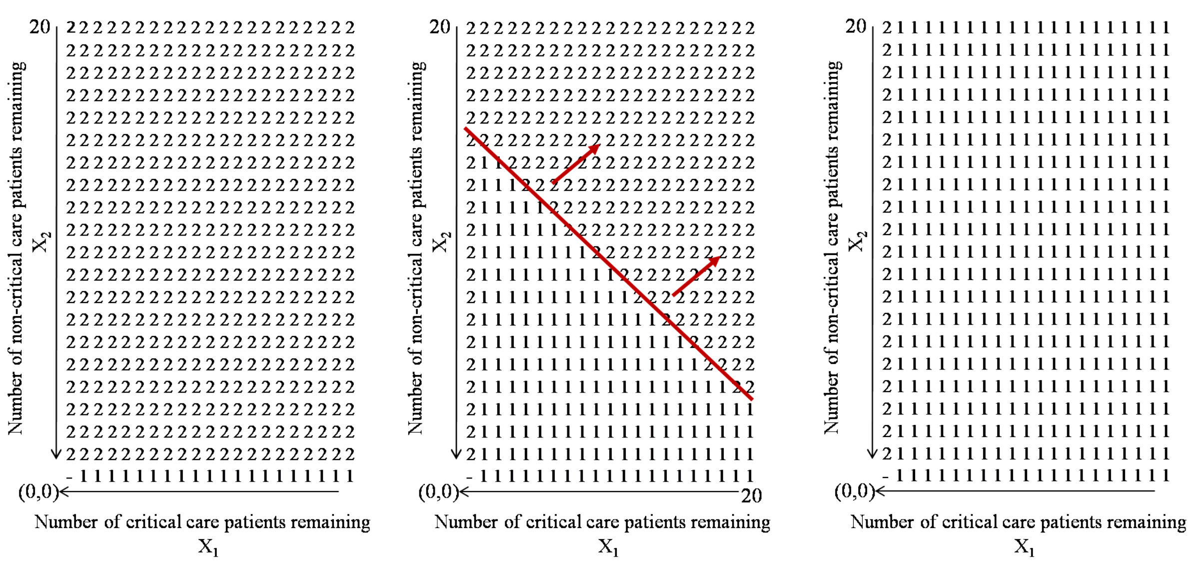


Figure 6.7: Sample policy diagrams at the low, medium, and high ratio settings.

For the set of parameters chosen for the sensitivity analysis, the optimal policy for the lowest values of λ_1 most often observed is a greedy, Type 2 policy. In only 3 of the 27 tests at this setting was the optimal policy a switching policy, and each of these occurred at the highest settings of h_1. All three policy options are most often observed at the highest values of λ_1 ($\lambda_1 = 3.5$). We also note that, within each subgroup, the value function is decreasing. This was expected as each subgroup represents increasing Type 1 holding costs.

The results were analyzed in Minitab to determine if there were any significant predictors of the optimal policy. First, the DOE was analyzed to determine which factors had a significant effect on the policy (each policy was coded categorically where 1 represented a greedy, Type 1 policy; 2 represented a greedy, Type 2 policy; and 0 represented a switching policy). Figure 6.8 represents the Minitab summary output. In the figure, factors A, B, C, and D represent the ratios of the λ, p, α, and h values, respectively. Any p-value less than 0.05 represents a factor that has a significant effect on the response. As expected, and based on the previous discussion, the rate of evacuation (Factor A) and the holding cost (Factor D) have the most significant effect on the policy. However, the death rate (Factor C) also significantly impacts the optimal policy. In addition, the interaction between the rate of evacuation and the holding cost (Factor A*D) also significantly impacts the optimal policy.

The results of the factorial design were also analyzed to study the effect on the value function. As expected, each primary factor, as well as most interactions, have a significant effect on the value function. An additional analysis showed that there is no correlation between the value function and the optimal policy.

6.1.3 Additional Sensitivity Tests

In this section, the effects of the parameters on the location of the switching curve are further examined. From the sensitivity analysis tests, the parameter combinations that resulted in a similarly

General Linear Model: Policy versus A, B, C, D

Factor	Type	Levels	Values
A	fixed	3	0.500, 0.750, 0.875
B	fixed	3	0.50, 0.75, 0.95
C	fixed	3	25, 50, 75
D	fixed	3	0.5, 1.0, 1.5

Analysis of Variance for Policy, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	2	8.0247	8.0247	4.0123	12.09	0.001
B	2	0.9136	0.9136	0.4568	1.38	0.281
C	2	3.7284	3.7284	1.8642	5.62	0.014
D	2	13.6543	13.6543	6.8272	20.58	0.000
A*B	4	0.4938	0.4938	0.1235	0.37	0.825
A*C	4	0.5679	0.5679	0.1420	0.43	0.786
A*D	4	6.6420	6.6420	1.6605	5.00	0.008
B*C	4	0.1235	0.1235	0.0309	0.09	0.983
B*D	4	0.6420	0.6420	0.1605	0.48	0.747
C*D	4	1.1605	1.1605	0.2901	0.87	0.501
A*B*C	8	1.8025	1.8025	0.2253	0.68	0.704
A*B*D	8	3.9506	3.9506	0.4938	1.49	0.237
A*C*D	8	5.2099	5.2099	0.6512	1.96	0.119
B*C*D	8	2.0988	2.0988	0.2623	0.79	0.618
Error	16	5.3086	5.3086	0.3318		
Total	80	54.3210				

S = 0.576012   R-Sq = 90.23%   R-Sq(adj) = 51.14%

Unusual Observations for Policy

Obs	Policy	Fit	SE Fit	Residual	St Resid	
14	2.00000	1.43210	0.51600	0.56790	2.22	R
40	1.00000	0.46914	0.51600	0.53086	2.07	R
41	2.00000	2.61728	0.51600	-0.61728	-2.41	R

R denotes an observation with a large standardized residual.

Figure 6.8: Factorial design analysis for impact on policy response.

sized region of Type 1 patients were chosen (i.e., the switching curve is located in approximately the same place). In the additional tests, three of the ratios were held constant at the initial settings while the fourth was incrementally increased. The tests chosen for further investigation are listed in Table 6.6, and the increments chosen are listed in Table 6.7.

For each additional test, four figures are shown together: one includes the incremental changes to λ_1, one includes the incremental changes to p_1, one includes the incremental changes to α_1, and one includes the incremental changes to h_1. Within each diagram, the original size of the Type 1

General Linear Model: Value versus A, B, C, D

Factor	Type	Levels	Values
A	fixed	3	0.500, 0.750, 0.875
B	fixed	3	0.50, 0.75, 0.95
C	fixed	3	25, 50, 75
D	fixed	3	0.5, 1.0, 1.5

Analysis of Variance for Value, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	2	17.03	17.03	8.51	247.89	0.000
B	2	2376.03	2376.03	1188.02	34585.84	0.000
C	2	321.79	321.79	160.89	4683.95	0.000
D	2	4064.43	4064.43	2032.21	59162.33	0.000
A*B	4	12.46	12.46	3.11	90.68	0.000
A*C	4	0.20	0.20	0.05	1.42	0.271
A*D	4	73.54	73.54	18.39	535.26	0.000
B*C	4	28.34	28.34	7.08	206.23	0.000
B*D	4	9.19	9.19	2.30	66.88	0.000
C*D	4	23.08	23.08	5.77	167.98	0.000
A*B*C	8	1.20	1.20	0.15	4.35	0.006
A*B*D	8	5.13	5.13	0.64	18.67	0.000
A*C*D	8	0.70	0.70	0.09	2.56	0.052
B*C*D	8	0.74	0.74	0.09	2.71	0.043
Error	16	0.55	0.55	0.03		
Total	80	6934.40				

S = 0.185337   R-Sq = 99.99%   R-Sq(adj) = 99.96%

Unusual Observations for Value

Obs	Value	Fit	SE Fit	Residual	St Resid
6	11.9913	11.8028	0.1660	0.1884	2.29 R
12	-7.2823	-7.4541	0.1660	0.1718	2.09 R
15	-2.9232	-2.7330	0.1660	-0.1902	-2.31 R
57	3.6501	3.4618	0.1660	0.1883	2.29 R
60	12.4080	12.6101	0.1660	-0.2021	-2.45 R
66	-6.1717	-5.9963	0.1660	-0.1754	-2.13 R
67	-23.4618	-23.2872	0.1660	-0.1745	-2.12 R
69	-1.8657	-2.0583	0.1660	0.1926	2.34 R

R denotes an observation with a large standardized residual.

Figure 6.9: Factorial design analysis for impact on value response.

region is represented by the solid line. In addition, if a particular linetype is shown in the legend but *not* in the diagram, this indicates that this particular parameter combination resulted in a greedy, Type 1 policy.

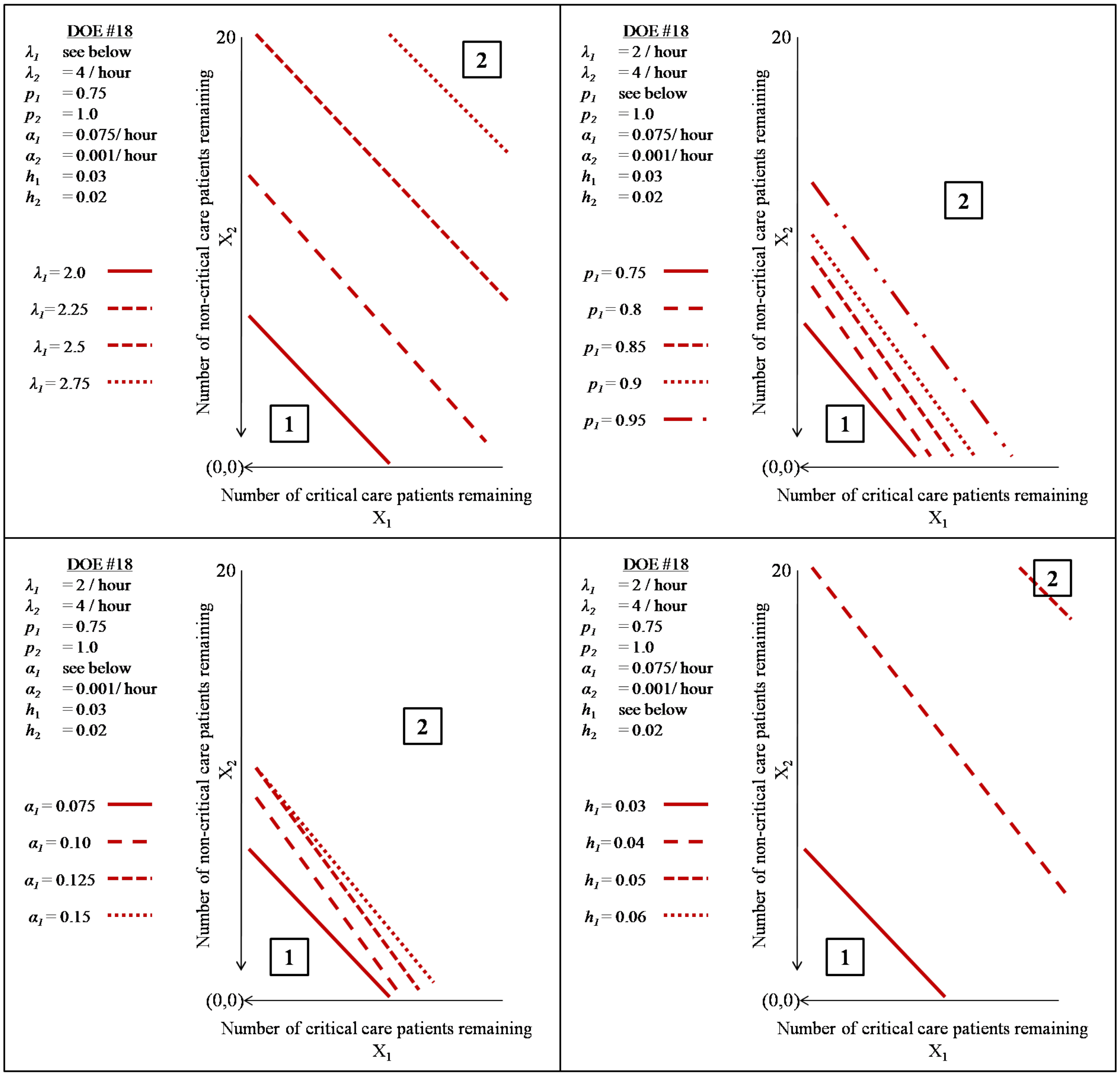


Figure 6.10: Incremental changes to DOE #18.

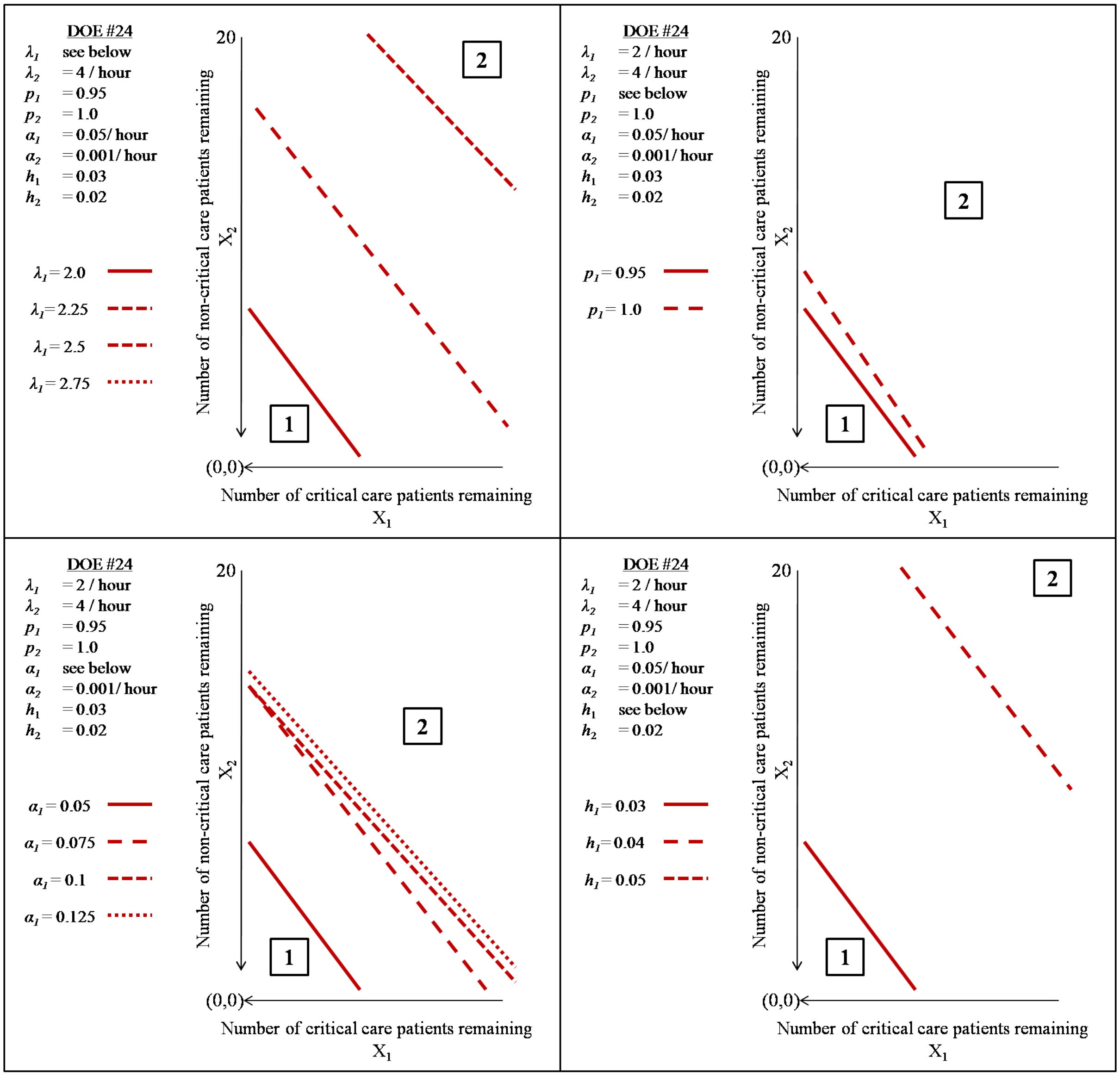


Figure 6.11: Incremental changes to DOE #24.

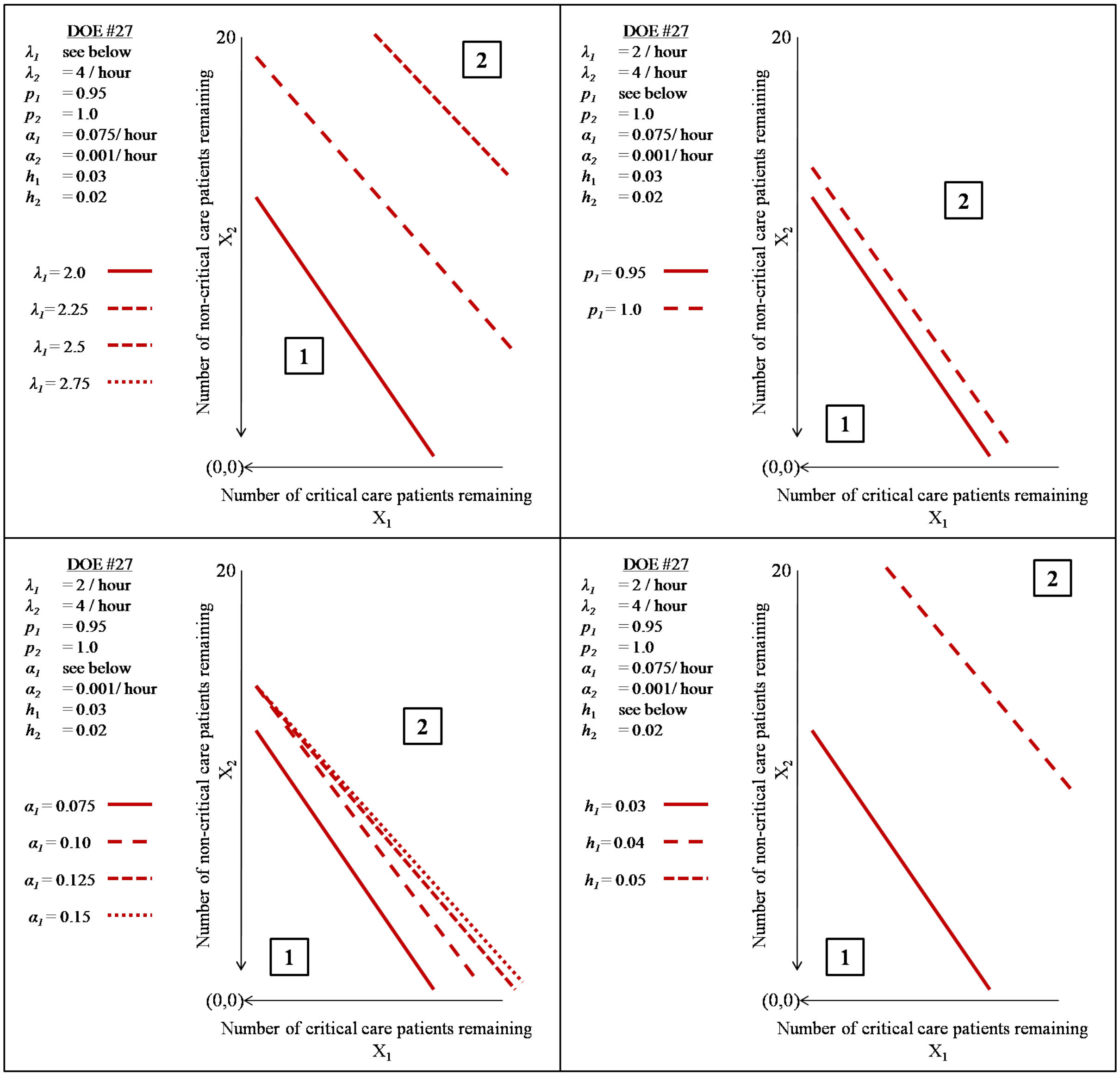


Figure 6.12: Incremental changes to DOE #27.

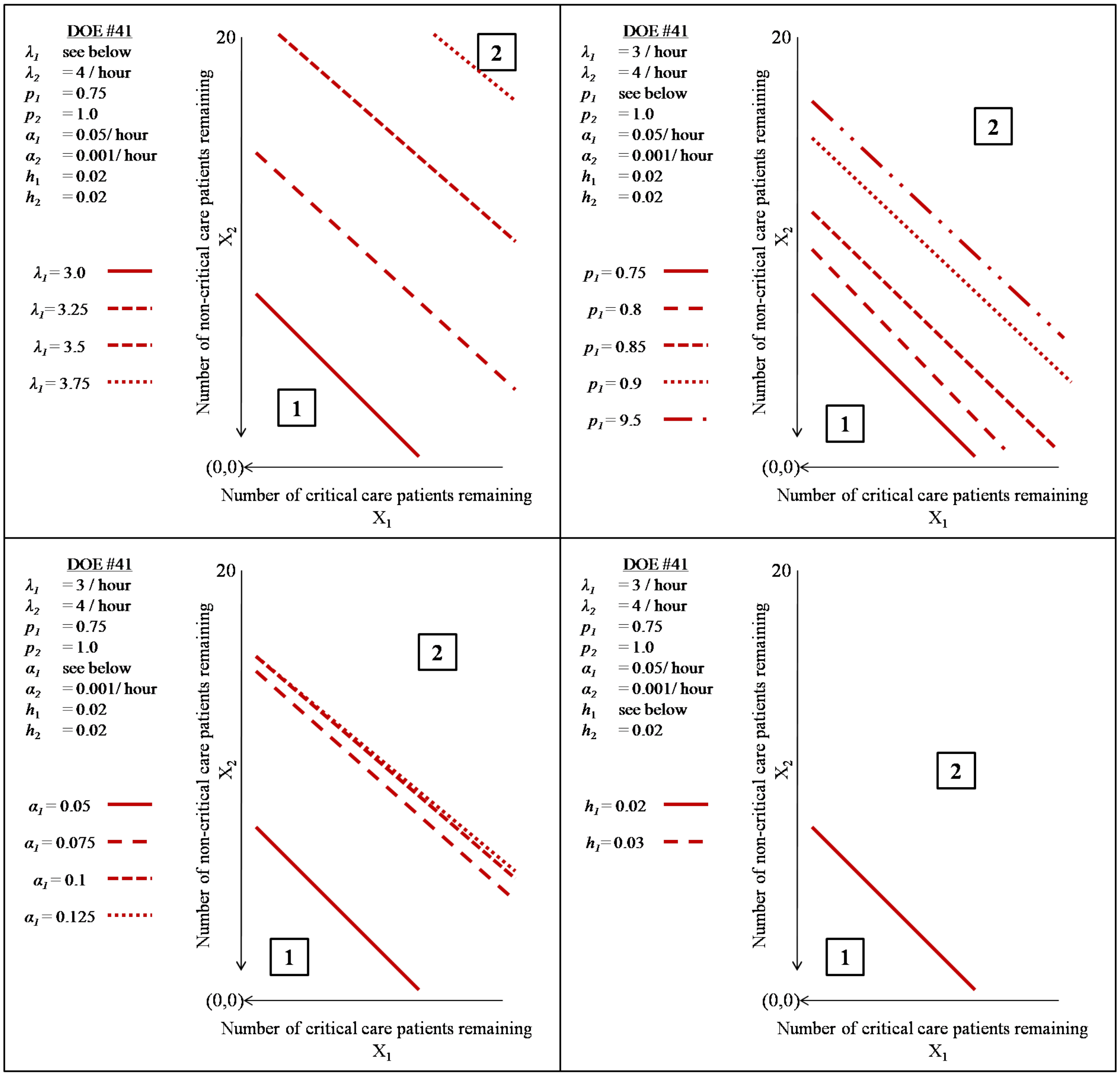


Figure 6.13: Incremental changes to DOE #41.

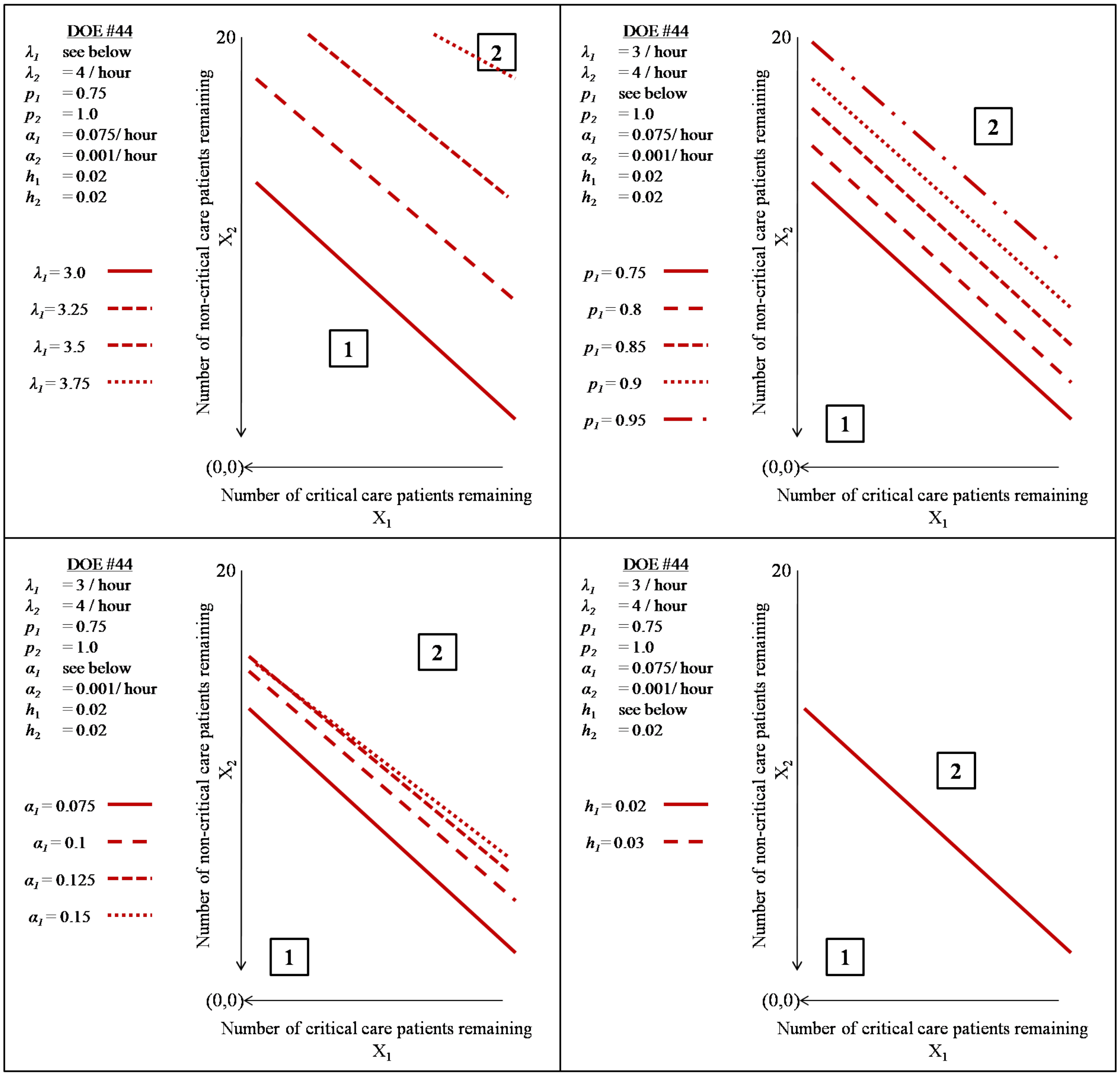


Figure 6.14: Incremental changes to DOE #44.

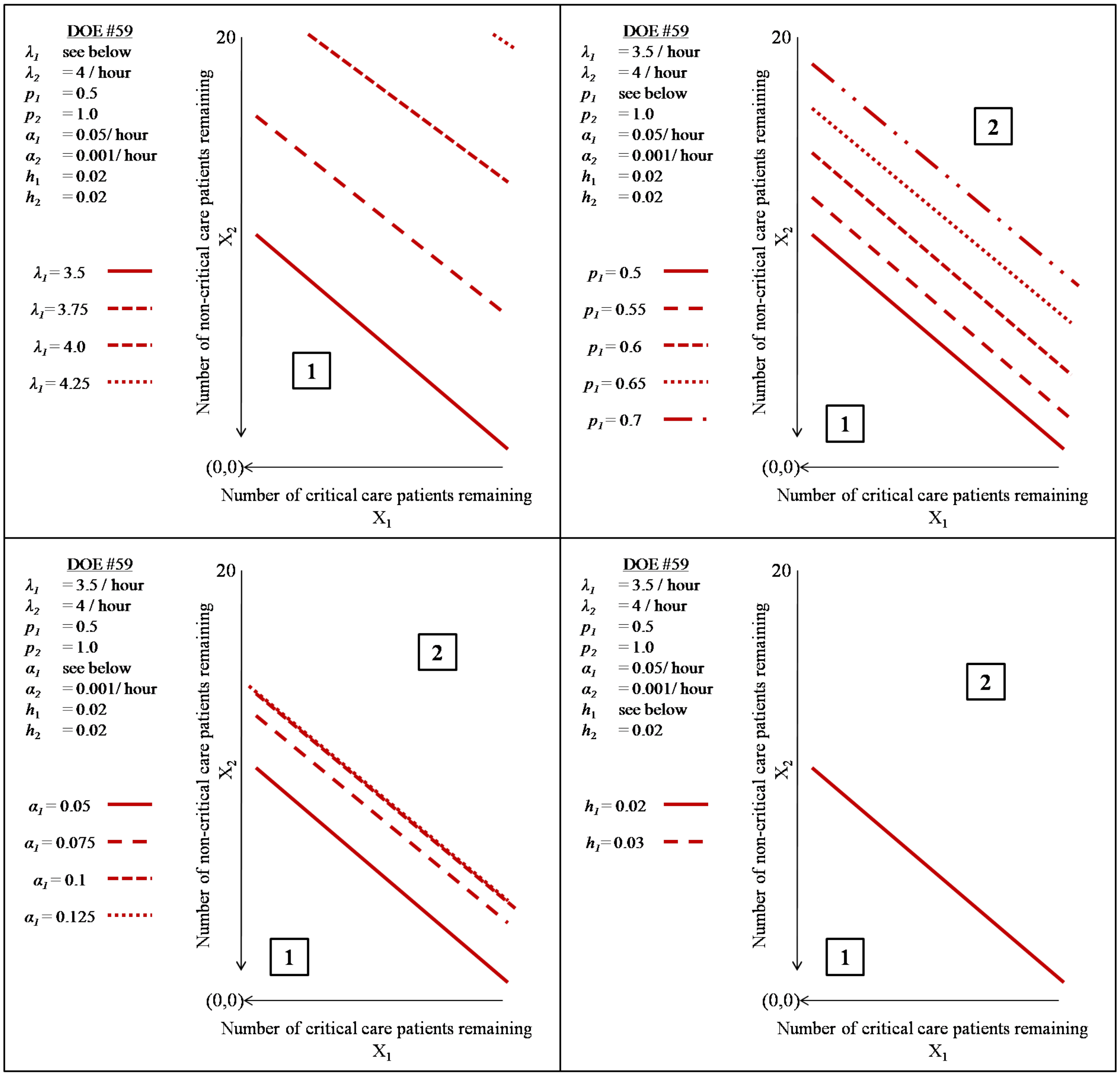


Figure 6.15: Incremental changes to DOE #59.

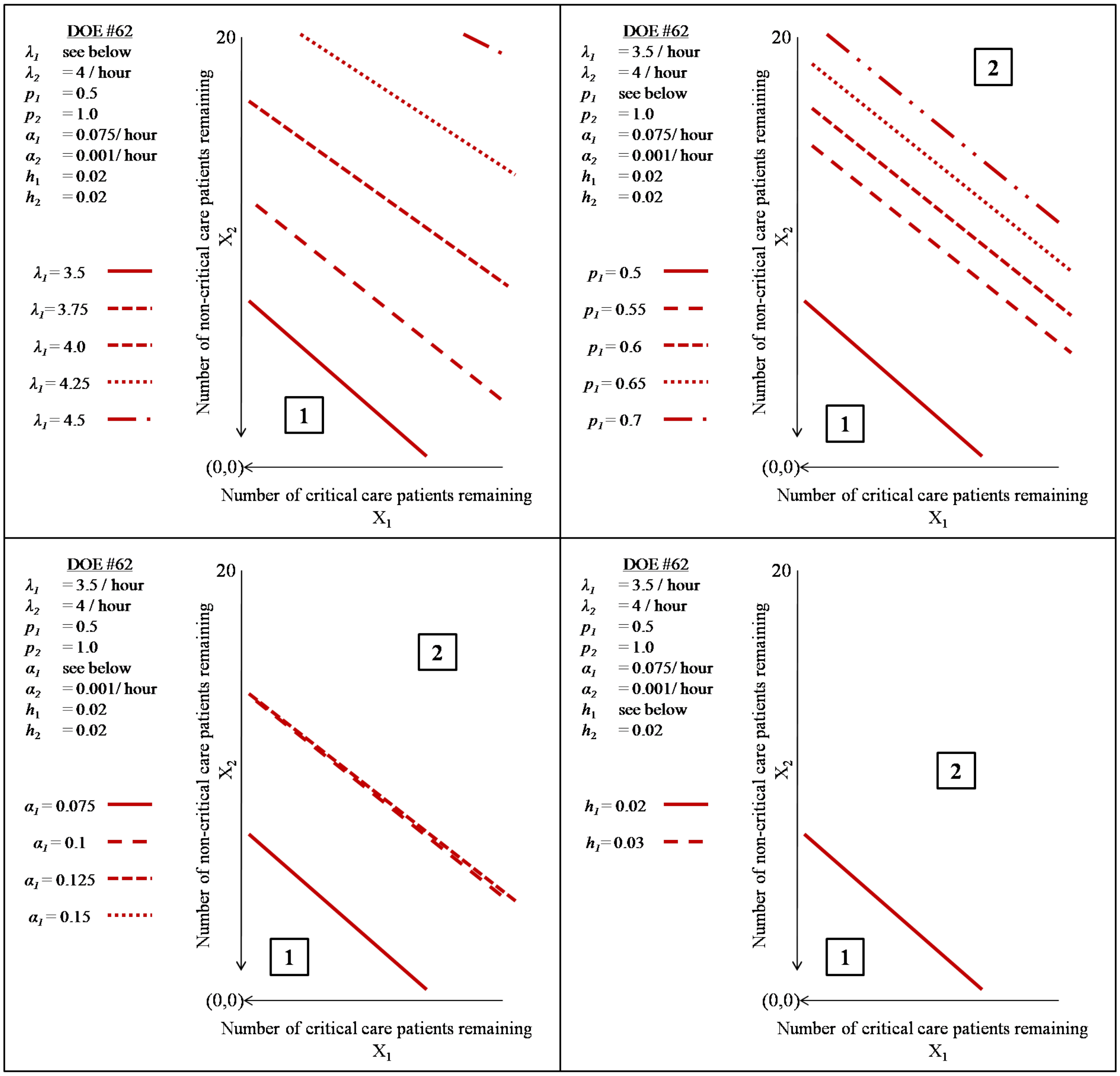


Figure 6.16: Incremental changes to DOE #62.

Changes to λ_1 show a fairly consistent trend in the movement and location of the switching curve. As expected, as the ratio λ_1/λ_2 increases, an incremental increase to h_1 becomes increasingly important to the location of the switching curve. In other words, faster evacuation rates for critical care patients results in holding costs increases having a larger impact.

One of the more noticeable trends during the testing phase was that incremental increases in α_1 have less and less of an effect on the location of the switching curve. Based on the values chosen for the sensitivity analysis, Tables 6.4 and 6.5 lead to the assumption that increasing the ratios increased the size of the Type 1 priority region. This would be true if holding costs were *not* included. During these further analyses, however, it was observed that as the value of α_1 (the death rate while waiting for evacuation) increased, the location of the switching curve seem to approach a limiting or bounding location on the (X_1, X_2) diagram. This observation lead to additional tests, that indicate that, when holding costs are included, additional incremental increases to α_1 actually cause the switching curve to start moving downward, thereby increasing the region in which Type 2 patients are given priority. This result is intuitive, however. Increasing the rate of a Type 1 patient evacuation, or increasing the probability of a successful Type 1 patient evacuation, encourages the selection of Type 1 patients. Likewise, increasing the holding costs associated with these patients makes it more expensive *not* to choose Type 1 patients for transport. It makes sense that, eventually, if the rate at which Type 1 patients die while waiting for evacuation is high enough, it will not be optimal to choose these patients. It should be noted however, that the α_1 rates at which the switching curve started moving downward were between 600 - 800 times the death rate of a Type 2 patient. This could be a realistic scenario, however, if a localized threat were to put some patients in immediate danger. At some point, the danger is just too great to put resources into moving these patients when efforts to move the other patients would provide value.

6.2 Structural Properties

Based on the 81 runs from the formalized design of experiments - and more than 25 other runs with randomly chosen values for the input parameters - several properties of the single-server model were identified. The electronic attachments include tabs where these relationships were identified with conditional statements. In this section, these properties and their implications for patient selection decisions are discussed. Though it has been difficult to attempt to prove mathematically, the following properties have been shown computationally:

1. The value function, $\nu(X_1, X_2)$, is concave in X_1 and X_2. For all (X_1, X_2),
   (a) $\nu(X_1+1, X_2) - \nu(X_1, X_2) \leq \nu(X_1, X_2) - \nu(X_1-1, X_2)$
   (b) $\nu(X_1, X_2+1) - \nu(X_1, X_2) \leq \nu(X_1, X_2) - \nu(X_1, X_2-1)$
2. (Supermodularity) For all (X_1, X_2),
   (a) $\nu(X_1, X_2+1) - \nu(X_1, X_2) \geq \nu(X_1+1, X_2+1) - \nu(X_1+1, X_2)$
3. (Diagonal Dominance) For all (X_1, X_2)
   (a) $\nu(X_1+1, X_2+1) - \nu(X_1, X_2) \geq \nu(X_1+1, X_2+2) - \nu(X_1, X_2+1)$
   (b) $\nu(X_1+1, X_2+1) - \nu(X_1, X_2) \geq \nu(X_1+2, X_2+1) - \nu(X_1+1, X_2)$

Refer back to Figures 6.5 and 6.6 to see these properties within the plots.

Concavity in X_1 and X_2 implies that the marginal change in the value associated with evacuating a patient is increasing as the number of patients in the system decreases. That is, the change in the value of evacuating a Type 1 patient is greater at a lower value of X_1 than a higher value of X_1, and the change in the value of selecting a Type 2 patient for evacuation is greater at a lower value of X_2 than at a higher value of X_2.

The supermodularity relationship implies that the action chosen is a function of the state; and in this case, the marginal change in the value of evacuating a Type 2 patient becomes greater as the number of Type 1 patients in the system decreases. That is, as more Type 1 patients are removed from the system, the marginal change in the value of choosing a Type 2 patient is increasing. Similarly, the marginal change in the value associated with evacuating a Type 1 patient becomes greater as the number of Type 2 patients in the system decreases. That is, as more Type 2 patients are removed from the system, the marginal change in the value of choosing a Type 1 patient is increasing.

The diagonal dominance relationship refers to the change in the value as a change is made to both X_1 and X_2. Though patient selection decisions cannot be made diagonally, the property may be helpful in future work. Again, the marginal change associated with a diagonal change is increasing as the number of patients in the system decreases. That is, the change in the value function associated with removing a patient from both groups is greater at lower values of both X_1 and X_2.

The insights for practitioners based on these relationships will be discussed in Chapter 8.

6.2.1 Policy Determination when Holding Costs are Excluded

In previous, informal testing of the optimality equation, the optimal policies were often shown to be either a switching policy or a greedy, Type 2 policy. The fact that all 81 DOE tests showed a greedy, Type 1 policy was initially surprising, but upon further examination and comparison to other policies, it was determined that a greedy policy could be predicted by examining a ratio consisting of the Type 1 and Type 2 parameter values. Similar to the $c\mu$ rule ([80] and [165]), which gives priority to jobs with the largest value of $c_i\mu_i$ (where c_i is the reward if a job is completed and μ_i is the service rate for jobs $i = 1, 2, ..., I$), the optimal policy for the evacuation systems can be predicted by considering the following relationship.

$$\frac{\lambda_1 p_1 \alpha_1}{\lambda_2 p_2 \alpha_2} \tag{6.1}$$

In all 81 DOE cases, the ratio of the input parameters ranges from 6.25 to 62.34375. As a comparison, more tests were run, and the ratios were calculated. Tables 6.8, 6.9, and 6.10 contain the input parameters for Type 1 policies, Type 2 policies, and switching policies, respectively.

It makes sense that, without holding costs, the patient group with the higher value of $\lambda p \alpha$ will more quickly contribute to the reward or incur a penalty; therefore, these patients should be evacuated first. It should be noted, however, that none of these ratios predicts that a switching policy will be optimal. Based on extensive testing, if the ratio is between 1 and 1.3, a switching policy may occur and the model should be run to determine if a switch would in fact be optimal.

In summary, if $h_1 = h_2 = 0$ and $\lambda_1 p_1 \alpha_1 / \lambda_2 p_2 \alpha_2$ is

- > 1.3, a greedy, Type 1 policy is likely the optimal policy,
- > 1 and < 1.3, a switching policy may occur, or
- < 1, a greedy, Type 2 policy is likely the optimal policy.

6.3 Policy Possibilities

Because the more interesting cases are for when holding costs are considered in the optimality equation, the discussions in the remainder of this chapter will assume that holding costs are included as input parameters.

As discussed in the previous sections, the switching curve moves up or down depending on the selected input parameters. The switching curve implies a monotone switching policy. That is, a switch can only be made up to one time. In addition, if a switch does occur, it will only be after the evacuation has begun with Type 2 patients, and a switch can be made to evacuate Type 1 patients. Once it is optimal to begin evacuating Type 1 patients after switching from Type 2 patients, it will be optimal to continue evacuating Type 1 patients until there are no more patients from this group remaining in the system. If the evacuation begins with Type 1 patients, the policy will be a greedy, Type 1 policy. That is, a switch from Type 1 patients to Type 2 patients is never optimal.

Tables 6.11 and 6.12 show the possible policies for critical and non-critical care patients. It has been difficult to prove that these switching relationships hold and therefore show that a switch can only occur up to one time.

6.4 Model Properties Conclusions

Because the appropriate input parameters are unknown, the purpose of this chapter was to examine the behavior and properties of the single server model. The model was discussed from two perspectives: without holding costs and with holding costs included. Without holding costs, increasing the values of the input parameters for either patient type moves the switching curve in favor of that patient. When holding costs are included, only increases to the rate of evacuation, probability of a successful evacuation, and holding cost move the switching curve in favor of that patient type. At lower values, increases to the death rate do move the switching curve to create a larger region of priority for that patient type. Eventually, however, increases in α approach some bounding point, and then the switching curve starts to move in the other direction thereby decreasing the region of priority for that patient. At higher evacuation rates, the model is more sensitive to the changes in the holding costs.

Several relationships were identified through extensive testing including concavity, supermodularity, and diagonal dominance for all (X_1, X_2). These relationships give insight into the marginal changes associated with choosing patients. Because the value function is concave in X_1 and X_2, the change in the value function when there are greater numbers of patients in the system is less than when there are less number of patients in the system. That is to say that when there are fewer patients remaining in the system, the choice has more of an impact on the overall reward. The supermodularity relationship implies that the marginal change associated with choosing Type 2 patients increases as the number of Type 1 patients in the system decreases. Similarly, the marginal change associated with choosing Type 1 patients for evacuation is increases as the number of Type 2 patients in the system decreases. The diagonal dominance relationship does not have any relevance for the two possible choices in our models, but the property will likely be valuable as the items presented in this chapter are proven in future work.

Table 6.4: Sensitivity Analysis Results for the Single Server Model, 1 of 2

Test #	λ_1	λ_2	p_1	p_2	α_1	α_2	h_1	h_2	Policy	$\nu(20,20)$
1	2	4	0.5	1	0.025	0.001	0.01	0.02	2	-1.865708
2	2	4	0.5	1	0.025	0.001	0.02	0.02	2	-12.663737
3	2	4	0.5	1	0.025	0.001	0.03	0.02	2	-23.461765
4	2	4	0.5	1	0.05	0.001	0.01	0.02	2	-4.245748
5	2	4	0.5	1	0.05	0.001	0.02	0.02	2	-14.054585
6	2	4	0.5	1	0.05	0.001	0.03	0.02	2	-23.863421
7	2	4	0.5	1	0.075	0.001	0.01	0.02	2	-6.171733
8	2	4	0.5	1	0.075	0.001	0.02	0.02	2	-15.282833
9	2	4	0.5	1	0.075	0.001	0.03	0.02	2	-24.393932
10	2	4	0.75	1	0.025	0.001	0.01	0.02	2	6.06414
11	2	4	0.75	1	0.025	0.001	0.02	0.02	2	-4.733889
12	2	4	0.75	1	0.025	0.001	0.03	0.02	2	-15.531917
13	2	4	0.75	1	0.05	0.001	0.01	0.02	2	2.261068
14	2	4	0.75	1	0.05	0.001	0.02	0.02	2	-7.547769
15	2	4	0.75	1	0.05	0.001	0.03	0.02	2	-17.356605
16	2	4	0.75	1	0.075	0.001	0.01	0.02	2	-0.715164
17	2	4	0.75	1	0.075	0.001	0.02	0.02	2	-9.826263
18	2	4	0.75	1	0.075	0.001	0.03	0.02	Switch	-18.937356
19	2	4	0.95	1	0.025	0.001	0.01	0.02	2	12.408018
20	2	4	0.95	1	0.025	0.001	0.02	0.02	2	1.609989
21	2	4	0.95	1	0.025	0.001	0.03	0.02	2	-9.18804
22	2	4	0.95	1	0.05	0.001	0.01	0.02	2	7.466521
23	2	4	0.95	1	0.05	0.001	0.02	0.02	2	-2.342316
24	2	4	0.95	1	0.05	0.001	0.03	0.02	Switch	-12.151153
25	2	4	0.95	1	0.075	0.001	0.01	0.02	2	3.650091
26	2	4	0.95	1	0.075	0.001	0.02	0.02	2	-5.461008
27	2	4	0.95	1	0.075	0.001	0.03	0.02	Switch	-14.565383
28	3	4	0.5	1	0.025	0.001	0.01	0.02	2	-2.376871
29	3	4	0.5	1	0.025	0.001	0.02	0.02	2	-13.186388
30	3	4	0.5	1	0.025	0.001	0.03	0.02	1	-22.312013
31	3	4	0.5	1	0.05	0.001	0.01	0.02	2	-4.77049
32	3	4	0.5	1	0.05	0.001	0.02	0.02	2	-14.794561
33	3	4	0.5	1	0.05	0.001	0.03	0.02	Switch	-23.487185
34	3	4	0.5	1	0.075	0.001	0.01	0.02	2	-6.757877
35	3	4	0.5	1	0.075	0.001	0.02	0.02	Switch	-16.191394
36	3	4	0.5	1	0.075	0.001	0.03	0.02	Switch	-24.405677
37	3	4	0.75	1	0.025	0.001	0.01	0.02	2	5.826339
38	3	4	0.75	1	0.025	0.001	0.02	0.02	2	-4.983177
39	3	4	0.75	1	0.025	0.001	0.03	0.02	1	-13.098592
40	3	4	0.75	1	0.05	0.001	0.01	0.02	2	2.104769
41	3	4	0.75	1	0.05	0.001	0.02	0.02	Switch	-7.919256
42	3	4	0.75	1	0.05	0.001	0.03	0.02	1	-14.977056

Table 6.5: Sensitivity Analysis Results for the Single Server Model, 2 of 2

Test #	λ_1	λ_2	p_1	p_2	α_1	α_2	h_1	h_2	Policy	$\nu(20,20)$
43	3	4	0.75	1	0.075	0.001	0.01	0.02	2	-0.909969
44	3	4	0.75	1	0.075	0.001	0.02	0.02	Switch	-10.248319
45	3	4	0.75	1	0.075	0.001	0.03	0.02	1	-16.698915
46	3	4	0.95	1	0.025	0.001	0.01	0.02	2	12.388908
47	3	4	0.95	1	0.025	0.001	0.02	0.02	2	1.579391
48	3	4	0.95	1	0.025	0.001	0.03	0.02	1	-5.727855
49	3	4	0.95	1	0.05	0.001	0.01	0.02	2	7.604976
50	3	4	0.95	1	0.05	0.001	0.02	0.02	Switch	-2.314622
51	3	4	0.95	1	0.05	0.001	0.03	0.02	1	-8.122454
52	3	4	0.95	1	0.075	0.001	0.01	0.02	2	3.768357
53	3	4	0.95	1	0.075	0.001	0.02	0.02	Switch	-5.019843
54	3	4	0.95	1	0.075	0.001	0.03	0.02	1	-10.277683
55	3.5	4	0.5	1	0.025	0.001	0.01	0.02	2	-2.923233
56	3.5	4	0.5	1	0.025	0.001	0.02	0.02	2	-13.921185
57	3.5	4	0.5	1	0.025	0.001	0.03	0.02	1	-20.186991
58	3.5	4	0.5	1	0.05	0.001	0.01	0.02	2	-5.294799
59	3.5	4	0.5	1	0.05	0.001	0.02	0.02	Switch	-15.540821
60	3.5	4	0.5	1	0.05	0.001	0.03	0.02	1	-21.505387
61	3.5	4	0.5	1	0.075	0.001	0.01	0.02	2	-7.282293
62	3.5	4	0.5	1	0.075	0.001	0.02	0.02	Switch	-16.848547
63	3.5	4	0.5	1	0.075	0.001	0.03	0.02	1	-22.756697
64	3.5	4	0.75	1	0.025	0.001	0.01	0.02	2	5.362605
65	3.5	4	0.75	1	0.025	0.001	0.02	0.02	Switch	-5.63015
66	3.5	4	0.75	1	0.025	0.001	0.03	0.02	1	-10.870981
67	3.5	4	0.75	1	0.05	0.001	0.01	0.02	2	1.695826
68	3.5	4	0.75	1	0.05	0.001	0.02	0.02	Switch	-8.055043
69	3.5	4	0.75	1	0.05	0.001	0.03	0.02	1	-12.76471
70	3.5	4	0.75	1	0.075	0.001	0.01	0.02	2	-1.309
71	3.5	4	0.75	1	0.075	0.001	0.02	0.02	Switch	-9.94716
72	3.5	4	0.75	1	0.075	0.001	0.03	0.02	1	-14.508837
73	3.5	4	0.95	1	0.025	0.001	0.01	0.02	2	11.991275
74	3.5	4	0.95	1	0.025	0.001	0.02	0.02	Switch	1.222262
75	3.5	4	0.95	1	0.025	0.001	0.03	0.02	1	-3.418173
76	3.5	4	0.95	1	0.05	0.001	0.01	0.02	2	7.288326
77	3.5	4	0.95	1	0.05	0.001	0.02	0.02	Switch	-1.467301
78	3.5	4	0.95	1	0.05	0.001	0.03	0.02	1	-5.772169
79	3.5	4	0.95	1	0.075	0.001	0.01	0.02	Switch	3.470242
80	3.5	4	0.95	1	0.075	0.001	0.02	0.02	1	-3.696098
81	3.5	4	0.95	1	0.075	0.001	0.03	0.02	1	-7.910549

Table 6.6: Sensitivity Runs Selected for Additional Analysis.

Run #	λ Ratio	p Ratio	α Ratio	h Ratio
18	Low	Medium	High	High
24	Low	High	Medium	High
27	Low	High	High	High
41	Medium	Medium	Medium	Medium
44	Medium	Medium	High	Medium
59	High	Low	Medium	Medium
62	High	Low	High	Medium

Table 6.7: Values Chosen for the Additional, Incremental Analysis.

Parameter	Change
λ_1	0.25
p_1	0.05
α_1	0.025
h_1	0.01

Table 6.8: Parameter Ratios for Greedy, Type 1 Policies with No Holding Costs.

Test #	λ_1	λ_2	p_1	p_2	α_1	α_2	Ratio
1	4	5	0.6	0.95	0.002	0.001	1.010526
2	2	15	0.75	0.95	0.01	0.001	1.052632
3	2	7	0.75	0.95	0.005	0.001	1.12782
4	2	10	0.6	0.95	0.01	0.001	1.263158
5	5	5	0.6	0.95	0.002	0.001	1.263158
6	2.7	4	0.95	0.999	0.11	0.056	1.307558
7	3.1	4	0.8	0.999	0.12	0.056	1.329901
8	3	16	0.75	0.95	0.01	0.001	1.480263
9	2	10	0.75	0.95	0.01	0.001	1.578947
10	6	12	0.4	0.999	0.16	0.017	1.884237
11	2	8	0.75	0.95	0.01	0.001	1.973684
12	4.5	16	0.8	0.9	0.08	0.01	2.000
13	6.635	12.5	0.4	0.999	0.16	0.017	2.000306
14	2	6	0.8	0.999	0.15	0.02	2.002002
15	4	6	0.8	0.999	0.075	0.02	2.002002
16	4	6	0.8	0.999	0.15	0.04	2.002002
17	2	6	0.8	0.999	0.15	0.02	2.002002
18	5	10	0.8	0.999	0.15	0.03	2.002002
19	6	12	0.08	0.999	0.15	0.03	2.002002
20	12	12	0.4	0.999	0.15	0.03	2.002002
21	6	12	0.4	0.999	0.15	0.015	2.002002
22	6.61	12.4	0.4	0.999	0.16	0.017	2.00884
23	3.75	4	0.8	0.999	0.15	0.056	2.01094
24	4.3	15	0.8	0.9	0.08	0.01	2.038519
25	4.6	16	0.8	0.9	0.08	0.01	2.044444
26	6.8	12.5	0.4	0.999	0.16	0.017	2.05005
27	4.5	16	0.7	0.95	0.01	0.001	2.072368
28	6.4	12	0.4	0.999	0.16	0.017	2.009853
29	3	9	0.6	0.95	0.01	0.001	2.105263
30	7	12	0.4	0.999	0.163	0.017	2.198277
31	10	12.4	0.4	0.999	0.16	0.017	3.039092
32	4	8	0.75	0.95	0.01	0.001	3.947368
33	1	16	0.9	0.5	0.09	0.017	5.955882
34	10	12.4	0.4	0.999	0.05	0.017	9.497163
35	10	12.4	0.4	0.999	0.9	0.017	17.09489

Table 6.9: Parameter Ratios for Greedy, Type 2 Policies with No Holding Costs.

Test #	λ_1	λ_2	p_1	p_2	α_1	α_2	Ratio
1	2	5.999	0.25	0.99	0.591	0.999	0.049806
2	2	5.999	0.25	0.99	0.29	0.05	0.488297
3	4	12	0.75	0.95	0.002	0.001	0.5263166
4	2	7	0.75	0.95	0.0025	0.001	0.56391
5	2	10	0.75	0.95	0.01	0.0025	0.631579
6	2	10	0.75	0.95	0.004	0.001	0.631579
7	2	12	0.75	0.95	0.01	0.002	0.657895
8	2	7	0.75	0.95	0.004	0.001	0.9022556
9	3.2	4	0.8	0.999	0.11	0.75	0.939606
10	3	4	0.85	0.999	0.11	0.073	0.961578
11	4	6	0.25	0.99	0.29	0.05	0.976431
12	4.097	6	0.25	0.99	0.29	0.051	0.980499
13	2	16	0.75	0.95	0.01	0.001	0.986842
14	2	8	0.75	0.95	0.01	0.002	0.986842
15	1	8	0.75	0.95	0.01	0.001	0.986842
16	4.05	6	0.25	0.99	0.29	0.05	0.988636
17	4.06	6	0.25	0.99	0.29	0.05	0.991077
18	3.2	0.5	0.99	0.99	0.11	0.071	0.991549
19	3.2	4	0.8	0.999	0.11	0.071	0.992542
20	4.07	6	0.25	0.99	0.29	0.05	0.993519
21	3.1	4	0.85	0.999	0.11	0.073	0.993631
22	3.3	5	0.99	0.99	0.11	0.073	0.994521
23	2	5.999	0.25	0.99	0.591	0.05	0.995115
24	5	6	0.25	0.99	0.35	0.074	0.995313
25	4.08	6	0.25	0.99	0.29	0.05	0.99596
26	3.2	4	0.85	0.999	0.11	0.075	0.998332
27	4.09	6	0.25	0.99	0.29	0.05	0.998401
28	4.095	5.999	0.25	0.99	0.29	0.05	0.999788
29	4.0955	5.999	0.25	0.99	0.29	0.05	0.99991
30	4.0958	5.999	0.25	0.99	0.29	0.05	0.999983
31	4.096	6	0.25	0.99	0.29	0.05	0.999865
32	4.097	6	0.25	0.99	0.29	0.05	1.000109
33	4.097	5.999	0.25	0.99	0.29	0.05	1.000276
34	3	4	0.75	0.999	0.1	0.056	1.00547
35	3.1	4	0.85	0.999	0.11	0.71	1.02162

Table 6.10: Parameter Ratios for Switching Policies with No Holding Costs.

Test #	λ_1	λ_2	p_1	p_2	α_1	α_2	Ratio
1	2.5	4	0.9	0.999	0.1	0.056	1.00547
2	3.1	4	0.85	0.999	0.11	0.072	1.007431
3	3.3	4	0.8	0.999	0.11	0.07	1.38181
4	2.25	4	0.999	0.999	0.1	0.055	1.022727
5	3.1	4	0.85	0.999	0.11	0.07	1.036215
6	3.2	4	0.8	0.999	0.11	0.068	1.03633
7	2.5	4	0.999	0.999	0.1	0.06	1.041667
8	2.6	4	0.9	0.999	0.1	0.056	1.045689
9	3.2	4	0.9	0.999	0.11	0.066	1.067734
10	3.2	4	0.8	0.999	0.11	0.065	1.084161
11	3.2	4	0.8	0.999	011	0.065	1.084161
12	2.8	4	0.8	0.999	0.11	0.056	1.101101
13	2.5	4	0.9	0.999	0.11	0.0526	1.106017
14	2.5	4.1	0.999	0.999	0.1	0.055	1.108647
15	2.5	4	0.999	0.999	0.1	0.056	1.116071
16	2.5	4	0.999	0.999	0.1	0.055	1.136364
17	2.9	4	0.8	0.999	0.11	0.056	1.140426
18	2.6	4	0.9	0.999	0.11	0.056	1.150257
19	2.5	4	0.999	0.999	0.1	0.054	1.157407
20	3.1	4	0.85	0.89	0.11	0.07	1.163122
21	2.5	3.9	0.999	0.999	0.1	0.055	1.165501
22	3.2	4	0.8	0.999	0.11	0.06	1.174508
23	3	4	0.8	0.999	0.11	0.056	1.179751
24	2.7	4	0.9	0.999	0.11	0.056	1.194498
25	3.1	4.4	0.8	0.999	0.12	0.056	1.209001
26	3.2	4	0.8	0.999	0.11	0.058	1.215008
27	2.7	4	0.9	0.999	0.11	0.055	1.216216
28	3.1	4	0.8	0.999	0.11	0.056	1.219076
29	3.2	4	0.8	0.999	0.11	0.057	1.236324
30	2.5	4	0.999	0.999	0.1	0.05	1.25
31	2.5	4	0.999	0.999	0.11	0.055	1.25
32	3.2	4	0.8	0.999	0.11	0.056	1.258401
33	2.7	4	0.95	0.999	0.11	0.056	1.260859
34	2.7	4	0.95	0.999	0.11	0.0555	1.272218
34	2.7	4	0.95	0.999	0.11	0.055	1.283784

Table 6.11: Possible Policies for the Single Server Model based on Changes in X_1.

Scenario	Policy at (X_1, X_2)	Policy at $(X_1 + 1, X_2)$	Possible?
1	1	1	yes
2	2	2	yes
3	1	2	yes
4	2	1	no

Table 6.12: Possible Policies for the Single Server Model based on Changes in X_2.

Scenario	Policy at (X_1, X_2)	Policy at $(X_1, X_2 + 1)$	Possible?
1	1	1	yes
2	2	2	yes
3	1	2	yes
4	2	1	no

Chapter 7

Modeling Extensions

This chapter proposes and discusses extensions to the basic model discussed in Chapters 5 and 6. The two additional models include a two-server model and a model that accounts for patient transitions between classes.

7.1 Two-server Model

There will likely be multiple teams available to evacuate patients during a unit-, floor-, or department-level evacuations. In this section, a model for assigning two servers - or evacuation teams - is examined with dynamic programming. Assume that that there are two evacuation teams available to move patients, and that the two teams can be allocated to patient evacuations according to any one of the following three policies: either both teams can evacuate Type 1 patients, the teams can be split so that one team is dedicated to moving Type 1 and one team is dedicated to moving Type 2 patients, or both teams can evacuate Type 2 patients. This leads to the following decision at any epoch:

$$\pi = \begin{cases} (2\lambda_1, 0) & \text{both teams evacuate Type 1 patients - Policy 1} \\ (\lambda_1, \lambda_2) & \text{teams split between both patient types - Policy 2} \\ (0, 2\lambda_2) & \text{both teams evacuate Type 2 patients - Policy 3} \end{cases}, \tag{7.1}$$

The state description as well as the n-stage expected reward remains the same as in the previously discussed models. The uniformization rate, based on the maximum rate of transition, used for this model is $\gamma = 2\lambda_1 + 2\lambda_2 + N_1\alpha_1 + N_2\alpha_2$. The transition diagram is similar to the one shown for the single server model in Chapter 5 though the transition rates are different. The fictitious transition rate in this case is $(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + 2\lambda_2$ when Policy 1 is chosen, $(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + \lambda_1 + \lambda_2$ when Policy 2 is chosen, and $(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + 2\lambda_1$ when Policy 3 is chosen. The optimality equation used to determine how the two evacuation teams should be allocated and therefore prioritize the patients for evacuation is shown in Equation (7.2) below.

$$\begin{aligned} \nu(X_1, X_2) = {} & X_1\alpha_1 \left[\nu(X_1 - 1, X_2) - l_1^d\right] + X_2\alpha_2 \left[\nu(X_1, X_2 - 1) - l_2^d\right] - h_1X_1 - h_2X_2 \\ & + \max \begin{cases} 2\lambda_1 p_1 \left[\nu(X_1 - 1, X_2) + l_1^e\right] + 2\lambda_1(1 - p_1) \left[\nu(X_1 - 1, X_2) - l_1^d\right] \\ +[(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + 2\lambda_2]\nu(X_1, X_2) \\ \lambda_1 p_1 \left[\nu(X_1 - 1, X_2) + l_1^e\right] + \lambda_1(1 - p_1) \left[\nu(X_1 - 1, X_2) - l_1^d\right] \\ +\lambda_2 p_2 \left[\nu(X_1, X_2 - 1) + l_2^e\right] + \lambda_2(1 - p_2) \left[\nu(X_1, X_2 - 1) - l_2^d\right] \\ +[(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + \lambda_1 + \lambda_2]\nu(X_1, X_2) \\ 2\lambda_2 p_2 \left[\nu(X_1, X_2 - 1) + l_2^e\right] + 2\lambda_2(1 - p_2) \left[\nu(X_1, X_2 - 1) - l_2^d\right] \\ +[(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + 2\lambda_1]\nu(X_1, X_2) \end{cases} \end{aligned} \tag{7.2}$$

As before, the first two terms of the optimality equation represent patient deaths while waiting for evacuation, and the second two terms represent the costs of holding all remaining patients of both types in the system. The final term represents the choice between the three allocation options, and each includes a fictitious transition rate.

7.1.1 Dynamic Programming Results for the Two-server Model

The two-server model was tested at each of the parameter settings used in the single server sensitivity analysis. The resulting policies are presented in two tables below. These tables also include the single server results as previously shown in Chapter 6 for comparison. As before, a "1" or "2" in the *Policy*[1] column represents a greedy Type 1 policy or a greedy Type 2 policy, respectively. In column *Policy*[2], a "1" indicates a greedy policy that chooses all Type 1 patients first, a "2" represents that the evacuation teams should be split, and a "3" represents a greedy policy that chooses to evacuate Type 2 patients first. The superscripts "1" and "2" represent the single server model and two-server model, respectively.

The table does not completely represent the fact that policy 2 is never optimal. That is, it is never optimal to split the evacuation teams between both patients. Therefore, a "Switch" in column *Policy*[2] represents an evacuation that begins by giving priority to Type 2 patients (both teams evacuate Type 2 patients) and then switches so that both teams evacuate Type 1 patients. The optimal policy is a switching policy for the following tests: #44, #53, #62, #68, #71, #77, and #80. These policy diagrams are shown below in Figures 7.1 - 7.4.

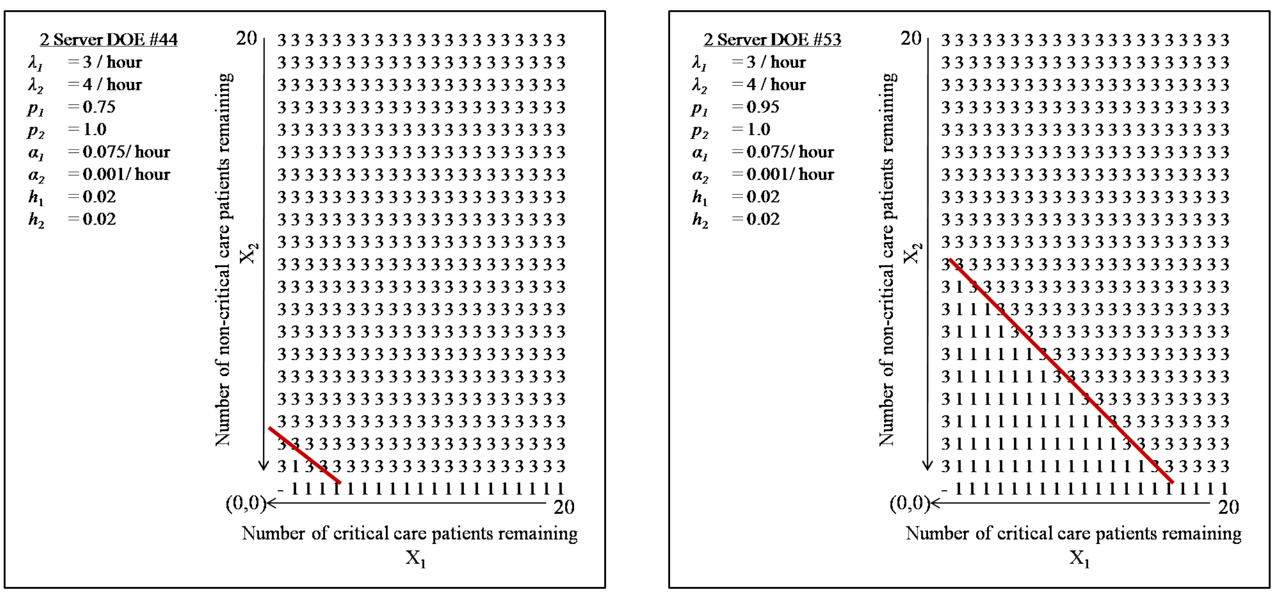


Figure 7.1: Optimal policies for the two-server: DOE Runs #44 and #53.

Table 7.1: Sensitivity Analysis Results for the Single Server Model, 1 of 2

Test #	λ_1	λ_2	p_1	p_2	α_1	α_2	h_1	h_2	$Policy^1$	$\nu(20,20)^1$	$Policy^2$	$\nu(20,20)^2$
1	2	4	0.5	1	0.025	0.001	0.01	0.02	2	-1.8657	3	-0.3598
2	2	4	0.5	1	0.025	0.001	0.02	0.02	2	-12.6637	3	-11.817
3	2	4	0.5	1	0.025	0.001	0.03	0.02	2	-23.4617	3	-23.275
4	2	4	0.5	1	0.05	0.001	0.01	0.02	2	-4.2457	3	-1.8065
5	2	4	0.5	1	0.05	0.001	0.02	0.02	2	-14.0545	3	-12.594
6	2	4	0.5	1	0.05	0.001	0.03	0.02	2	-23.8634	3	-23.381
7	2	4	0.5	1	0.075	0.001	0.01	0.02	2	-6.1717	3	-3.0690
8	2	4	0.5	1	0.075	0.001	0.02	0.02	2	-15.2828	3	-13.3157
9	2	4	0.5	1	0.075	0.001	0.03	0.02	2	-24.3939	3	-23.5623
10	2	4	0.75	1	0.025	0.001	0.01	0.02	2	6.0641	3	8.4961
11	2	4	0.75	1	0.025	0.001	0.02	0.02	2	-4.7338	3	-2.9615
12	2	4	0.75	1	0.025	0.001	0.03	0.02	2	-15.5319	1	-14.4193
13	2	4	0.75	1	0.05	0.001	0.01	0.02	2	2.2610	3	-6.1221
14	2	4	0.75	1	0.05	0.001	0.02	0.02	2	-7.5477	3	-4.6654
15	2	4	0.75	1	0.05	0.001	0.03	0.02	2	-17.3566	3	-15.453
16	2	4	0.75	1	0.075	0.001	0.01	0.02	2	-0.7151	3	4.0888
17	2	4	0.75	1	0.075	0.001	0.02	0.02	2	-9.8262	3	-6.1577
18	2	4	0.75	1	0.075	0.001	0.03	0.02	Switch	-18.9373	3	-16.4044
19	2	4	0.95	1	0.025	0.001	0.01	0.02	2	12.4080	3	15.5809
20	2	4	0.95	1	0.025	0.001	0.02	0.02	2	1.6099	3	4.1232
21	2	4	0.95	1	0.025	0.001	0.03	0.02	2	-9.1880	3	-7.3344
22	2	4	0.95	1	0.05	0.001	0.01	0.02	2	7.4665	3	12.4650
23	2	4	0.95	1	0.05	0.001	0.02	0.02	2	-2.3423	3	1.6774
24	2	4	0.95	1	0.05	0.001	0.03	0.02	Switch	-12.1511	3	-9.1100
25	2	4	0.95	1	0.075	0.001	0.01	0.02	2	3.6500	3	9.8151
26	2	4	0.95	1	0.075	0.001	0.02	0.02	2	-5.4610	3	-0.4314
27	2	4	0.95	1	0.075	0.001	0.03	0.02	Switch	-14.5653	3	-10.6781
28	3	4	0.5	1	0.025	0.001	0.01	0.02	2	-2.3768	3	-0.9119
29	3	4	0.5	1	0.025	0.001	0.02	0.02	2	-13.1863	3	-12.2154
30	3	4	0.5	1	0.025	0.001	0.03	0.02	1	-22.3120	1	-21.5288
31	3	4	0.5	1	0.05	0.001	0.01	0.02	2	-4.7704	3	-2.3231
32	3	4	0.5	1	0.05	0.001	0.02	0.02	2	-14.7945	3	-13.1258
33	3	4	0.5	1	0.05	0.001	0.03	0.02	Switch	-23.4871	1	-22.1731
34	3	4	0.5	1	0.075	0.001	0.01	0.02	2	-6.7578	3	-3.5827
35	3	4	0.5	1	0.075	0.001	0.02	0.02	Switch	-16.1913	3	-13.9628
36	3	4	0.5	1	0.075	0.001	0.03	0.02	Switch	-24.4056	1	-22.8021
37	3	4	0.75	1	0.025	0.001	0.01	0.02	2	5.8263	3	8.1149
38	3	4	0.75	1	0.025	0.001	0.02	0.02	2	-4.9831	3	-3.1884
39	3	4	0.75	1	0.025	0.001	0.03	0.02	T 1	-13.0985	1	-11.9429
40	3	4	0.75	1	0.05	0.001	0.01	0.02	2	2.1047	3	5.8787
41	3	4	0.75	1	0.05	0.001	0.02	0.02	Switch	-7.9192	3	-4.92387
42	3	4	0.75	1	0.05	0.001	0.03	0.02	1	-14.9770	1	-12.9597

Table 7.2: Sensitivity Analysis Results for the Single Server Model, 2 of 2

Test #	λ_1	λ_2	p_1	p_2	α_1	α_2	h_1	h_2	$Policy^1$	$\nu(20,20)^1$	$Policy^2$	$\nu(20,20)^2$
43	3	4	0.75	1	0.075	0.001	0.01	0.02	2	-0.9099	3	3.9092
44	3	4	0.75	1	0.075	0.001	0.02	0.02	Switch	-10.2483	Switch	-6.4708
45	3	4	0.75	1	0.075	0.001	0.03	0.02	1	-16.6989	1	-13.9262
46	3	4	0.95	1	0.025	0.001	0.01	0.02	2	12.3889	3	15.3364
47	3	4	0.95	1	0.025	0.001	0.02	0.02	2	1.5793	3	4.0330
48	3	4	0.95	1	0.025	0.001	0.03	0.02	1	-5.7278	1	-4.2742
49	3	4	0.95	1	0.05	0.001	0.01	0.02	2	7.6049	3	12.44033
50	3	4	0.95	1	0.05	0.001	0.02	0.02	Switch	-2.3146	3	1.6376
51	3	4	0.95	1	0.05	0.001	0.03	0.02	1	-8.1224	1	-5.5889
52	3	4	0.95	1	0.075	0.001	0.01	0.02	2	3.7683	3	9.90274
53	3	4	0.95	1	0.075	0.001	0.02	0.02	Switch	-5.0198	Switch	-0.4768
54	3	4	0.95	1	0.075	0.001	0.03	0.02	1	-10.2776	1	-6.8254
55	3.5	4	0.5	1	0.025	0.001	0.01	0.02	2	-2.9232	3	-1.488
56	3.5	4	0.5	1	0.025	0.001	0.02	0.02	2	-13.9211	3	-12.9441
57	3.5	4	0.5	1	0.025	0.001	0.03	0.02	1	-20.1869	1	-19.3687
58	3.5	4	0.5	1	0.05	0.001	0.01	0.02	2	-5.2947	3	-2.8718
59	3.5	4	0.5	1	0.05	0.001	0.02	0.02	Switch	-15.5408	3	9.8151
60	3.5	4	0.5	1	0.05	0.001	0.03	0.02	1	-21.5053	1	-20.0616
61	3.5	4	0.5	1	0.075	0.001	0.01	0.02	2	-7.2822	3	-4.1161
62	3.5	4	0.5	1	0.075	0.001	0.02	0.02	Switch	-16.8485	Switch	-14.7115
63	3.5	4	0.5	1	0.075	0.001	0.03	0.02	1	-22.7566	1	-20.7342
64	3.5	4	0.75	1	0.025	0.001	0.01	0.02	2	5.3626	3	7.5892
65	3.5	4	0.75	1	0.025	0.001	0.02	0.02	Switch	-5.630	3	-3.8668
66	3.5	4	0.75	1	0.025	0.001	0.03	0.02	1	-10.8709	1	-9.7263
67	3.5	4	0.75	1	0.05	0.001	0.01	0.02	2	1.6958	3	5.4127
68	3.5	4	0.75	1	0.05	0.001	0.02	0.02	Switch	-8.0550	Switch	-5.5675
69	3.5	4	0.75	1	0.05	0.001	0.03	0.02	1	-12.7647	1	-10.7455
70	3.5	4	0.75	1	0.075	0.001	0.01	0.02	2	-1.309	3	3.4786
71	3.5	4	0.75	1	0.075	0.001	0.02	0.02	Switch	-9.9471		-6.8777
72	3.5	4	0.75	1	0.075	0.001	0.03	0.02	1	-14.5088	1	-11.7175
73	3.5	4	0.95	1	0.025	0.001	0.01	0.02	2	11.9912	3	14.8511
74	3.5	4	0.95	1	0.025	0.001	0.02	0.02	Switch	1.2222	3	3.3950
75	3.5	4	0.95	1	0.025	0.001	0.03	0.02	1	-3.4181	1	-2.0124
76	3.5	4	0.95	1	0.05	0.001	0.01	0.02	2	7.2883	3	12.0404
77	3.5	4	0.95	1	0.05	0.001	0.02	0.02	Switch	-1.46730	Switch	1.3145
78	3.5	4	0.95	1	0.05	0.001	0.03	0.02	1	-5.7721	1	-3.2927
79	3.5	4	0.95	1	0.075	0.001	0.01	0.02	Switch	3.4702	3	9.5545
80	3.5	4	0.95	1	0.075	0.001	0.02	0.02	1	-3.6960	Switch	-0.1199
81	3.5	4	0.95	1	0.075	0.001	0.03	0.02	1	-7.9105	1	-4.5042

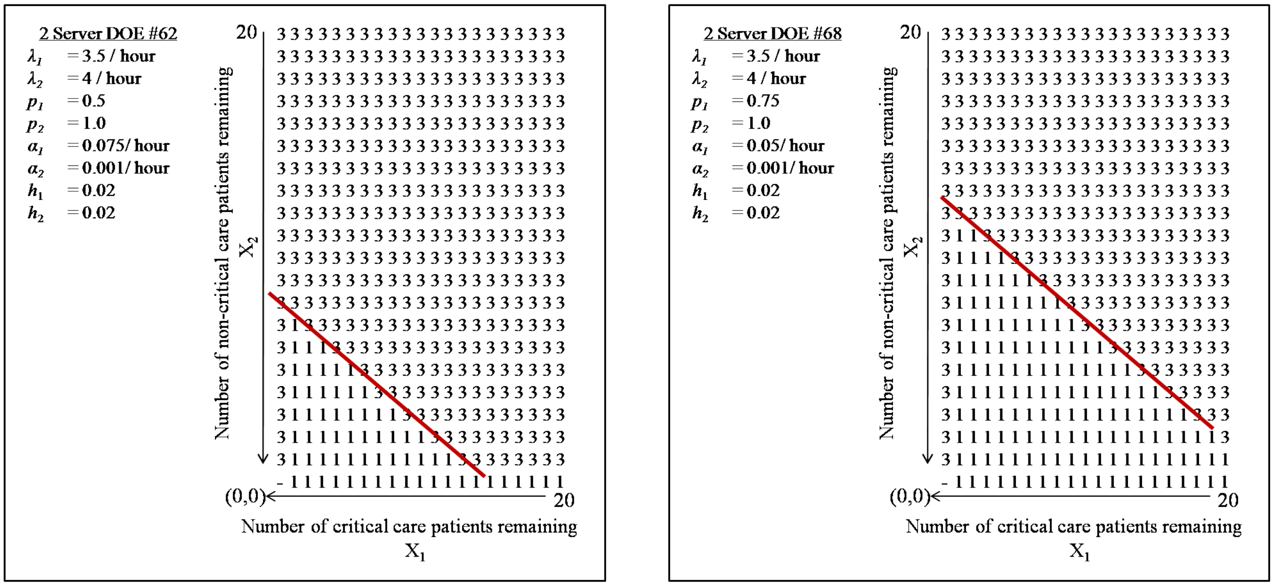


Figure 7.2: Optimal policies for the two-server: DOE Runs #62 and #68.

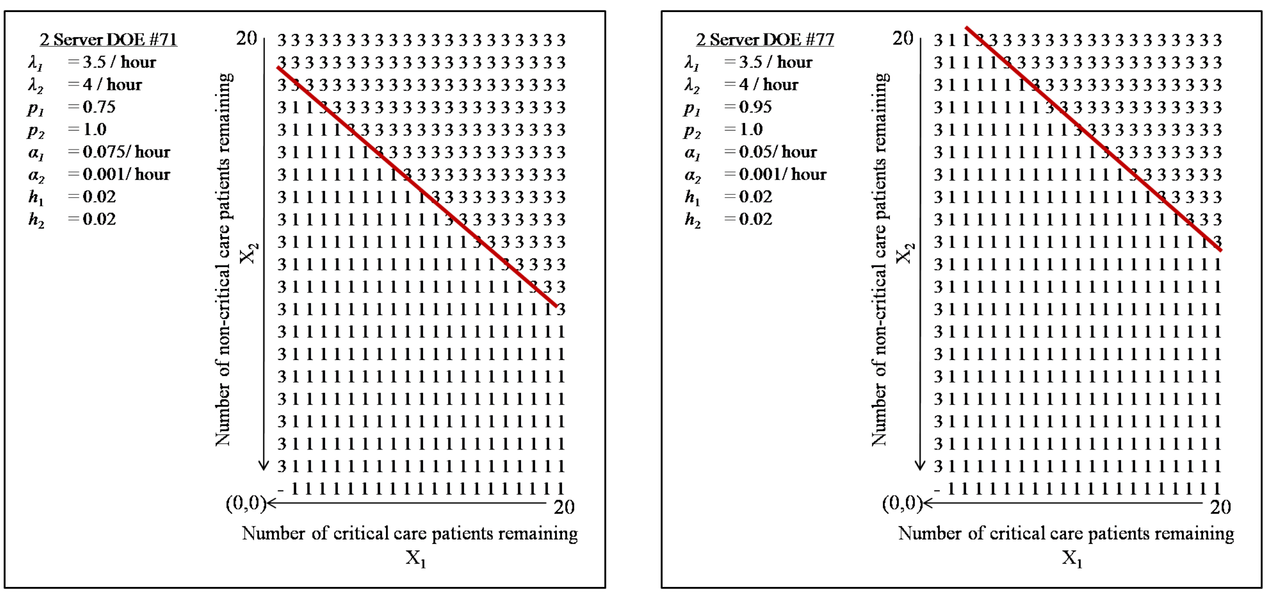


Figure 7.3: Optimal policies for the two-server: DOE Runs #71 and #77.

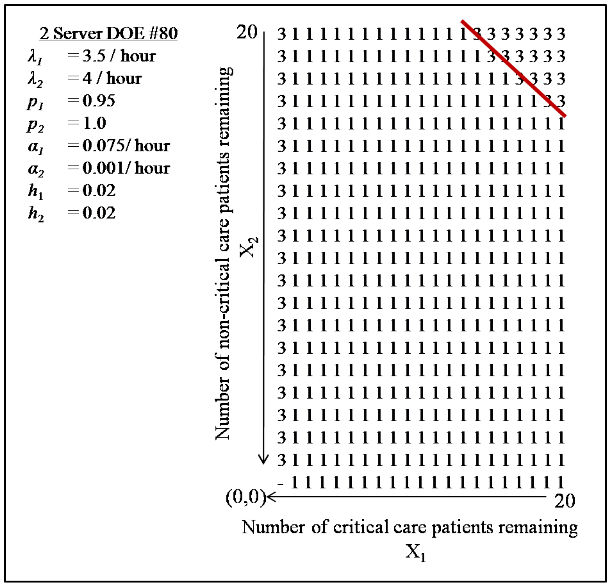


Figure 7.4: Optimal policies for the two-server: DOE Run #80.

It can be shown mathematically that the optimal policy for the two-server model is to allocate the two evacuation teams to the same patient group such that two patient evacuations from the same class occur simultaneously.

7.1.2 Optimal Server Allocation

As shown in the previous section, the optimal policy for the two-server model is either Policy 1 or Policy 3 (evacuation teams should both be allocated to evacuate Type 1 patients or Type 2 patients, respectively). It is never optimal to split the evacuation teams between the two patient groups (Policy 2). Though the structural properties of the optimality equations are difficult to prove, it is relatively easy to show that the evacuation teams should be allocated to the same patient group.

Theorem 1. *The optimal policy for Equation (7.2) is either to assign both evacuation teams to Type 1 patients or to assign both evacuation teams to Type 2 patients; therefore, it is never optimal to split the two evacuation teams between the two patient groups so that one team evacuates Type 1 patients and one team evacuates Type 2 patients.*

Proof. From the two-server optimality equation (Equation [7.2]), we see that the choice is between three options, and $\nu(X_1, X_2)$ is optimized by determining the maximum of applying Policies 1, 2, and 3. With a bit of algebra, this implies a comparison of

$$\max \begin{cases} 2\lambda_1 v(X_1 - 1, X_2) + 2\lambda_2 v(X_1, X_2) \\ \lambda_1 v(X_1 - 1, X_2) + \lambda_2 v(X_1, X_2 - 1) + (\lambda_1 + \lambda_2) v(X_1, X_2) \\ 2\lambda_2 v(X_1, X_2 - 1) + 2\lambda_1 v(X_1, X_2) \end{cases} \tag{7.3}$$

First, suppose that applying Policy 1 results in a higher value than applying Policy 3. This implies that

$$2\lambda_1 v(X_1 - 1, X_2) + 2\lambda_2 v(X_1, X_2) > 2\lambda_2 v(X_1, X_2 - 1) + 2\lambda_1 v(X_1, X_2) \tag{7.4}$$

from Equation (7.3). Dividing both sides of Equation (7.4) by 2, results in the following:

$$\lambda_1 v(X_1 - 1, X_2) + \lambda_2 v(X_1, X_2) > \lambda_2 v(X_1, X_2 - 1) + \lambda_1 v(X_1, X_2), \tag{7.5}$$

and by adding $\lambda_2 \nu(X_1, X_2)$ to both sides, the following is obtained:

$$\lambda_1 v(X_1 - 1, X_2) + 2\lambda_2 v(X_1, X_2) > \lambda_2 v(X_1, X_2 - 1) + (\lambda_1 + \lambda_2) v(X_1, X_2). \tag{7.6}$$

Next, by adding $\lambda_2 \nu(X_1 - 1, X_2)$ to both sides of Equation (7.6), a final inequality is obtained:

$$2\lambda_1 v(X_1 - 1, X_2) + 2\lambda_2 v(X_1, X_2) > \lambda_1 v(X_1 - 1, X_2) + \lambda_2 v(X_1, X_2 - 1) + (\lambda_1 + \lambda_2) v(X_1, X_2). \tag{7.7}$$

Note that the left hand side of Equation (7.7) still represents the value of applying Policy 1, but now the right hand side of Equation (7.7) is equal to the value of applying Policy 2. Therefore, to assume that Policy 1 results in a greater value than Policy 3 is also to assume that Policy 1 results in a greater value than Policy 2.

Now suppose that Policy 3 results in a higher value than applying Policy 1. Similar logic shows that if Policy 3 results in a greater value than Policy 1, the value from applying Policy 3 must also be greater than the value from applying Policy 2. First, suppose that applying Policy 3 results in a higher value than applying Policy 1. This implies that

$$2\lambda_2 v(X_1, X_2 - 1) + 2\lambda_1 v(X_1, X_2) > 2\lambda_1 v(X_1 - 1, X_2) + 2\lambda_2 v(X_1, X_2) \tag{7.8}$$

from Equation (7.3). Dividing both sides of Equation (7.8) by 2, the following is obtained

$$\lambda_2 v(X_1, X_2 - 1) + \lambda_1 v(X_1, X_2) > \lambda_1 v(X_1 - 1, X_2) + \lambda_2 v(X_1, X_2), \tag{7.9}$$

and by adding $\lambda_1 \nu(X_1, X_2)$ to both sides, the following is obtained:

$$\lambda_2 v(X_1, X_2 - 1) + 2\lambda_1 v(X_1, X_2) > \lambda_1 v(X_1 - 1, X_2) + (\lambda_1 + \lambda_2) v(X_1, X_2), \tag{7.10}$$

Next, by adding $\lambda_2 \nu(X_1, X_2 - 1)$ to both sides of the equation, a final inequality is obtained:

$$2\lambda_2 v(X_1, X_2 - 1) + 2\lambda_1 v(X_1, X_2) > \lambda_1 v(X_1 - 1, X_2) + \lambda_2 v(X_1, X_2 - 1) + (\lambda_1 + \lambda_2) v(X_1, X_2) \tag{7.11}$$

Note that the left hand side of Equation (7.11) still represents the value of applying Policy 3, but now the right hand side of Equation (7.11) is equal to the value of applying Policy 2. Therefore, to assume that Policy 3 results in a greater value than Policy 1 is also to assume that Policy 3 results in a greater value than Policy 2.

Therefore, the optimal policy decision in the two-server model is either to allocate both teams to evacuate Type 1 patients or to allocate both teams to evacuate Type 2 patients.

□

7.2 Patient Transitions between Classes

As mentioned in Chapter 5, there is a chance that the patients' classification could change during the course of the evacuation. For example, a patient's health status could diminish from a non-critical care patient or a patient could be relocated so that their physical position relative to location of the emergency within the facility changes their rates for evacuation and chances for survival while waiting to be evacuated. In addition, the standard of care could change so that some critical care patients are treated like non-critical care patients.

In this section, the model formulations are only set up (there is no discussion or testing) and include the β_i parameter to represent the rate at which type i patients become a type j patient. Such a transition would decrease the number of type i patients $(X_i - 1)$ and increase the number of type j patients $(X_j + 1)$.

7.2.1 Single Server Beta Model

Equation (7.12) presents the optimality equation for the single server beta model.

$$\begin{aligned}
&\nu(X_1, X_2) = X_1\alpha_1 \left[\nu(X_1 - 1, X_2) - l_1^d\right] + X_2\alpha_2 \left[\nu(X_1, X_2 - 1) - l_2^d\right] \\
&+X_1\beta_1 \left[\nu(X_1 - 1, X_2 + 1)\right] + X_2\beta_2 \left[\nu(X_1 + 1, X_2 - 1)\right] - h_1X_1 - h_2X_2 \\
&+\max \begin{cases} \lambda_1 p_1 \left[\nu(X_1 - 1, X_2) + l_1^e\right] + \lambda_1(1 - p_1) \left[\nu(X_1 - 1, X_2) - l_1^d\right] \\ +[(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + (N_1 - X_1)\beta_1 + (N_2 - X_2)\beta_2 + \lambda_2]\nu(X_1, X_2) \\ \lambda_2 p_2 \left[\nu(X_1, X_2 - 1) + l_2^e\right] + \lambda_2(1 - p_2) \left[\nu(X_1, X_2 - 1) - l_2^d\right] \\ +[(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + (N_1 - X_1)\beta_1 + (N_2 - X_2)\beta_2 + \lambda_1]\nu(X_1, X_2) \end{cases}
\end{aligned} \tag{7.12}$$

First, the model was tested with $\beta_1 = \beta_2 = 0$ to ensure the optimal policies were consistent with the results presented in Chapter 5.

7.2.2 Two-server Transitions Model

Though no formal tests have been completed, Equation (7.13) presents the optimality equation for the the two-server beta model.

$$
\begin{aligned}
&\nu(X_1, X_2) = X_1\alpha_1 \left[\nu(X_1 - 1, X_2) - l_1^d\right] + X_2\alpha_2 \left[\nu(X_1, X_2 - 1) - l_2^d\right] \\
&+X_1\beta_1[\nu(X_1 - 1, X_2 + 1) + X_2\beta_2[\nu(X_1 + 1, X_2 - 1) - h_1X_1 - h_2X_2 \\
&+\max \begin{cases}
2\lambda_1 p_1 \left[\nu(X_1 - 1, X_2) + l_1^e\right] + 2\lambda_1(1 - p_1) \left[\nu(X_1 - 1, X_2) - l_1^d\right] \\
+[(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + (N_1 - X_1)\beta_1 + (N_2 - X_2)\beta_2 + \lambda_2]\nu(X_1, X_2) \\
\lambda_1 p_1 \left[\nu(X_1 - 1, X_2) + l_1^e\right] + \lambda_1(1 - p_1) \left[\nu(X_1 - 1, X_2) - l_1^d\right] \\
+\lambda_2 p_2 \left[\nu(X_1, X_2 - 1) + l_2^e\right] + \lambda_2(1 - p_2) \left[\nu(X_1, X_2 - 1) - l_2^d\right] \\
+[(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + (N_1 - X_1)\beta_1 + (N_2 - X_2)\beta_2 + \lambda_1]\nu(X_1, X_2) \\
2\lambda_2 p_2 \left[\nu(X_1, X_2 - 1) + l_2^e\right] + 2\lambda_2(1 - p_2) \left[\nu(X_1, X_2 - 1) - l_2^d\right] \\
+[(N_1 - X_1)\alpha_1 + (N_2 - X_2)\alpha_2 + \lambda_1]\nu(X_1, X_2)
\end{cases}
\end{aligned}
\tag{7.13}
$$

Chapter 8

Findings, Implications, and Conclusions

Over the course of developing this research, it has become obvious to me that the most difficult piece of this problem to discuss, write, or model is the ability of clinicians and healthcare administrators to actually make patient prioritization decisions - whether it be because the resources to make the decisions or carry out the decisions are unavailable, or because clinicians themselves have ethical concerns or even liability concerns. Therefore, it seems that there is a need and significance for this research. In June 2010, the South Carolina Hospital Association held a meeting: the "Summit on Lessons Learned from the H1N1 Outbreak and Making Medical Decisions During Incidents with Scarce Resources." The purpose of the meeting was to discuss the state's response to the recent H1N1 outbreak from the hospitals' perspectives. The first presentation, given by Joseph Barbera, MD and Associate Professor of Engineering Management from George Washington University, discussed "Critical Care Delivery in the Scarce Resource Situation" [12]. In this presentation, the standard of care during emergency situations was discussed, and it was obvious that there are a variety of liability concerns and ethical conflicts associated with making such decisions. There were no fixed conclusions for how scarce resources should be allocated — "in emergency type x do y,"— but there was consensus that data-driven, ethical models are needed well in advance of an emergency situation in which they could be put to use. In addition, clinicians want consensus on what decisions should and can be made — from all levels of their management all the way up to the accrediting and licensing agencies — for protection of their own decisions during actual emergency events.

The purpose of this research is therefore to provide insights into the problem of patient prioritization during complete evacuations from healthcare facilities. To date, this problem has been rarely discussed - likely due to the fact that most facilities have system redundancies in place (to protect their patients, equipment, supplies, pharmacy, etc. so that an emergency does not create the need for an evacuation) as well as the highly ethical nature of the prioritization discussion. In the few cases where patient prioritization strategies are suggested or explained, there is a lack of consensus about (1) which patients *should* be selected first and (2) which patients *were* selected first during actual emergency evacuations.

Every prioritization policy discussed in the literature, however, is an all-or-nothing, greedy policy. That is, the policies in the literature choose either critical care or non-critical care patients for evacuation. It has been shown, however, that a greedy policy is not always optimal. In his presentation, Dr. Barbera challenged the audience multiple times to avoid "all-or-nothing" decisions when making scarce resource allocation decisions. Instead of decisions that just benefit one person (or group), creative solutions that give more opportunities to the patients are necessary. Though speaking specifically about ventilator allocation during a pandemic influenza outbreak, the point translates to this research.

During an actual emergency evacuation event, transportation decisions would likely depend on more than the number and classification of the patients in the system. The availability of transportation resources and beds at receiving facilities are likely a large determinant of how patients are chosen for evacuation. For example, if an ambulance capable of transporting an ICU patient is available, and an ICU bed is open at a neighboring facility, it is highly unlikely that this ambulance would transport a non-critical care patient. Particularly during a regional disaster, it is likely that evacuation prioritization decisions will be very highly dependent on the transportation resources that can even be made available to the patients since multiple facilities often have contracts with the same transportation services and will therefore be competing for their use. Reducing the prioritization problem to a decision based on the number of the patients in the system — as presented in Chapters 5 - 7 — is an unlikely representation of the system in practice, but it is the first step in understanding the problem. During an evacuation, clinicians and hospital administrators would be required to make a variety of decisions under uncertainty, continually changing conditions, and incomplete information. Having understood and practiced the insights from this research may enable decision makers to be more comfortable with the patient prioritization problem.

8.1 Modeling Conclusions and Insights for Practitioners

The following section summarizes the insights from the literature review as well as the models that were presented and tested in Chapters 5 - 7.

There is a lack of consensus about which patient type should be given priority during a complete healthcare facility evacuation. Some papers suggest that critical care patients should be transported away from the facility first, and others recommend that non-critical care patients be given evacuation priority. The dynamic programming models indicate that such greedy policies are not always optimal for patient selection decisions.

Clinicians generally make ethical decisions based on values and virtues. Their jobs are to care for patients, and therefore prioritization decisions may be difficult for nurses and doctors. Public policy decisions, however, are based on the utilitarian principle of doing the most good for the most amount. In this framework, ethical decisions are resolved by considering how the overall utility can be maximized, and at times, the resolutions to which virtues and values lead may be in direct conflict.

The optimal policies for the evacuation dynamic programming model can be characterized as one of three different policy types: either a greedy, Type 1 policy; a switching policy; or a greedy, Type 2 policy. In fact, the switching curve is embedded even within the greedy policies, but it has either located so far down and to the left or up and to the right so that only one policy is shown for all decision points (except when there are 0 patients remaining of a certain patient type; then the only other choice is to evacuate the other patient type). In the context of critical and non-critical care patients, a downward shift in the location of the switching curve results in a greedy policy in favor of the non-critical care patients. A shift upwards results in a greedy policy in favor of the critical care patients. This implies that a switching policy should begin with the evacuation team — or teams — selecting non-critical care patients first for evacuation. At some point, depending on the patient classification rates, a switch should be made so that all remaining critical care patients are selected for evacuation. Once all critical care patients have been removed from the system, all remaining non-critical care patients should be transported away from the facility. When holding costs are not considered, it has been shown that using the dynamic programming policies saves more lives than using a greedy policy similar to those suggested in the literature.

When holding costs are *not* included as a variable for determining which patients should be chosen, and in the event that a patient group can be evacuated more quickly and also die more quickly while waiting to be evacuated, it is obvious that this patient group should be given priority. Such a scenario could occur based on the patients' relative location to the hazard. It is more likely, however, that patients will be categorized as critical or non-critical care patients. This assumes that non-critical care patients can be evacuated more quickly, that non-critical care patients have a higher probability of a successful evacuation, and that critical care patients die while waiting to be evacuated more quickly than non-critical care patients. When holding costs are not considered, a greedy policy can very likely be predicted by considering the ratio of the input parameters. When the ratio $\lambda_1 p_1 \alpha_1 / \lambda_2 p_2 \alpha_2 < 1$, a greedy, Type 2 policy is most likely optimal. If $\lambda_1 p_1 \alpha_1 / \lambda_2 p_2 \alpha_2 > 1$ and $\lambda_1 p_1 \alpha_1 / \lambda_2 p_2 \alpha_2 < 1.3$, a switching policy is much more likely to occur, and the model should be run to determine the exact patient prioritization scheme. If $\lambda_1 p_1 \alpha_1 / \lambda_2 p_2 \alpha_2 > 1.3$, it is likely that a greedy, Type 1 policy is optimal.

When discussing our models, I have heard it said that cost should not be considered when making evacuation decisions. Whether the actual monetary costs should be included may be debatable, but it is certain that there are costs associated with choosing one patient group over another. For example, choosing to evacuate non-critical care patients leaves critical care patients in the facility, and these patients require more resources. When holding costs *are* included, it is more difficult to predict whether a greedy or a switching policy is optimal. When examining the output of more than 100 tests, however, a number of common properties were identified for the single server model (both with and without holding costs) as well as the two-server model. It was shown that the value function is concave in both X_1 and X_2 and that supermodularity and diagonal dominance relationships exist (both with and without holding costs).

In terms of critical and non-critical care patients, the concavity relationships imply that the change in the average reward per patient associated with selecting a critical or non-critical care patient increases as the number of critical or non-critical care patients in the system, respectively, decreases. The supermodularity relationship implies that the change in the average value resulting from evacuating non-critical care patients increases as the number of critical care patients in the system decreases. Similarly, the change in the value associated with evacuating critical care patients becomes greater as the number of non-critical care patients in the system decreases. Therefore, as the number of patients in the system decreases, the decisions between the two patient groups have more of an impact than those decisions made at the beginning of the evacuation.

The models are most sensitive to holding costs, and the holding costs have a more significant impact on the location of the switching curve when the ratio of λ_1/λ_2 is increased. Incremental increases to the rates of evacuation, probability of a successful evacuation, and holding costs move the switching curve in favor of that particular patient type. For example, in the sensitivity analysis from Chapter 7, these parameters were increased for Type 1 patients, and as a result, the switching curve moved up in turn creating a larger region of Type 1 priorities. If these parameters had been increased for the Type 2 patients, the switching curve would have moved downward and therefore created a larger region of Type 2 priorities. Eventually, incremental increases to these parameters result in greedy policies. This is not true, however, of the α values. At certain values, incremental changes to α "work in favor" of that patient type. Eventually, the switching curve will start to move in the other direction and therefore decrease the region of priority for that patient type. For example, when α_1 was increased in the sensitivity analysis, the switching curve starting moving upwards and created a larger region of Type 1 priorities. However, at a certain point — the exact values have not yet been determined — the switching curve started moving back down and therefore decreasing the Type 1 region. If the death rate of one patient group is very large, at some point, it is not optimal to use resources to attempt to evacuate these patients but instead save the patients who will contribute to the overall reward.

When there are two evacuation teams available to move patients, the optimal policy is either to assign both teams to transport Type 1 patients or to assign both teams to evacuate Type 2 patients; it is never optimal to split the evacuation teams between the two patient groups. However, a switching policy may still be the optimal choice, and in the case of critical and non-critical care patients, a switching policy should begin with non-critical care patient evacuations followed by a switch to critical care patient evacuations.

8.2 Need for Future Research

There are certainly opportunities for a variety of modeling extensions. The current model looks only at the prioritization decision; a more realistic model would consider the availability of transportation resources as well as the availability of beds at receiving facilities.

It may be beneficial to extend the number of patient classifications. For example, there are neonatal intensive care unit (NICU) babies that are likely to have different requirements and characteristics than those of adult ICU patients. Along those same lines, the rewards for the patient classifications could be expanded further solely than counting the number of saved lives. For example, the number of life years after the evacuation, quality-adjusted life years, or some other measure would allow for further prioritization within the groups. In addition, the effects of incorrectly classifying a patient as a critical or non-critical care patient — or incorrectly assigning the input parameters — need consideration. Regardless of how the models are altered, a better understanding of the actual values for the input parameters would improve the modeling efforts. While the rates of evacuation chosen in the previous chapters were based on observations at mock evacuations, there are no data available for estimating the holding costs. Knowing the input values would allow a better analysis of the location and movement of the switching curve.

A major assumption of these models is that the input parameters are stationary. In reality, the rates at which patients can be evacuated, the rates at which patients die while waiting to be evacuated, and the probability of a successful evacuation are likely to change over time as the evacuation window decreases.

Maybe most importantly, there needs to be continued discussion among healthcare workers about the ethical dilemmas associated with making evacuation decisions as well as other scarce resource allocation decisions. Even if the insights from this research were presented to a hospital staff, clinicians are not likely to be comfortable making these decisions because of the ethical dilemmas and potential legal consequences. Without support from all levels and management, as well as accrediting and licensing agencies, data-driven optimization models and research will not be as beneficial as possible.

8.3 Concluding Remarks

These models may not yet be ready for implementation, but they are certainly ready for discussion. It has been shown that the optimal policy resulting from the dynamic programs may be different from those described in the literature. Switching policies may be considered a more ethical approach than greedy policies to a virtues-based thinker, and when optimal, they are also the best policies from a utilitarian perspective. Making data-driven evacuation decisions is improvement, and continued discussion, data collection, and modeling efforts can help clinicians improve evacuations. The hope is that the insights from this research have laid a foundation and will encourage discussions for improving existing emergency plans.

Appendices

Appendix A Hospital Evacuation Survey

Information Concerning Participation in a Research Study

Evacuation Survey for Healthcare Facilities

Dr. Kevin Taaffe and Ashley Kay Childers, Clemson University

Dr. Eva Njoku and Dr. Innocent Nkwocha, South Carolina State University

You are invited to participate in a research study conducted by Dr. Kevin Taaffe and Ashley Kay Childers of Clemson University and Drs. Eva Njoku and Innocent Nkwocha of South Carolina State University. The purpose of this research is to examine the decisions that are made for prioritizing patients for evacuation during emergencies.

Your participation will involve completing the survey included and submitting your facility's evacuation plans. The survey should take only a few minutes for a person who is familiar with your facility's evacuation plan.

Potential benefits

Reviewing your evacuation plans will help us to understand the structure of evacuation plans and help us identify any current policies for determining the order to transport patients when there is a limited window for evacuation.

For your participation, we will provide your facility with any of the results of our research. In the short-term, we will only be evaluating evacuation plans. In the long-term, we hope to develop guidelines to aid healthcare officials in evacuation decision making.

Voluntary participation

Your participation in this research study is voluntary. You may choose not to participate and you may withdraw your consent to participate at any time. You will not be penalized in any way should you decide not to participate or to withdraw from this study.

Contact information

If you have any questions or concerns about this study or if any problems arise, please contact Ashley Kay Childers (akchild@clemson.edu).

Evacuation Decision Survey
May 2008

I. DEMOGRAPHIC INFORMATION

1. How many licensed beds are in your facility? ____
2. How many staffed beds are in your facility? ____
   a. Breakdown of beds by type (ICU, CCU, PICU, etc.)

      ______________________________ ____
      ______________________________ ____
      ______________________________ ____
      ______________________________ ____
      ______________________________ ____
      ______________________________ ____
      ______________________________ ____
      ______________________________ ____

3. How many floors tall is your facility? ____

II. TRANSPORTATION/PATIENT TRANSFER

1. With regard to evacuation, are there strategies used to determine transfer/movement priority in the evacuation plan?

   ____ Yes. If so, please describe below.
   ____ No.

2. Other than the clinical staff, who is allowed to move patients? Please describe how this protocol changes as the immediacy of the emergency increases.

____ Volunteers
____ Family
____ Other staff members
____ Other patients

3. Does your evacuation plan address horizontal and vertical evacuation? (check)

____ Yes.
____ No, but this is included in another plan.
____ No, this issue has not been addressed.

4. Does your evacuation plan address patient evacuation out of the facility? (check)

____ Yes.
____ No, but this is included in another plan.
____ No, this issue has not been addressed.

5. Does the plan include an estimate for the time required for a full evacuation?

____ Yes. Estimate: ______________________
____ No.

6. Does the evacuation plan address what to do if there is a limited time window for evacuation (not enough time to get all patients out of the facility)?

____ Yes. If yes, please describe below.
____ No.

7. What transportation resources are available to actually move patients? (check all that apply)

____ Ambulance
____ Facility-owned, non-emergency vehicles
____ Public safety vehicles (police, fire, etc.)
____ Public buses
____ Personal vehicles
____ Helicopters
____Other: ____

8. Does the disaster plan specify transferring (please check):
____ Medical records?
____ Medication? (if yes, for how many days?) ______________________________
____ Equipment?
____ Other? (please describe)____

9. Where is the nearest shelter to transport patients?
   ____ within 5 miles or less
   ____ more than 5 miles (estimation?)____

10. What is the largest transportation vehicle available to you to transport patients?
    ____ Ambulance
    ____ Mini van
    ____ Bus
    ____ Other (please specify) ____

11. What is the largest number of patients that can be transported at one time?
    ____ Under 5 people
    ____ More than 10 people
    Estimation: ____

12. Which patient group would you most likely transport first?
    ____ Hospice patients
    ____ Acutely ill patients
    ____ Chronically ill patients
    ____ Intermediate care patients
    ____ Other (please specify) ____

13. Which patient age group do you think have priority in transporting to safety?
    ____ Infants
    ____ Young children
    ____ Young adults 21 – 35
    ____ Middle adults 35 – 65
    ____ Older adults 66 and older

III. OTHER DISASTER PLAN CHARACTERISTICS

1. Is the evacuation plan generic to all hazards or is it specific to a particular threat? (check)

   ____ Generic; covers evacuation decisions and procedures that are used for any evacuation.
   ____ Event-specific (please describe).

2. Is your evacuation plan community- or system-based or specific to your facility? (check)

   ____ Community/System-based ____ Facility-specific

3. What position in your organization is authorized by the evacuation plan to activate it?

   Name and title: ______________________________

   Alternate: ______________________________

4. Does the evacuation plan specify criteria on which to base the decision to activate evacuation?
   ____ Yes, the principle criteria are:
      ____ City, county, or state emergency declaration
      ____ Environmental conditions
      ____ Facility conditions
      ____ Other: ____
   ____ Yes, but the criteria are not explicitly stated; this decision is left to those in charge.
   ____ No.

5. How are receiving facilities chosen?

   ____ Facilities where mutual aid and sheltering agreements are in place
   ____ Facilities that are geographically closest
   ____ Facilities with specialized equipment or capacity
   ____ Facilities with available beds
   ____ Contacting facilities outside of the area of impact
   ____ Other (please describe below)

6. Does the evacuation plan explicitly outline mutual aid agreements with other facilities? (check)

   ____ Yes. Does this include?
      ____ Exchange of equipment?
      ____ Exchange of staff?
      ____ Movement of patients? Does this include?
   ____ No

7. What regulatory or accrediting agencies affect evacuation planning? (please list)

8. Which pieces of data from the medical record are available to classify patients for evacuation decision making?

IV. SOCIAL WORK AND PERSONNEL

1. How many staff persons do you have in each of the following areas:

   ____ Social workers
   ____ Counselors
   ____ Other (please describe below)
   ____ Nurses
   ____ Volunteers

2. Please describe the role of professional caregivers in the evacuation process below.

3. Are all staff and personnel aware of your evacuation plan?

____ Yes
____ No
____ Not sure

4. How do you make staff and professional caregivers aware of your emergency evacuation plan? Please explain any training or strategies used to inform all hospital staff about the emergency evacuation plan.

5. How often do you provide evacuation training for hospital personnel?

____ Annually
____ Bi-annually
____ Not sure
____ Do not know
____ Other

6. Which of the following personnel are usually included in evacuation training?

____ Social workers
____ Nurses
____ Doctors
____ Volunteers
____ Aides
____ Others (please describe)

7. When was the last evacuation training in your facility?

____ Within the last 3 months
____ Within the last 6 months
____ Last year
____ More than one year ago
____ Don't know

Please provide a copy of your current evacuation plan and any other documents that may address evacuation decision-making.

Thank you for participating, and we look forward to working with you in the coming months! If you have any questions, please contact Ashley Kay Childers at akchild@clemson.edu

This survey uses questions and amends the data collection tool published by Schultz et al.

Schultz CH, Koenig KL, Auf der Heide E: Benchmarking for hospital evacuation: A critical data collection tool. *Prehospital Disaster Medicine* 2005; 20(5) 331-342.

Appendix B Mock Evacuation Experiences

In the Spring and Fall semesters of 2008, an undergraduate Creative Inquiry team gathered data at two mock evacuations. The data collected is included below in Tables 1 and 2. Patient types are listed as “Non” to represent inpatients from floors, and “Critical” represents those patients that were transferred from an ICU bed.

Table 1: Mock Evacuation Data Collection - Facility 1.

Type	Start	Prep [min]	Move [min]	Stage [min]	Load [min]	Depart
Non	8:04	7.17	2.83	0	0.75	8:15
Non	8:10	12.0	2.0	0	0.5	8:25
Non	8:22	28.6	4	0	1.43	8:56
Non	8:35	14.48	5.98	0.1	0.4	8:56
Non	9:11	9.95	3.48	0.17	0.67	9:28
Non	9:29	12.1	3.21	0	0.87	9:45
Non	9:40	5.87	3.93	0	0.8	9:49
Non	9:55	3.32	4.93	0	0.88	10:04
Non	10:08	4	3.33	2	2.5	10:20
Non	10:17	9.78	2.88	1.45	0.57	10:29
Non	9:22	9.3	4	0	0.38	10:36
Non	10:15	23	3.38	0	1.17	10:45
Non	10:42	5.4	3.12	0	1.43	10:53
Non	10:49	3.3.5	5.97	0	0.73	11:01
Non	11:06	10.07	5.55	1.7	0.5	11:24
Non	11:20	4.2	6.08	0.72	1.08	11:33
Non	11:32	14.1	2.45	0	0	11:50
Non	11:44	7.72	3.68	0.52	1.33	11:57
Non	11:52	3	2.72	3.07	0.53	12:02
Non	12:24	4.95	3	1.65	0.95	12:34
Non	12:27	9	5.12	0	1.0	12:43
Non	12:47	8	4.28	0	1.42	1:01
Non	1:02	13.85	5.22	0.33	1.33	1:23
Critical	8:10	27	4.83	0	0.5	8:43
Critical	8:03	35	5.75	0	1.5	8:45
Critical	8:35	19	3.6	15.83	3.25	9:16
Critical	8:57	24	7.67	0	0	9.31
Critical	9:25	25.72	3.97	0	1.85	9:57
Critical	10:32	16.5	3.23	0	0.57	10:54

Table 2: Mock Evacuation Data Collection - Facility 2.

Type	Start	Prep [min]	Move [min]	Stage [min]	Load [min]	Depart
Non	unknown	3.97	1.72	1.05	0.72	unknown
Non	unknown	5.75	2.23	0.77	1.23	unknown
Non	10:18	5.0	2.0	2.0	1.0	10:31
Non	10:28	5.55	2.5	0.78	2.9	10:40
Non	10:42	2.0	2.98	0.33	0.63	10:51
Non	11:02	4.0	2.0	2.0	1.0	11:15
Non	11:12	14.82	1.63	0.67	1.35	11:31
Non	11:21	7.0	3.0	1.0	1.0	11:37
Non	11:54	6.17	4.2	0.68	1.75	12:07
Non	12:15	10.0	2.45	0.7	0.8	12:38
Non	12:16	3.32	2.12	0.48	1.12	12:25
Non	12:17	7.0	2.0	1.0	1.0	12:28
Non	12:37	5.0	3.0	2.0	1.0	12:48
Non	12:44	4.08	3.83	0.75	1.7	12:55
Non	1:03	3.55	2.38	1.38	0.97	1:13
Critical	9:12	8.0	8.0	1.0	1.0	9:30
Critical	9:28	7.5	2.03	2.08	1.52	9:44
Critical	9:33	9.33	3.53	2.5	2.0	10:03
Critical	9:36	1.0	7.0	1.0	1.0	9:56
Critical	10:05	14.15	1.85	0.5	0.47	10:21

Appendix C Dynamic Programming Models

The code for solving the dynamic program was written in Microsoft Visual Studio. A description of the code follows:

- Declare the number of critical and non-critical care patients to be evacuated.
- Declare global variables and functions.
  - For example, the variables "VOLD[N1+1][N2+1]" and "VNEW[N1+1][N2+1]" track the value of the function at the previous and current iterations.
- The rates are scaled to convert the continuous-time problem to an equivalent discrete-time problem.
- The main program consists of the following functions, and they are called in the following order:
  - Read-data - Reads values from the text file "DataIn.txt" in the following order:
    * λ_1 - the rate Type 1 patients are evacuated
    * λ_2 - the rate Type 2 patients are evacuated
    * p_1 - the probability of a successful evacuation of a Type 1 patient
    * p_2 - the probability of a successful evacuation of a Type 2 patient
    * α_1 - the death rate while waiting of a Type 1 patient
    * α_2 - the death rate while waiting of a Type 2 patient
    * r_1 - the reward or penalty for an evacuee or death of a Type 1 patient
    * r_2 - the reward or penalty for an evacuee or death of a Type 2 patient
  - Initialize - the value function is set to 0
  - Formulation - evaluates the value function for all policy options
  - Iteration - determines if an iteration should be included for (X_1, X_2)
  - Exchange - if an iteration is carried out, the value function is updated

  - Find Policy - determines which policy maximizes the value function
  - Store - writes data to output files

- The program returns the following output files:

  - "DataOut.txt" - returns the value at each combination of X_1 and X_2
  - "DataPolicy.txt" - returns the optimal policy at each combination of X_1 and X_2
  - "FinalPolicy1.txt" - returns the value of choosing Policy 1 at each combination of X_1 and X_2
  - "FinalPolicy2.txt" - returns the value of choosing Policy 2 at each combination of X_1 and X_2

Appendix D Simulation

This section describes the simulation used to test the optimal policies or examine “switch times.”

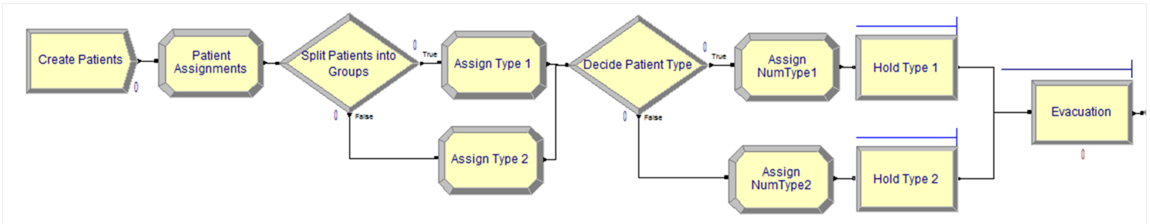


Figure 1: Simulation screen shot: Patient creation and classification.

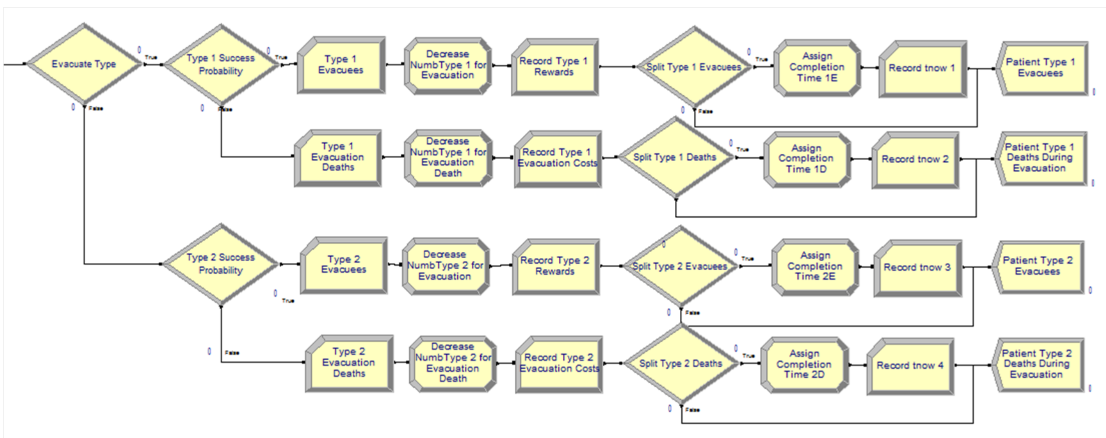


Figure 2: Simulation screen shot: Hold then evacuate.

Figures 1 and 2 represent the main portion of the simulation logic for patient evacuations. At the beginning of the simulation, patients are split into their categories and then held according to appropriate policy. For example, the following conditions were used to hold patients for Test 2 described in Chapter 5. Figure 2 shows the remainder of the evacuation portion of the simulation.

For example, Figure 3 shows the logic used to hold Type 1 patients while Type 2 patients are given priority for evacuation.

Figures 4 and 5 show the “background” portion of the simulation. There are two control entities that search the Type 1 and Type 2 holding queues to remove patients; this represents α_i, or the

```
(tnow > 0 && ((NumType1 == 1 && NumType2 <=14) ||
(NumType1 == 2 && NumType2 <= 13) || (NumType1 == 3 && NumType2 <=12) ||
(NumType1 == 4 && NumType2 <=12) || (NumType1 == 5 && NumType2 <= 11) ||
 (NumType1 == 6 && NumType2 <=10) || (NumType1 == 7 && NumType2 <= 10) ||
(NumType1 == 8 && NumType2 <= 9) || (NumType1 == 9 && NumType2 <= 8) ||
(NumType1 == 10 && NumType2 <= 8) || (NumType1 == 11 && NumType2 <= 7) ||
(NumType1 == 12 && NumType2 <= 6) || (NumType1 == 13 && NumType2 <= 5 ) ||
(NumType1 == 14 && NumType2 <= 5) || (NumType1 == 15 && NumType2 <=4) ||
(NumType1 == 16 && NumType2 <= 3) || (NumType1 == 17 && NumType2 <=3) ||
(NumType1 == 18 && NumType2 <=2) || (NumType1 == 19 && NumType2 <= 1) ||
(NumType1 == 20 && NumType2 <= 1))) &&
NR(Evacuation Team)== 0
```

Figure 3: Simulation logic: Hold Type 1 patients and evacuate Type 2.

death rate while waiting for an evacuation for a type i patient. There is a third control entity that determines the percentage of incomplete evacuations; that is, the proportion of runs in which the facility was not completely cleared of all of its patients.

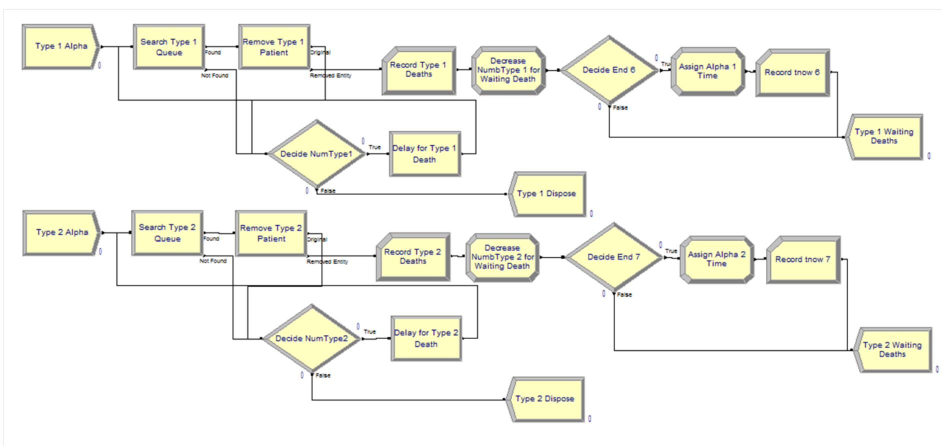


Figure 4: Simulation screen shot: Remove patients from evacuation queues.

The simulation output includes

- The number of successful Type 1 evacuations.
- The number of successful Type 2 evacuations.
- The number of Type 1 patients that died during evacuation.

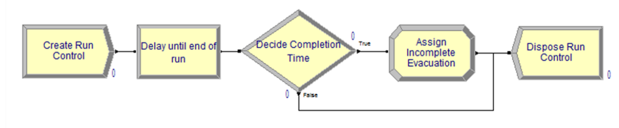


Figure 5: Simulation screen shot: Control entity to determine incomplete evacuations.

- The number of Type 2 patients that died during evacuation.
- The number of Type 1 patients that died while waiting to be evacuated.
- The number of Type 2 patients that died while waiting to be evacuated.
- The average time to completely clear the patients from the system.
- The percentage of incomplete evacuations.

In addition to running simulations of the optimal policies from the dynamic program, the simulation was also used to determine the optimal switch time. In these cases, the decisions are based on the time rather than the state of the system. There are two different models to examine the switch time: one that begins by evacuating Type 1 patients and another that begins by evacuating Type 2 patients. A variable to represent the "switch time" is included. In these models, the holding conditions are based on whether the switch time has passed and whether there are still patients in the other queue.

Appendix E Electronic Attachments

E.1 Sensitivity Analysis Files

The electronic attachments include the results of the design of experiments tests. Because the DOE was created as a list of randomized trials, the order in which the tests were run does not correspond to how the tests are presented in Tables 6.4 and 6.5. The following table maps the order of the runs in the Excel file to the order in which they are displayed in this document.

Table 3: List of Randomized Sensitivity Analysis Trials for the Single Server Model, 1 of 2

In Document	In File
1	14
2	51
3	52
4	65
5	1
6	23
7	63
8	3
9	16
10	50
11	5
12	18
13	44
14	34
15	71
16	54
17	9
18	42
19	61
20	49
21	64
22	33
23	27
24	59
25	19
26	78
27	55
28	48
29	77
30	13
31	12
32	15
33	30
34	56
35	25
36	8
37	69
38	62
39	68
40	60
41	39

Table 4: List of Randomized Sensitivity Analysis Trials for the Single Server Model, 2 of 2

In Document	In File
42	21
43	36
44	53
45	46
46	80
47	37
48	40
49	41
50	76
51	70
52	43
53	24
54	22
55	28
56	26
57	38
58	29
59	20
60	7
61	11
62	72
63	6
64	35
65	75
66	81
67	73
68	74
69	58
70	17
71	79
72	32
73	66
74	45
75	31
76	47
77	57
78	4
79	10
80	2
81	67

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