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Using Computer Simulation Modeling To Evaluate The Bioterrorismresponse Plan At A Local Hospital Facility

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USING COMPUTER SIMULATION MODELING TO EVALUATE THE BIOTERRORISM RESPONSE PLAN AT A LOCAL HOSPITAL FACILITY

by

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ABSTRACT

The terrorist attacks of September 11th, 2001 and the subsequent anthrax mail attack have forced health care administrators and policy makers to place a new emphasis on disaster planning at hospital facilities—specifically bioterrorism planning. Yet how does one truly “prepare” for the unpredictable? In spite of accreditation requirements, which demand hospitals put in to place preparations to deal with bioterrorism events, a recent study from the General Accounting Office (GAO) concluded that most hospitals are still not capable of dealing with such threats (Gonzalez, 2004). This dissertation uses computer simulation modeling to test the effectiveness of bioterrorism planning at a local hospital facility in Central Florida, Winter Park Memorial Hospital. It is limited to the response plan developed by the hospital’s Emergency Department. It evaluates the plan’s effectiveness in dealing with an inhalational anthrax attack. Using Arena computer simulation software, and grounded within the theoretical framework of Complexity Science, we were able to test the effectiveness of the response plan in relation to Emergency Department bed capacity. Our results indicated that the response plan’s flexibility was able to accommodate an increased patient load due to an attack, including an influx of the “worried well.” Topics of future work and study are proposed.

This dissertation is dedicated to my parents, Gene and Clare Bebber, who instilled in me the value of education and challenged me to never stop learning.

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CHAPTER ONE: INTRODUCTION

Introduction

> *America must know that the battle will not leave its land, God willing, until America leaves our land, until it stops supporting Israel, until it stops the blockade [now occupation] against Iraq.* Osama bin Laden, 1998[1]

The terrorist attacks of September 11th, 2001 and the subsequent anthrax mail attack have forced health care administrators and policy makers to place a new emphasis on disaster planning at hospital facilities – specifically bioterrorism planning. This was followed by an emphasis from federal policy makers on preparations for a bioterrorist attack in the form of the introduction of smallpox into a community. Reinforcing this emphasis on bioterrorism preparedness were outbreaks of new, natural diseases such as Severe Acute Respiratory syndrome (SARS) and avian flu (H5N1). Yet how does one truly "prepare" for the unpredictable? In spite of accreditation requirements which demand hospitals put in to place preparations to deal with bioterrorism events, a recent study from the General Accounting Office (GAO) concluded that most hospitals are still not capable of dealing with such threats (Gonzalez, 2004). No doubt there are many factors contributing to hospital unpreparedness, notwithstanding the still present issues that existed prior to 2001 (declining reimbursement from government and private third party payers, the growing number of the uninsured, consumer driven health plans, etc.) and still affect hospitals today.

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[1] Statement, translated by the Associated Press, October 9th, 2001, available at http://users.skynet.be/terrorism/html/laden_statement.htm and accessed August 30th, 2006

Health care components of disaster preparedness have received haphazard treatment. It is generally assumed that the locus of the health care response to a mass-casualty event will be the local hospital facility or facilities. These facilities, however, have been under increasing financial pressures from other societal problems, namely the growing number of uninsured Americans seeking care while reimbursement rates from federal and state social insurance programs and private managed care companies have been declining.

America’s health care system faces a unique set of challenges. Increasing systemic costs associated with rising health insurance premiums, new technologies, and greater demand coupled with planned reductions in Medicare and Medicaid expenditures, results in dwindling resources. Since 2001, there have been annual, double-digit increases in health insurance premiums for firms with 200 or more employees, with an additional 11.4 percent increase projected for 2004 (Kaiser/HRET, 2004). By 2013, national health expenditures are expected to rise to $3.3 billion, or 18.4% of Gross National Product (Heffler et al, 2004).

Hospitals are not immune. They are under pressure for cost transparency from consumers and regulators. There is a powerful movement toward improved quality of service delivery and patient safety. Expectations from patients that newly introduced technologies will be available put upward pressure on expenses. At the same time, managed care companies have continued to slow their rates of reimbursement, while pharmaceutical companies drive drug prices higher and higher. Governments are placing greater regulatory burdens on hospitals, along with accreditation agencies. While hospitals are facing significant workforce shortages in states such as Florida, they continue to see a greater number of patients with severe, chronic conditions (FHA, 2004).

Hospitals are also expected to bear a greater fiscal burden for social problems. For example, in Florida, the number of non-elderly uninsured rose to 2.9 million (EBRI, 2004). The percent of Floridians who have employer-based health insurance declined to 57 percent in 2003, down from a high of 61.1% in 2000 (EBRI, 2003). The total cost of uncompensated care provided by Florida hospitals went from $1.2 billion in 1998 to $1.5 billion in 2002 (AHCA, 2003). This burden is as a result of federally mandated care provided through the “Emergency Medical Treatment and Labor Act” or EMTALA.

In fact, hospitals in the United States are being compared to the plight of major American airlines. The similarities are striking. “Both comprise companies that built a complex infrastructure and provided cross-subsidized services.” Cross-subsidized services are necessary for hospitals since a great deal of the services they provide are not paid for. Hospitals provide care to Medicare and Medicaid patients under costs (i.e., they receive less in reimbursement than it costs to care for those patients). In the emergency care setting, hospitals are required to provide care *regardless* of a patient’s ability to pay. In the past, hospitals were able to make up for these losses because of the lack of price transparency and price sensitivity on the part of insurers. This is similar to the airline industry, which was created on a “fly anyone to everywhere” principle. An airline was able to receive less than costs to fly some people some places, because it could make up for it on other routes. Price transparency and low-cost airlines have nearly eliminated the ability of airlines to cross-subsidize, forcing some of the major carriers into bankruptcy or near bankruptcy. In much the same way that general airlines such as Delta or U.S. Air may become a thing of the past, so too may general hospitals that cannot compete with the growing number of specialty facilities who are under no obligation to provide the same level of care in all circumstances (Altman, et al, 2006).

Operating in this environment, hospitals are expected to prepare contingency plans to serve as a primary responder to, and sometimes sentinel of, bioterrorist attack. Planning for these potential inevitabilities can be exceedingly difficult, as facilities must balance the resources used to prepare for uncertainty with the everyday realities of the changing health care market described above.

While there has been some study of hospital preparedness issues in a macro-sense (Aguirre et al, 2005; Braun et al, 2006; Burstein, 2006; GAO, 2003; Helde, 2006; Katz et al, 2006; Murphy, 2004; Perry & Lindell, 2006; Wetter et al, 2001), to date there has been no study of a specific bioterrorism response plan using computer simulation modeling to attempt to judge its effectiveness. What this dissertation proposes to do is evaluate the bioterrorism plan of a local hospital facility in the Orlando area of Florida. The study is further limited to the response plan developed by the hospital's emergency department, which will be the focus of any response effort.

As it in an evaluation of an existing plan, this dissertation is practical in nature and more representative of a case-study. Through the use of computer simulation modeling (or discrete-event simulation) it can observe the effectiveness of the proposed strategy, show how that strategy will affect the ability of the emergency department to function and continue to provide emergency care services, and make recommendations on how the plan can be improved.

Simulation modeling is a powerful tool that can assist decision-makers in evaluating current organizational systems and proposed alternatives. As with all potential tools, it is not the final word in whether a decision is to be made. Our world is impossibly complex, and we cannot ever hope to have all information available prior to taking any consequential action. Modeling can hopefully open our eyes to potential problems and evaluate alternative solutions, but it is only as good as the information inputted into the model and the users who program and use the model for decision-making purposes. Ultimately, we live in a world of unknowns. We can only attempt to mitigate those unknowns as best as possible.

Analyzing the Threat

There remains much debate on the likelihood of the use of a biological weapon by terrorist organizations on targets in the United States. This stems from two main assumptions. First, conventional weapons have already proven themselves as effective against targets around the world and in America and therefore terrorist organizations would be most likely to use proven technology rather than relying on a weapon which is more complex to use and may not prove effective. Second, biological weapons are notoriously difficult to maintain and deploy on the scale that a weapon of mass destruction would imply, i.e., deaths in the thousands or more (CRS, 2004).

Part of the reasons these assumptions hold sway is that much analysis of biological warfare is viewed through the lens of a military weapons system used primarily by a state. We tend to think of the list of state sponsors of terrorism, compiled by the U.S. Department of State each year, as being the nations most likely to seek development of biological and chemical weapons in lieu of pursuing nuclear weapons. States such as Syria, Iran, Libya, North Korea and prior to *Operation Iraqi Freedom* in 2003, Iraq, are high on the list of states suspected of pursing these weapons systems (State, 2003).

However, terrorist organizations may be willing to forgo mass casualties in exchange for the mass terror that the intentional release of biological agents on a civilian population would bring. If one considers the question from an economic perspective, the “barriers to entry” for a terrorist organization to manufacture and deploy a biological weapon capable of mass destruction are high, while the probability of their effective deployment remains uncertain. However, settling on a smaller-scale attack vastly reduces the entry cost while increases the probability of effective use. Indeed, one need only look at the impact of the anthrax attacks subsequent to the attacks on September 11th, 2001, delivered in the form of powder contained in letters, to see how a small attack and limited use (22 people got sick and 5 died) can have a massive impact on the public and the restructuring of daily life. From a *cost-benefit analysis* perspective, the terrorist or terrorists who committed the acts spent very little in terms of money and resources while the United States government and the public were forced to divert considerable funds and resources to respond the attack (Dando, 2005).

National security and homeland security policymakers are rightly concerned about the linkage between state actors and state sponsors with terrorist organizations such as al Qaeda. After the terrorist attacks of 2001, the Bush Administration fundamentally changed U.S. strategy to one of *pre-emption* against terrorist groups and their supporters. Instead of relying on deterrence and defensive measures to discourage attack, the logic was transformed to one of "taking the fight to the enemy." In response, the United States invaded both Afghanistan and Iraq and conducts special operations around the world against number of terrorist groups. It provides military, political and economic assistance to nations involved in fights on their own home territory against terrorist organizations. It also uses diplomatic and economic means to isolate nations which actively support terrorist groups and provide them safe haven (Security, 2006).

We can visualize the reach of terrorist organizations on the following chart. Figure 1 below shows the various levels on which terrorist groups operate. Some operate within a single nation-state or area, while others have regional and global reach. Ultimately, U.S. strategy seeks to reduce the impact and reach of terrorist groups to that of a local criminal problem, as shown in the subsequent figure.

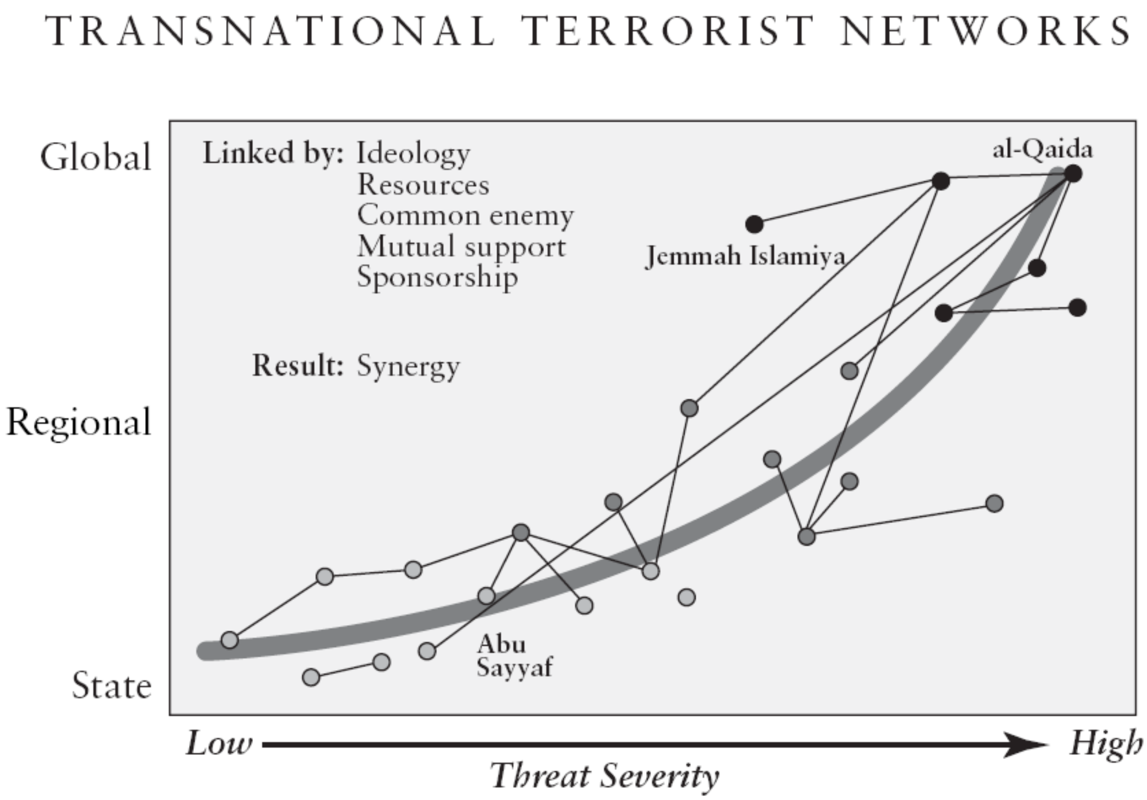

Figure 1: Transnational Terrorist Networks (State, 2003)

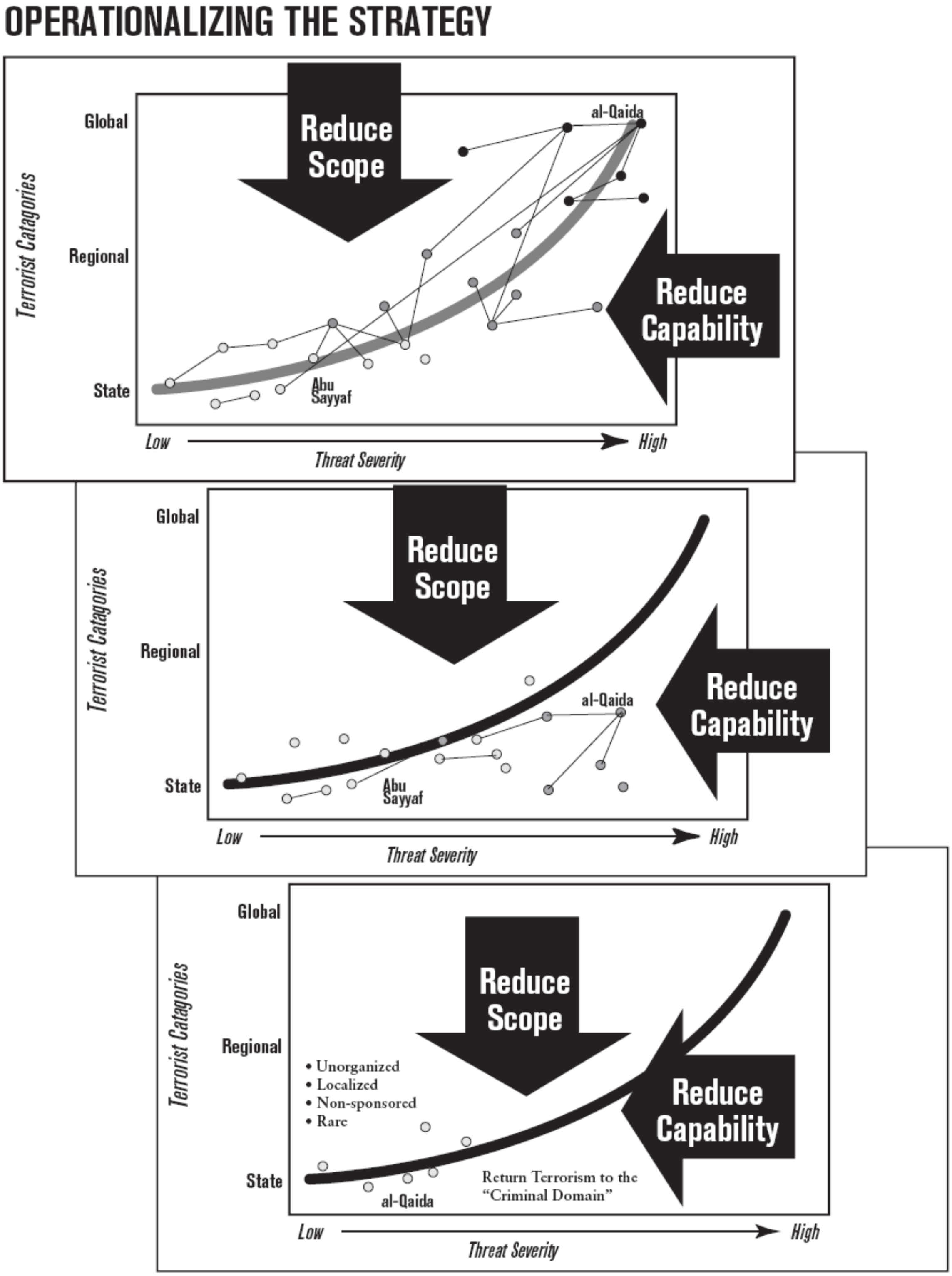

Figure 2: Operationalizing the Strategy (State, 2003)

In spite of this fundamental shift in U.S. strategy, the threat remains that terrorist organizations will seek to inflict damage on the American homefront. Recently, Franck and Melese (2004) used game theory to model the decision-making process that terrorist groups may take to decide whether to employ a weapon such as anthrax. Their hypotheses were supported by their findings which suggest that the type of organization and the “macro-technology” of conflict (p. 369) matters. A *politically* motivated terrorist group, such as the Basque separatists in Spain, is less likely to use a weapon of mass destruction as opposed to a *fanatical* group. Macro-technology includes not only the countermeasures employed by the target country, but also the diplomacy and good relations the target country maintains with its own population in relation to the attack by the terrorist group (Franck & Melese, 2004). As an example, consider the divergent public responses to terrorist attacks from al Qaeda in the United States and Spain. The first attack resulted in an initial “coming together” of the population against the interests of al Qaeda and ultimately, an American military response. The second in Spain led to the overthrow of the Anzar government in Spain in favor of a left-wing government which promised to end Spain’s participation in the Iraq War.

The use of biological agents in warfare dates back to antiquity. The Assyrians used rye ergot to poison the wells of their enemies in the sixth century B.C. The Greeks used animal corpses to infect enemy water supplies, a practice later adopted by the Romans and Persians. In 1346-1347 A.D., the Muslim Tartar, De Mussis, catapulted bubonic-plague infected corpses over the walls of Caffa in the Russian Crimea, causing an epidemic. Defending Christian Geonese sailors fled back to Italy, possibly bringing with them the Black Plague which caused the infamous pandemic, leading to the death of a third of Europe’s population (Iserson, 2001).

Biological agents do make attractive weapons. Being living organisms, they can replicate once disseminated, so a small infection can result in significant exposure to a large population. Illness can take time to be discovered, leading to a spread of infection and a lateness in appropriate response. Of course, the spread of an intentionally introduced biological agent can result in political and social upheaval and disorganization, and paralyze military operations (Globalsecurity.org, 2007).

Due to their susceptibility to environmental degradation, stabilization and dissemination become the important issues related to the use of biological weapons, not unlike the problems encountered in the development of pharmaceutical products. Exposure to heat, pressure, and natural elements, for example, can significantly degrade and render useless any potential bioweapon. Also, deploying a bioweapon system is dependent upon other natural factors, such as wind and rain. Yet in spite of these challenges, a single aircraft which using an aerosol generator to deliver 1-10 micron size droplets can disperse 100 kg of anthrax over a 300 square mile area, potentially infecting millions in an area where the population density is 10,000 people per square kilometer. The dissemination efficiency depends on the system used, with most aerosol delivery systems having a rate of 40 to 60 percent, while explosives are only 1 to 5 percent (Globalsecurity.org, 2007).

According to the Centers for Disease Control (CDC), anthrax is a disease caused by the bacteria *Bacillus anthracis* which forms spores. It is actually a small, one-celled organism. There are three types of anthrax: cutaneous (skin), inhalation (lungs), and gastrointestinal (digestive). It is possible for humans to become infected from handling products from infected animals, or breathing anthrax spores from infected animal products or eating undercooked meat from infected animals. Anthrax can also be used as a weapon, which occurred in the United States in 2001 (CDC, 2003).

Among the three types of anthrax, inhalation anthrax is the most severe. In 2001, almost half of all cases of inhalation anthrax resulted in death. The first symptoms of inhalation anthrax are similar to cold or flu like symptoms. They also include sore throat, mild fever and muscle aches. Later symptoms include cough, chest discomfort, shortness of breath, tiredness, and muscle aches. These symptoms can appear within seven days of coming in contact with all three types of anthrax. For inhalation anthrax, these symptoms can appear within a week to up to 42 days. Early diagnosis is critical to survival, and a case of inhalation anthrax can be treated with antibiotics, such as ciprofloxacin, levofloxacin, doxycycline or penicillin (CDC, 2003).

An inhalation anthrax attack represents an attractive scenario for this model simulation. It presents with common flu like symptoms and therefore detection of the disease is difficult. The inhalation strain of anthrax is not contagious which simplifies the model by not requiring additional isolation and quarantine procedures. Finally, it can easily be dispersed in a populated area through the use of crop dusting planes.

CHAPTER TWO: SIMULATION IN HEALTH CARE, EMERGENCY DEPARTMENT OPERATIONS, AND BIOTERRORISM PREPAREDNESS: A REVIEW OF THE LITERATURE

Computer simulation is proving to be a useful tool in health care and hospital management. What follows is a brief overview of literature related to the use of computer simulation and modeling in the hospital and health care setting. We find that simulation modeling has been used for a variety of studies, including emergency department operations (Blake et al, 1996; Haugh, 2004; Rossetti et al, 1999; Sinreich & Marmor, 2005), cost-benefit analysis (Anderson et al, 2002; Stahl et al, 2004), physician staffing (Dittus et al, 1996; Rossetti et al, 1999), emergency medical services (Su & Shih, 2003), hospital processes (Kumar & Shim, 2005), and health care organization optimization (Alexopolous et al, 2001; Ashton et al, 2005; Masterson et al, 2004; Pasin et al, 2002). More recently, we find studies using computer simulation modeling to analyze bioterrorism preparedness issues (Brookmeyer & Blades, 2003; Buckeridge et al, 2006; Kleinman et al, 2005).

Emergency Department Operations

Noting that health care is not unlike the service industry, Sinreich and Marmor (2005), state that “hospital managers and other health-care policy makers are being forced to search for ways to reduce costs and improve productivity.” As they describe it, their research project aimed to address the principles that the simulation tool be “general and flexible enough” to model many different possible ED (emergency department) settings, that it be “intuitive and simple to use,” and that it include “reasonable default values for many of the system parameters” (2005, p. 734). It was hoped that by fulfilling these objectives, managers would be more willing to use simulation as a decision-making tool.

Examining five different hospitals, they divided facilities based on certain characteristics. Hospital EDs were classified according to physician type (a physician trained in Emergency Medicine or a physician trained in another specialty, such as internal medicine, surgery or orthopedics), patient condition (acute or ambulatory) and whether the facility puts the patient through the same process regardless of condition (separate or not separate) (2005, p. 234).

After meeting with key staff, Sinreich and Marmor had teams of students equipped with standardized code list of the different process elements conduct time and motion studies at each hospital. A total sample size of 16,250 elements was gathered by the teams, while patient types were identified through interviews with senior staff. These were combined to form eight patient types, including fast track, internal, surgical, orthopedic, trauma, walk-in surgical, walk-in orthopedic and internal/surgical. Based on this data, the authors were able to develop a unique process chart for each patient type at each hospital. These charts included duration of each element in the process and the frequency of each of the connections between the different elements. Because these process charts were very similar, the researchers finally were able to develop a unified process chart detailing all the different elements and transitions (2005, p. 236).

Sinreich and Marmor were able to develop a general simulation model of the emergency department that was not dependent on which of the five hospitals the patient visited, showing that patients are better characterized by type (internal, surgical or orthopedic). They determined the average duration of the basic elements in the patient's process which could be used at the default values that could "reduce the need, in some cases, for elaborate time and motion studies in the future." They identified the basic patient streams that triggered different processes and developed estimation models. From this, they were able to develop a main operation screen illustrating the process a patient goes through in the emergency department, including the different elements that can be adjusted to fit each patient type at each hospital (2005, p. 244).

Rossetti et al (1999) used computer simulation to determine the optimal attending physician staffing level at the Emergency Department at the University of Virginia Medical Center in Charlottesville, Virginia. They were able to test alternative ED attending physician-staffing schedules and then analyze the corresponding impact on patient throughput and resource utilization. Without having to disturb the actual system, they could evaluate the effects of staffing, layout, resources and patient flow changes.

Due to the complexity of the information already being collected by the hospital (the ED’s computerized patient tracking system, lab computerized databases, etc.) the data collection effort was divided into four phases. These included a patient-visit time study (detailed information on each stage of the patient visit, such as registration, triage, and discharge), a service distribution time study (the amount of time providers spent providing care to patients), the patient arrival process (walk-in, ambulance or helicopter) and transport and routing times (time between various arrival stations and ED areas and between areas in the ED) (1999, p. 1537).

Rossetti et al then tested four alternative staffing schedules. The current staffing schedule had one attending physician to cover the entire ED 24 hours a day, as well as one pediatric attending physician to cover the pediatric wing and minor emergency area for twelve hours a day (11:00 am to 11:00 pm) The first alternative was taken from input given by the ED management, taking advantage of their specialized knowledge of the system. The second approach used was to maintain the 8 hour double coverage shift of the current schedule, but to vary when that shift was scheduled. The third approach used the same logic but added a second double shift. The fourth approach made use of variations in the patient arrivals by weekday (1999, p. 1537-1538).

All alternatives were tested using a two-stage Bonferroni Approach to conduct the comparison. The main goal of the simulation was to select the best scheduling alternative, which was defined as being that which "minimized the total average patient time within the ED." Their simulation model was able to offer a proposed staffing schedule which decreased the average time a patient was in their ED system by 14.5 minutes per patient or 40 hours per day (1999, p. 1538-1539).

An earlier analysis of emergency room wait times was conducted by Blake, Carter, and Richardson (1996). Their study of Children's Hospital of Eastern Ontario attempted to "determine the flow of patients through the emergency room and to identify the data elements required to complete a quantitative analysis" (1996, p. 266). They hypothesized that patient wait times were influenced by a shortage of scarce resources, the inability of the system to return to normal after the arrival of an emergency case or the "queue discipline" administered in the emergency room. The study was conducted in three phases. The first phase was a three-day field observation of emergency room operations over different shifts. Phase II was the building and validation of a simulation model to test the impact of hypothesized factors on patient wait times. During Phase III, the model was extended to simulate the effect of different operating strategies on patient wait times (1996, p. 266).

The authors noted that Phase II produced some intriguing results. Patient wait-times were shown to be a function of the number of casualty officers available to provide care and the amount of time they were able to provide care to patients. The authors had wondered whether the amount of time casualty officers spent training residents would also affect patient wait times.

Their data showed that queue discipline had little to no effect. Since casualty officers were proving to be the critical element in patient wait times, it was found that by reducing the number of residents in the emergency room (thereby reducing the amount of time casualty officers are educating residents and increasing the amount of time available for patient care) service times may be improved (Blake et al, 1996).

Various operational scenarios were proposed by the hospital in Phase III in the hopes of identifying a way to reduce patient wait times. The hospital decided that its role as a teaching institution remained too valuable to the community to eliminate any resident positions. Therefore the scenarios focused on the number and placement of available physicians to reduce wait times. Such options explored included the creation of a “fast track” to handle “minor emergencies,” and the diversion of patients with minor conditions from the emergency room to the hospital clinic. Through the simulation analysis, the hospital adopted a “fast track” process, expanding its resources and reducing patient wait times (Blake et al, 1996).

Cost-Benefit Analysis

In an era of ever-increasing financial pressures on hospitals, discrete simulation modeling holds some promise as an effective tool to evaluate the costs and benefits of improved clinical care for a variety of procedures. Recently, Stahl et al (2004) used computer modeling to compare current surgical practice with a new modular system in which patient care is handed off between two anesthesiologists, as part of the “OR [Operating Room] of the Future Project” at Massachusetts General Hospital, a teaching facility in Boston. Surgery departments may wish to increase patient volume to improve efficiency, but are wary of adversely affecting patient safety. Most hospital protocols require that the anesthesiologist remain with the patient through surgery and recovery, yet from a productivity perspective, this leaves the operating room and the surgeon "idle." The authors focused on laparoscopic cholecystectomy, analyzing the problem from hospital and clinical staffing costs—most relevant to the organization (Stahl et al, 2004).

The authors chose to use discrete-event simulation (what this author's research uses as well) because it is "methodologically designed to capture flow time, waiting time, competition for resources, and the interdependency of events providing insight into the simulated systems dynamics" (2004, p. 462). Two models are tested. First, the current hospital practice of having both nurses (RN) and anesthesiologists (MDA) present at anesthesia induction and accompany the patient from induction through recovery. A new patient cannot be induced until both the RN and MDA have finished with the current patient. This was compared to a new staffing strategy using 2 MDAs to work in tandem. The first anesthesiologist is responsible for induction. Patient care is then transferred to the second anesthesiologist, who is responsible for interoperative monitoring and recovery. This handoff cannot occur unless the second anesthesiologist is free. Process time data, length of stay data and cost data were modeled as "univariate statistical distributions" within the model. It was analyzed from a "health care delivery system perspective" (using hospital and health care professional staff costs) and focused on the outcome on patient flow time, throughput, waiting time and costs (Stahl et al, 2004).

Discrete-event simulation provided the authors with a useful way to test the effectiveness of alternative systems of care, "particularly when resource constraints and the interdependence of events are important" (Stahl et al, 2004). The proposed staffing strategy was found to be more effective and less expensive than the current strategy. The higher fixed costs of additional staff were able to spread over more patients, thus reducing the total cost per patient treated (Stahl et al, 2004).

Anderson et al (2002) developed a computer simulation model to predict costs and patient outcomes of coronary artery bypass graft (CABG) surgery—one of the most common surgical procedures conducted. While other traditional studies have provided insight into the risk factors associated with variations in operative mortality rates, "less is known about post-operative complication rates and variations in cost" (2002, p. 103). They also point out that "very little is known about factors that are predictive of health care quality of life following CABG surgery" (2002, p. 103).

The authors based their model on all Medicare patients who underwent CABG operations at Methodist Hospital in Indiana from May 1993 to March 1994. Data was collected on length of stay, number of specialists, age, diagnosis related group (DRG), gender, whether the surgery was a reoperation, operative status and the cardiovascular surgeon who performed the operation. Hospital charges and physician charges were also collected, providing complete data for 173 patients (Anderson et al, 2002).

The researchers used a systems dynamics model which uses stack-and-flow diagrams to describe the system's structure. The diagram symbols have definitions associated with them which describe the quantitative relationship that exist among the various model components. Four subsystems were included in the model. The first subsystem generates patients according to a Monte Carlo distribution and assigned a set of preoperative characteristics. In the next subsystem, patients are assigned to one of the five cardiovascular surgeons. Surgeons will vary in their use of specialists and hospital resources. In the third subsystem, patients are hospitalized for treatment and preoperative and postoperative length of stays is modeled with conveyors. Transit times vary and are a function of patient characteristics, the specific surgeon, and the number of specialists who consult for patient care. Finally, the fourth subsystem—the outcomes subsystem

– use data from the other three subsystems to generate patient costs and outcomes (Anderson et al, 2002).

Through their simulation work, the authors were able to determine that gender played an important role in predicting length of stay and patient costs. Female patients were hospitalized longer, thereby incurring more charges. They also tended to have poorer postoperative quality of life, which may be a result of being diagnosed at a later stage in the disease life. Age was also a significant factor in length of stay, patient costs, and postoperative quality of life. Patients over the age of 80 tended not to recover most of the postoperative functional status, calling in to question the cost-effectiveness of performing this procedure on the very elderly. Clinical factors who proved themselves predictors of costs and outcomes included the patient's operative status, reoperations and postoperative complications (Anderson et al, 2002).

Physician Staffing

Concerns regarding patient safety have caused a re-examination of resident physician work schedules. Dittus et al (1996) used computer simulation modeling to evaluate alternative approaches to resident work schedules prior to implementation. They were able to predict the effects on sleep and activity profiles as well as patient demand and job descriptions of the housestaff (Dittus et al, 1996).

The authors used the internal medicine resident rotation at Wishard Memorial Hospital, an urban public facility affiliated with the Indiana University School of Medicine. Their data set is from 1989. The interns' rotation average 97 hours per week at the hospital. Of this time, approximately 68 hours was spent on inpatient care, four hours on outpatient clinic care, and four hours on educational conference demands. The remaining 21 "idle" hours included 9 hours of sleep broken out over 2.3 days. Residents are classified based on their year in residency (interns being first year students, followed by second year residents, third year residents, and senior medical students). Residents and students are groups into "ward teams" which are collectively known as "housestaff" (Dittus et al, 1996).

Model development was approached with the goal of identifying optimal team composition (how many of what type of physician), on-call and vacation/day-off schedule rotation, admitting and primary physician assignment and special considerations to deal with the clinic schedule and providing backup. Important questions include: (1) how much do working long hours and lack of sleep affect quality of care? (2) can learning be adequate without long hours? (3) how important is continuity of care to the housestaff and the patients? (4) what are the effects on nursing and ancillary staff? (Dittus et al, 1996).

The authors chose to use INSIGHT simulation language because it "provided structures to model complex decisions by resources in determining which activities to pursue, the ability of one activity to interrupt another, statistical integrity and an extensive collection of input process distributions" (Dittus et al, 1996, p. 894).

A baseline model was created producing a series of outcome measures: (1) total and maximum number of hours of sleep of housestaff while on call; (2) percentage of time spent at various activities; (3) percentage of educational conferences housestaff was able to attend; (4) percentage of days in which residents taught junior students; (5) total time housestaff spent at the hospital; (6) the time of the patient's request for care until the completion of that care; and (7) measures of the patient's continuity of care. The baseline model was then verified and validated, allowing the researchers to begin altering inputs in order to generate modified models for comparison purposes (Dittus et al, 1996).

The authors note that one of the most important outcomes was the model's ability to predict the amount of sleep a resident would receive under various scheduling alternatives. This could further be explored by examining the amount of uninterrupted hours of sleep, the percentage of call nights the resident has no sleep and the percentage of tired housestaff the following day. The model was able to provide certain measures related to the patient quality of care in relation to resident fatigue. The model can also provide information on timeliness of care by showing how various scheduling alternatives affect the time it takes for patients to receive care from the physician, as well as the interruptions that the resident physician sees during the workday. Continuity of care can be simulated, as well as the impact of alternative schedules on educational components of the resident program (Dittus et al, 1996).

Examining physician staffing issues in the emergency department at the University of Virginia Medical Center in Charlottsville, Virginia, Rosetti, Trzcinski and Synerud (1999) used computer simulation modeling to test alternative emergency department attending physician staffing schedules and to analyze the corresponding impact on patient throughput, resource utilization and overall staffing expense. The management of the emergency department hoped to be able to reduce staffing at slower times to reduce operating expenses and increase staff resource utilization. Of course, reducing staff may result in increased medical errors — an undesirable effect. The authors wished to develop an understanding of system performance relative to various attending staffing schedules (Rosetti et al, 1999).

Using Arena 3.0 simulation logic software, the researchers modeled overall patient flow through the emergency department and ED system processes for realistic operating conditions. The authors chose Arena because it "allows the user to model real world and proposed systems using a set of templates of graphical modules, elements and support blocks for different modeling constructs and capabilities" (Rosetti et al, 1999, p. 1535).

Because of the large amount of complex data elements in the patient flow process, the data collection effort was separated into four different phases: patient visit time study, service distribution time study, patient arrival processes, and transport and routing times. Based on this data collection, four different scheduling approaches were examined. The first was to ask the management of the Emergency Department for their strategies for staffing change. The second approach used was to maintain an 8-hour double coverage shift of the current schedule but to vary when that shift was scheduled. The third approach added a second double coverage shift to the current schedule. The final alternative used patient arrival times to determine when the maximum arrival rate was achieved and selected that time as the time period for double coverage (Rosetti et al, 1999).

The authors used the Two-Stage Bonferroni Approach to conduct the comparative analysis. The simulation showed how the best model decreased current total patient system time in the emergency department by an average of 14.5 minutes per patient, or approximately 40 hours per day. It also showed that it decreased both utilization and percentage of long visits (Rosetti et al, 1999).

Emergency Medical Services (EMS)

In an attempt to improve prehospital response and care, and thereby decrease patient mortality and morbidity, Su and Shih (2003) used computer simulation modeling to evaluate an existing Emergency Medical Services (EMS) system in Taipei, Taiwan and suggest improvements. Their study focused on 23 networked EMS hospitals affiliated with 36 emergency response units that perform two-tier rescues (advanced life support or ALS in addition to basic life support, or BLS).

The researchers used the eM-Plant simulation program to build the model. Prehospital rescue data from December 1-31, 2000, was collected, which included ALS and BLS information. Data elements included the name of the response unit, time dispatch notified, time unit notified, time unit responds, time of arrival at scene, time at which the unit left the scene, time of arrival at the destination hospital, time at which the unit left the hospital and the time the unit was back in service and available for the next call. Best-fit software was then used to determine the best-fitting distribution of the times, at which point the distributions were fed into the simulation. Additional distributions included type of rescue (BLS or ALS), utilization distribution of the two rescue types and percentage of each assigned network hospital as a rescue determination (Su & Shih, 2003).

After building the basic model, it was validated and verified by presenting it to experts in the local EMS system familiar with prehospital rescue to ensure that it to the “correctness and logic of the system flow” (2003, p. 61). Experts in computer simulation also verified the simulation model, and output data was compared with empirical data in order to ensure appropriate reflection of real-world activity (Su & Shih, 2003).

The authors analyzed potential alternatives to improve system performance by examining performance variables. These variables included *call waiting*—when a call for ambulance dispatch is awaiting execution, and includes waiting time as a result of no unit being available; *ALS and BLS event-site arrival time*—the interval between the dispatching call and the arrival of the ALS or BLS unit; *hospital arrival time*—the period between the dispatching of the call and the patient’s arrival at the hospital, including on-site rescue time; *ambulance utilization rate*—

the percentage of time the ambulance is being used as opposed to remaining idle; and *turn-around time*—the interval between the dispatch call and the unit's return back to its subgroup (Su & Shih, 2003).

Four alternatives where then compared. The first was to have one fixed network hospital assigned to each emergency services subgroup to provide two-tier rescue. The second alternative had the number of two-tier rescue units (rescuers and ambulances) assigned to each hospital adjusted based on utilization rates and probability of patients have to wait for rescue (Su & Shih, 2003).

The third scenario altered the cooperative team mix between the emergency services subgroup and the assigned network hospital, taking proximity into consideration. Each subgroup could arrange dispatch sequences among hospitals in advance, establishing a rule set (when subgroup sequence is not available, the second is selected and so on). Based on this rule set, three dispatch models were simulated separately and compared (one fixed hospital, two hospitals in prearranged sequence and three hospitals in prearranged sequence) (Su & Shih, 2003).

The fourth alternative varied dispatch rates. The three dispatch models from the third alternative were used and the dispatch rate of the two-tier rescue was manipulated as 2, 10, and 20% respectively. The *dispatch rate* was defined as the "percentage of runs to which a given ALS ambulance might be assigned" (2003, p. 63).

Using computer simulation, the authors were able to recommend that the second dispatch model (two hospitals per subgroup) be established as the optimum model. It was shown to decrease wait time probability as well as enhance proper prehospital treatment. It also streamlined the dispatching process and decreased the random potential. Each EMS subgroup was recommended to cooperate with two selected hospitals in a prearranged dispatch sequence, thereby simplifying the dispatcher's decision procedure. The simulation was also able to identify Hospital 22 as requiring unique attention, and its rescue teams should be increased to two instead of one (Su & Shih, 2003).

Hospital Processes

Organizations are always under pressure to contain costs, improve efficiency, and remain competitive, and health care organizations are no different. Computer simulation modeling has proven itself a useful tool in this regard, with its process reengineering analysis tools being applied to the health care setting.

Kumar and Shim (2005) note that hospitals "traditionally emphasize breakthroughs" in procedures and technology in surgical care to stay competitive, yet patients may have trouble discerning between all the available options in the health care marketplace. Hospitals therefore seek to improve the surgical care process, since it "consumes significant resources, while it generates significant revenues *if managed properly* [emphasis added]." They used computer simulation to search for a more efficient surgical care process in hospitals which does not compromise patient care. They used as their case study the National Hospital of Singapore (Kumar & Shim, 2005).

As the demand for outpatient surgical operations increased over the years, coupled with an acute shortage in health care manpower, hospital administrators turned to reengineering the surgical care process to improve efficiency. Not surprisingly, managing surgical operations is highly complex. There were a total of 21 operating theaters at the hospital, which in 2000 performed 59,377 surgical operations, 45 percent of which were outpatient surgeries. Out of the 21 theaters, 19 were allocated for outpatient surgeries. Many complexities arise in attempting to reengineer the surgical process. A large portion of the personnel working in the operating theater are not under the direct control of the operating theater manager. Deviations from the daily operating schedule are frequent and expected. The facility must account for emergency operations, operations may be longer or shorter than anticipated, patients may be late or fail to arrive or personnel can become sick or ill during the day (Kumar & Shim, 2005).

The model is constructed using entities, resources, and locations. Entities refer to “an object or person that a simulated model processes.” The entities in this model represent patients (classified by type and corresponding surgical discipline) and setup. Before a patient can be routed to an operating theater, a set up is routed first, including the anesthetist. Locations represent the fixed places in the system where entities are routed for processing or some other activity or decision. These included the entrance, pre-op, the operating theater, recovery, and exit. A resource is a “person, piece of equipment or some other device” used to treat or move patients, assist in the performing of tasks for entities at locations or perform maintenance on locations or other resources. There are three different resources (surgeon, anesthetist and gurney) classified into 10 groups, of which 8 represent surgical disciplines and the last two represent the anesthetist and gurney resources. The entities and resources follow the same path network—the route taken by an entity or resource as it travels between locations (Kumar & Shim, 2005).

Historical data was used from January 2001 to September 2001. The authors had to make several assumptions in order to create a more manageable simulation, including that patients arrived following a Poisson distribution. Second, it had to assume that all patients stayed in pre-operation for 30 minutes and recovery for 15 minutes. Third, it assumed no change in available resources from January to September (Kumar & Shim, 2005).

Working with the Department of Surgery, three alternative scenarios were constructed and tested. The first extended operating hours of operating theaters without additional resources. The second extended operating hours of operating theaters with additional resources. The third declassified operating theaters across surgical disciplines—that is, each operating theater did not have its own exclusive surgical discipline and could operate on a "first come, first serve" basis (Kumar & Shim, 2005).

Each model was tested using the MedModel simulation program, which is "widely used in evaluating, planning or re-designing hospitals, and operating other health care systems" (Kumar & Shim, 2005). The original baseline simulation of the current process showed bottlenecks occurring in patient wait times in theaters reserved for orthopedic surgery and in the use of anesthetic resources. Scenarios one and two, which lengthened the operating time of the theater while adjusting or not adjusting the available resources, did not significantly alleviate any bottlenecks. Alternative three, which declassified operating theaters, significantly reduced the bottle-neck in the pre-operation location, reduced patient arrival failures, and improved system efficiency. Hospital administrators then modified scenario three and adopted it for use (Kumar & Shim, 2005).

Health Care Organization Optimization

As mentioned in the above case study, computer simulation is often used by large hospitals and other organizations to improve efficiency and remain competitive in the health care marketplace. Alexopoulos et al (2001) note that "small healthcare facilities serving the poor are equally in need" but often lack the finances and personnel required to develop and implement simulation solutions (2001, p. 1386). They go on to explain that their project developed a "low-cost, generic, discrete-event simulation model populated by a workflow Excel spreadsheet that can be completed by clinic staff themselves, thus ‘customizing’ the simulation for their own purposes” (2001, p. 1386). Their model focuses on childhood immunization services, but the tool is intended to be flexible enough to serve other healthcare service delivery needs (Alexopolous et al, 2001).

The authors used the Partnership of Immunization Providers (PIP), a collaborative public/private effort created by the University of California, San Diego School of Medicine, Division of Community Pediatrics, and an association of community clinics and small, private provider practices. It was funded through the Centers of Disease Control and Prevention (Alexopolous et al, 2001).

Health care facilities serving the poor often face unique challenges. Their facilities are typically donated, clientele have financial and transportation issues, payment is minimal and the clinics rely on grants and subsidies, and providers are motivated more by altruism. In spite of these issues, they continue to face classic industrial engineering problems involving resource management and efficiency (Alexopolous et al, 2001).

Using a workflow data acquisition tool which had already been created (the Observational Checklist of Patient Encounters, or OCPE), the authors collected data and put it into functional relationships in which to build the initial model of clinical operation. The initial model is broken out into activities, including check-in, waiting room and pre-exam, exam, checkout and charting and post-checkout. They then used the Arena computer software program to generate a discrete-simulation. Finally, the OCPE was merged with the Arena model. While they had to overcome certain technical issues in input analysis, process flow and output data analysis, their research proved that a workable model was possible (Alexopolous et al, 2001).

Ashton et al conducted a simulation based project in Great Britain to help the North Mercy Community National Health Service Trust design and plan a NHS Walk-In Centre. During the summer of 2001, the authors performed a study of the operation of a walk-in centre at Old Swan in Liverpool, England. Their aim was to assist in a planned move and examine how the different services could be operated to the best effect. They paid special attention to patient flow, an assessment of how different levels of demand would affect wait time and the number of patients in the waiting room (Ashton et al, 2005).

Using Micro Saint, a "visual interactive model system," the authors developed a model with three main parts: one for generating patient arrivals, one for clinics, and one for the walk-in center (2005, p. 155). Data was gathered from a variety of sources, including NHS Clinical Assessment System Reports, the baseline number of treatment rooms used on weekdays and weekends, Monthly Service Reports of the Department of Health and clinical staff interviews. The model was validated by comparing it to actual historical data for accuracy and reviewing it with experts (Ashton et al, 2005).

While the model itself was very flexible, the main experiments were designed to test staff suggestions and "best practices" obtained from other clinics. Several options were explored, including examining the effect of using the current practice, reorganizing the reception area, using different triage systems, and the timing and scheduling of the clinic and staff. The researchers developed a number of alternatives to present to stakeholders and it remains a tool for clinic staff to use to explore other reengineering issues (Ashton et al, 2005).

Masterson et al (2004) used a case study of the intensive care unit (ICU) at the US Air Force's Wilford Hall Medical Center to identify changes to improve the quality and delivery of care within the Military Health System. The intensive care unit accounts for only 8 percent of inpatient admission, yet 30 percent of expenditures. The authors noted that the Military Health System must “balance access to the intensive care environment with an opportunity for military healthcare providers to maintain skills necessary to complete missions related to delivery of care in wartime or other contingencies” (2004, p. 217). This study also serves to show that simulation modeling can be applied to other health care environment outside the market world, much like Alexopolous et al (clinics for the poor) and Ashton et al (a public walk-in clinic).

Wilford Hall Medical Center (WHMC) is a 275-bed trauma center in San Antonio, Texas, which provides Level I trauma care for eligible military beneficiaries and all the citizens of Southwest Texas. Because of limited resources, the ICU is sometimes closed to ambulance traffic creating diversion to other facilities. WHMC required an accurate assessment of demand for ICU services and capabilities, as well as analyzing different patient loads, ICU sizes and operating policies (Masterson et al, 2004).

The authors employed the MedModel simulation program “to allow a more robust simulation of multiple patient types, multiple bed types and alternative ICU operating policies” (2004, p. 218). The model generates patients desiring ICU services and processes them according to patient needs, number of available beds, and policies for bed utilization. Outputs are expressed in terms of patients by type deferred, bed occupancy rates, percent of time the ICU is open to trauma patients, costs and revenue streams and GME compliance (the extent to which the ICU supports the graduate resident training requirements) (Masterson et al, 2004).

The first topic explored addressed ICU sizing, which attempted to ascertain the most effective number and size of beds of each type over time. This included a series of options to compare to the current configuration. Option 1 had fewer pediatric units in favor of more ICU beds, while Option 2 had no pediatric beds altogether. Option 3 relocated the pediatric beds and

Option 4 involved a reconstruction of the ICU floor. The model showed how, over time, Options 3 and 4 performed better in the long run (Masterson et al, 2004).

Next, the authors simulated the effect of the bed closure policy—the policy by which the ICU is closed to certain patient types when the ICU reaches near capacity in order to ensure availability of beds for emergencies. The first policy closes the ICU to medicine patients when only one ICU bed remain unoccupied, while the other policy closes the ICU to trauma patients when only one bed is unoccupied. Neither policy had much of an effect on the total number of patients turned away or the bed occupancy (Masterson et al, 2004).

Partitioning policies were also examined. These policies limit certain patients to certain bed types (medicine patients to medicine beds, surgical patients to surgical beds, etc.). Model experiments that did impose partitioning improved the alignment of patients to bed types, but had the negative effect of reducing overall access to the ICU (Masterson et al, 2004).

Finally, and not surprisingly for a military facility, the authors explored the effect of military deployment of healthcare personnel. The authors were able to determine that closing the ICU to certain patient types was able to mitigate some impacts, but overall a large detrimental effect is still observed (Masterson et al, 2004).

Pasin, Jobin, and Cordeau (2002) used computer simulation to study the effect of equipment pooling on a group of community service centers in Montreal, Canada. It attempted to quantify the pooling process as well as allow stakeholders to reach agreement on polling scenarios and to identify the conditions that would ensure equity. Local health service centers were reluctant to participate because they feared losing control, a reduction in service level and an unfair distribution of the costs of pooling resources (Pasin et al, 2002).

The authors used AutoMod to develop the model. Complete pooling of resources, along with other limited pooling models were tested. The limited pooling models were delineated by rule sets, such as a local service center only having to make its excess inventory available if a minimum amount of resources is maintained. They hoped to determine the total cost reduction to all centers from pooling, to see whether certain centers would be worse off than others and to see if the service centers had similar average unit costs (Pasin et al, 2002).

The simulation proved successful in quantifying the overall benefits of pooling as well as showed that the significant losers were those centers with significant equipment overcapacity. The simulation also showed that maintaining similar levels of overcapacity is preferable to maintaining a minimum stock, maximum contribution or maximum debt rule in reducing overall costs (Pasin et al, 2002).

Bioterrorism Preparedness

In the post-September 11th world, researchers are beginning to use computer simulation modeling to examine various aspects of bioterrorism preparedness and response. Brookmeyer and Blades (2003) published a study developing a statistical model to determine how many cases of the disease may have been prevented by public health intervention. Kleinman et al (2005) use simulation to test early warning systems of a biological attack based on health-care encounters. Buckeridge et al (2006) also use simulation to determine the effectiveness of detecting an inhalational anthrax outbreak (which this dissertation focuses on).

In developing their model, Brookmeyer and Blades (2003) distinguish between a *common source outbreak* (one in which all cases were exposed to the same anthrax spores at the same time and place) and a *multicommon source outbreak* (several distinct common source outbreaks that may be separated in both time and place). As an example, the 2001 anthrax outbreak in the United States was a multicommon source outbreak. The key component of their model is known as the *iceberg effect*. The cases initially observed in a common source outbreak are those with a short incubation period, representing the "tip of the iceberg" of all potential cases. Those cases with longer incubation periods in the lungs "might be prevented if they are receiving antibiotics when anthrax spores in their lungs germinate" (2003, p. 782). It is therefore possible to estimate the total number of potential cases (the iceberg), and therefore the number of cases that may have been prevented from data on the observed cases and the incubation period (Brookmeyer & Blades, 2003).

The authors estimate the number of potential cases and unknown dates of exposure using information about the incubation period based on the 1979 Sverdlovsk outbreak in the former Soviet Union, which occurred when spores were accidentally released through an open vent from a facility doing bioweapons research. Related data is also taken from the HIV/AIDS epidemic and the dual epidemics of bovine spongiform encephalophathy (mad cow disease) in animals and Creutzfeldt-Jakob disease in humans (Brookmeyer & Blades, 2003).

The authors developed their simulation model based on variations in the size of the outbreak (very small, small, and moderate) and the rate of detection (the difference in time from the onset of the outbreak to the detection by public health officials of an anthrax case). Five hundred simulations were performed on each of the nine combinations corresponding to the sample sizes. Based on their study, they found that antibiotic use decreased the number of cases of inhalational anthrax perhaps by half, although variations in sampling and uncertainty in the incubation period distribution leave it an open question. Regardless, their analysis suggests that there would not have been more than 50 cases of inhalational anthrax before antibiotic prophylaxis would be administered, and therefore an attack would not become very large before a general response was provided. Therefore, swift public health reaction is critical to reduce expected mortality and morbidity. A note of caution is given by the authors, since mass antibiotic prophylaxis administration on thousands of people may result in individuals suffering from side effects of the antibiotics, and therefore public health officials should be prepared to deal with cases of people becoming ill from the antibiotics (Brookmeyer & Blades, 2003).

Kleinman et al (2005) note that the first indication of a biological terrorist attack will likely be people becoming ill. Syndrome surveillance systems have been developed in an attempt to detect early this warning sign, not only of a biological attack but of other developing pandemics (avian flu for example). The key to these systems is the techniques used to determine when "too many" people are showing similar symptoms and have become ill. The authors suggest that limited comparative work has been done on these syndrome detection systems. They state that "theoretical comparisons are probably not possible in realistic settings and practical experience is limited by small numbers of attack-like events" (2005, p. 101). Therefore, the use of computer simulation modeling becomes an important evaluation tool (Kleinman et al, 2005).

Kleinman et al (2005) use the outpatient surveillance system to model, since it is the most likely to be the type of system which detects an outbreak and it is simple and easy to replicate. They relied on data collected as part of an outpatient surveillance system near Boston, Massachusetts which classifies patient contacts by the common code, *International Classification of Diseases, Ninth Revision* (ICD-9). Each visit is classified into broad groups or syndromes and then each encounter had patient census location ZIP code attached. A count for each syndrome in each region was used for analysis (Kleinman et al, 2005).

Conceptually, the authors must include in their simulation a number of complex elements. The simulation must determine *who* becomes ill, since exposure to anthrax does not necessarily mean that a person becomes sick. The next step is that if the person is to become ill, *when* does that occur? The time from infection to showing symptoms varies. The third step is to determine among those persons eligible for surveillance the probability that he or she will seek care at an outpatient clinic and if so, when that occurs. They assumed that the anthrax would be introduced via crop dusting planes. They also assumed that this occurred only in the ZIP code of residence and to all residents of each ZIP code (Kleinman et al, 2005).

Once these concepts were translated into the computer simulation model, two statistical methods used in syndrome surveillance were compared: small area regression and testing (SMART) and a SaTScan approach. "In the SMART score, generalized linear models are used to establish the expected count per ZIP code per day, adjusting for seasonal, weekly, and temporal trends, and holiday status" (2005, p. 105). A reoccurrence interval for each ZIP code is developed for each day, based on the theoretical distribution of case counts and correcting for multiple testing (Kleinman et al, 2005).

SaTScan identifies unusual clusters of ZIP codes each day. First, every possible combination of ZIP code within a circular area around each ZIP code is considered and ranked by likelihood to find the most unusual cluster. A Monte Carlo step determines whether that cluster is actually unusual. The input to the SaTScan is adjusted by using the SMART scores to account for the trends described above (Kleinman et al, 2005).

In their simulated scenario, a release took place in an urban area. The affected ZIP codes showed little or no response on days one and two, but by days three and four a noticeable difference was observed. The authors found that the two methods were "similar in their diagnostic value” but SaTScan appeared slightly superior. SaTScan identified 85 percent of attacks within nine days, while SMART identified 83 percent. At four days, SaTScan identified 57 percent, but SMART only identified 50 percent. While both methods appear to operate effectively, the authors were able to conclude that SaTScan was superior to SMART scores in detection of an inhalation anthrax outbreak (Kleinman et al, 2005).

Buckeridge et al (2006) conducted a study comparing the use of syndrome surveillance relative to clinical case finding for detection of an inhalational anthrax outbreak. Traditionally, public health authorities have relied on clinical sentinel cases to identify and rapidly report any outbreak, in spite of substantial investment in and availability of computer syndromic surveillance systems, such as BioSense, developed by the Centers for Disease Control and Prevention (CDC). Rapid detection and reaction to any outbreak is believed to be key to reducing mortality and morbidity. The authors aimed to develop a model for simulating the use of healthcare services after a large-scale exposure to aerosol anthrax spores and then to use this model to compare the benefit of syndromic surveillance to clinical case finding (Buckeridge et al, 2006).

Their study design created a model simulating the dispersion of released anthrax spores, the infection of exposed individuals, the progression of the disease in the exposed people and the symptomatic person’s use of healthcare services. They generated outbreak signals and time until the first clinical diagnoses for three amounts of spores released. This was superimposed onto baseline administrative records of ambulatory healthcare visits in the Norfolk, Virginia area. The usefulness of syndromic surveillance was assessed by modeling the healthcare system use that would occur after an attack and compare this to actual administrative data over a one year period.

The sensitivity and timeliness of syndromic surveillance and the detection benefit were compared with clinical case finding for each simulated outbreak (Buckeridge et al, 2006).

There were four components to the simulation model: dispersion, infection, disease, and healthcare system use. Three scenarios were defined by the amount of spores released (1 kg, 0.1 kg and 0.01 kg) and 1,000 simulations were performed on each scenario. Clinical case finding was shown to detect outbreaks from an average of 3.7 to 4.1 days of release, depending on the amount of spores released. Syndromic surveillance was shown to have a mean detection time of 3.1 to 3.6 days at a specificity level of 0.9 (resulting in 1 false positive every 10 days). When the specificity level was increased to 0.975 (1 false positive every 40 days) the mean detection time dropped to 4.3 to 5.1 days. Therefore, there is a trade-off in the benefit of syndromic surveillance in specificity, but one which may be well worth it (Buckeridge et al, 2006).

CHAPTER THREE: METHODOLOGY

Statement of Theoretical Context

A theoretical framework is the lens through which we try and make sense of the world around us. They are "abstract generalizations that present systematic explanations about the relationships among phenomena; theories also knit together observations and facts into an orderly system" (Wan, 2002). They "seek to explain or gain understanding and comprehension of the environment, behaviors and events around us" (Beech, 2004). This understanding of theories and theoretical frameworks is important. How we conceptualize the events, behavior or general phenomena, which we observe, will greatly influence our understanding and response. This dissertation will use complexity theory as its theoretical foundation from which to view bioterrorism planning at a local hospital facility.

Complexity science does not fit neatly into a mainstream linear framework. When component parts are examined individually, we may not see the interactions that produce collective behaviors and characteristics (Beech, 2004). The world and human behavior is "orderly, complex and disorderly" all at the same time, and these phenomena exist and interact continuously (Cooper et al, 2004). Complexity science, therefore, is a *holistic* understanding. It has become popular today because of the inability of traditional scientific methodology to explain the world and human behavior. By viewing the world through the lens of complexity theory, we can hopefully obtain better insight into complex patterns and behaviors, giving us guidance in how we address important public policy issues.

As complexity theory migrated from the physical and natural sciences into the social sciences, it has been adapted to a wide range of phenomena and behavior. Today, there probably exists no social science discipline that complexity science has not at least been attempted to explain. Health care is no exception. Specific health care issues have been adapted and viewed through complexity theory, such as health care systems and organizations (Begun et al, 2003; Tan et al, 2005), management (Zimmerman, 1999), risk (Feinendegen & Neumann, 2006), public health (Bar-Yam, 2006), nursing (Clancy & Delaney, 2005), health information outreach and communication (Olney, 2005; Vogt, 2002), interprofessional education in health care (Cooper et al, 2004), disease control (Rouse, 2000), hospital waiting lists (Smethurst & Williams, 2001) and of course, bioterrorism preparedness (McDaniel, 2004). The Institute of Medicine (IOM) has also suggested that the best way to improve our health care system is to adapt complexity theory to health care (Institute of Medicine, 2001).

Organizations and aggregates of organizations are generally thought of as "complex adaptive systems," or "CAS." Complex adaptive systems are all around us, from the stock market to human bodies to organizations. "Complex" implies diversity, "adaptive" implies ability to change, and "system" is a set of interconnected or interdependent things. In CAS, the "things" are the agents, whether people or institutions. Their actions are based on the information they receive from the environment and conditions. A CAS is a densely connected web of interacting agents, each operating from its own schema or knowledge (Begun et al, 2003).

Basic characteristics of Complex Adaptive Systems (CAS) include:

- They exist in a dynamic state, with a large number of connections between agents and environmental forces creating constant change
- The relationships within CAS are complicated, entangled, and enmeshed. They can also be nonlinear and discontinuous. A small change in one variable can create large changes

down the road. Conversely, a large change in another variable can only have a small impact. Feedback loops among agents generate either change or stability.

- CASs exhibit emergent or self-organizing behavior. In other words, they adjust their behavior based on the characteristics of other parties in the interaction.
- CASs may be more sensitive to small changes in material conditions. An apparently trivial difference in the beginning state of the system may result in an enormously different outcome (unexpected too). This is known as the “butterfly effect.”

Complex Adaptive Systems are robust, and exhibit the ability to alter themselves according to feedback. They possess a range of coupling patterns, ranging from tight to loose, and these different patterns help organizations survive a variety of environmental conditions. Loosely coupled structures cushion and moderate responses to strong shocks. More tightly coupled structures tend to identify and implement quickly to a response. If one pattern of interdependency is interrupted, other units can respond. CAS permits us to focus on nonlinear relationships, looking at the system as a whole and not reduced to its component parts. Instead of focusing on the margin (looking for variation as in modern scientific inquiry), CAS seeks the critical mass threshold (Begun et al, 2003).

We can visualize Complex Adaptive Systems along a continuum as shown below in Figure 3 (Tan et al, 2005).

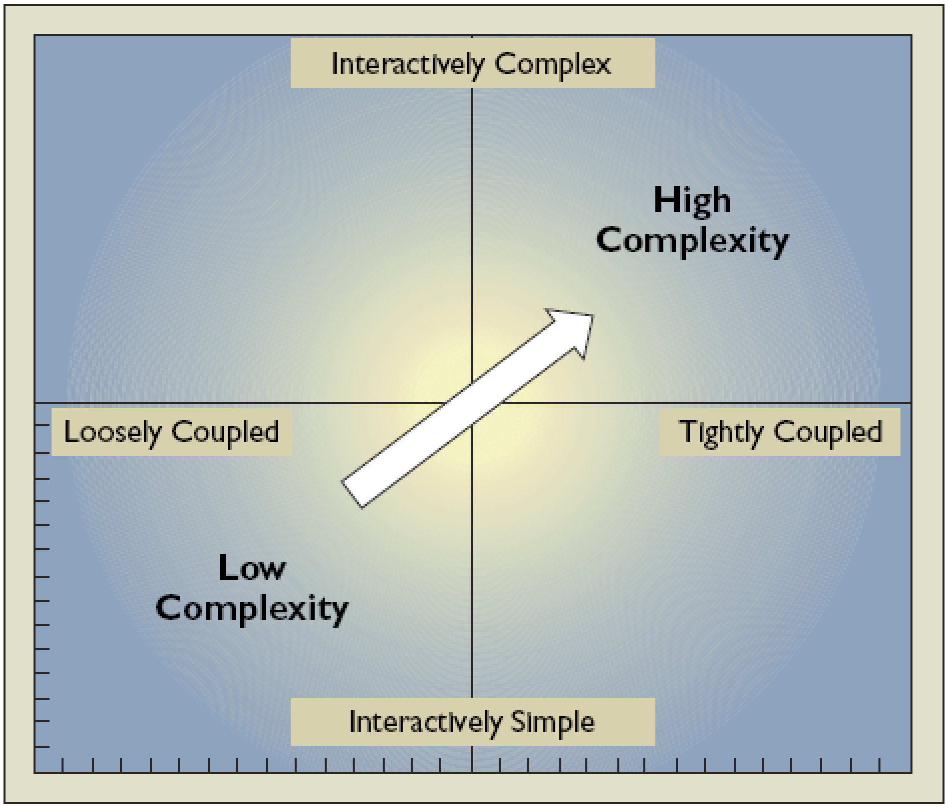

Figure 3: Perrow's Framework of Complexity

Health care is a “human-based system and preferences often change in human-oriented systems.” The processes in health care are “invariably complex.” Consider that

> There are more than 1,000 diseases, each of which in theory could have a different pathway or guideline … ‘No carmaker produces 1,000 different models of cars or provides for each model 2,500 different types of paint, 300 different arrangements of wheels, or 1,100 different locations for each driver’s seat’ (Tan et al, 2005).

Other elements of health care systems reinforce the notion that it is indeed a Complex Adaptive System. The underlying cause of complexity in health care is the improved access to information, which is being driven by advances in technology. As the growth in informational requirements continues, the organization's goals, division of labor and performance level are affected. Local market pressures, regulatory pressures and a wide variety of other systemic issues previously mentioned combine to further influence health care performance. Health care organizations respond to these ever-changing needs through organizational change, moving away from hierarchical structures to matrix-based systems and designs (Clancy & Delaney, 2005).

Another "telltale sign" of health care being a Complex Adaptive System is the "tendency to exhibit unanticipated and often undesirable behavior" (Clancy & Delaney, 2005). Recent health care policy changes have brought about examples of unintended consequences.

- The introduction of low tar and nicotine cigarettes has actually increased the intake of carcinogens as smokers compensate by smoking more cigarettes.
- Recent reports highlighting patient safety issues in hospitals have placed significant awareness on medication errors. In spite of increased reporting, the "unanticipated distribution of harmful errors has increased (emphasis added) as reporting has improved."
- The use of "restricted formularies" by managed care organizations to lower utilization of expensive medications has "actually increased health care system costs" in some cases.
- The overuse of antibiotics is creating a growth in drug-resistant pathogens.
- The growth in information technology has led to an increase in per capita paper consumption within health care organizations (Clancy & Delaney, 2005).

These elements have significant impact on strategic management and change. Long-term planning becomes very difficult. Formulating a long-term plan is a key strategic task within any organization, yet in complex systems "small disturbances multiply over time because of nonlinear relationships and the dynamic, repetitive nature of chaotic systems." As systems evolve, they are subject to a "myriad of small random (or perhaps chaotic) influences that cannot be incorporated" into a strategic plan (Levy, 1994).

Industries do not reach an equilibrium state, which is contrary to traditional economic firm behavior. In fact, they can "never pass through the same exact state more than once." Changes in industry structure are "endogenous" and systems can "spontaneously self-organize into more complex structures." Dramatic change comes unexpectedly, often from the "dynamics of the systems rather than from the influence of external shocks" (Levy, 1994).

While long-term planning is difficult at best, there is a surprising degree of order in Complex Adaptive Systems. The improvement in computer simulation modeling capabilities can yield accurate forecasts for at least several time periods. Outcomes are often "bounded" in chaotic systems—that is, they fluctuate within certain bounds that are "determined by the structure of the system and its parameters but not its initial condition." In the same vein, while we cannot know the precise state of a system in the long-term, we can trace repetitive patterns, which provide useful information. In a way, this creates "deterministic chaos" which is "characterized by self-sustained oscillations whose period and amplitude are nonrepetitive and unpredictable, yet generated by a system devoid of randomness." Levy uses the examples of hurricanes and tornadoes. We cannot know exactly when they will strike, but we can know the conditions that are likely to lead to their occurrence. The implication on organizations within Complex Adaptive Systems is that guidelines are the most useful tool to cope with complexity. "We need general guidelines because it is impossible to specify the optimal course of action for every possible scenario" (Levy, 1994).

This paper has briefly outlined the main features of complexity science, and shown how they apply to health care systems and organizations. It now turns to a specific issue of national importance: bioterrorism preparations at hospital facilities. How best can hospital administrators and health care executives prepare for an eventuality which can be best described as a "low probability, high casualty" event? Noted earlier was the recent GAO report showing that hospitals were woefully inadequate in their preparations. In a recent study, only 21 percent of physicians reported feeling "fully prepared" to treat victims of bioterrorism, but 80 percent felt they were willing to do so should an event occur and they had not yet received adequate training (Alexander & Wynia, 2003).

We tend to think of a bioterrorist attack as being a large event. Consider that bioterrorism attacks are considered under the umbrella of "weapons of mass destruction," conjuring up images of mass-casualty events, where thousands or more are killed or injured. Yet any terrorist organization, adversarial state or merely disturbed individual who wished to commit such an atrocity would face significant hurdles in introducing a large-scale attack on the United States. The Congressional Research Service (CRS) noted this in a report to Congress (Congressional Research Service, 2004). Rather it is a small-scale attack that should warrant real concern.

Indeed, despite the expenditure of billions of dollars on bioterrorism preparedness, many would argue little progress has been made. "Vaccines and antidotes remain in short supply, local officials have not developed plans to distribute medical supplies in a timely manner to citizens and hospitals do not have the capacity to handle a sudden surge of patients" (Dando, 2005).

In fact, terrorists would not need to create mass casualties to create mass panic. A small-scale attack that only resulted in a few dozen injured and dead would almost certainly lead to mass panic. Governments would respond by diverting even more resources toward homeland security and disaster preparations (Dando, 2005). Such a massive diversion of resources is bound to have repercussions throughout society as money is channeled away from other programs and into increased homeland security and disaster planning. This is a good example of a small perturbation resulting in massive change, a component of modern complexity theory.

Evidence shows that larger, urban hospitals tend to be “better prepared” for a bioterrorist attack as compared to more rural facilities (Scharoun, 2005). Indeed, larger communities seem to have superior disaster medical response capabilities as compared to smaller ones (Harrison, 2005). Whether or not a plan is in place, there is usually a significant gap in the communication of that plan to hospital staff, pointing to a “disconnect between planned policies and procedures, and relay of such information to all hospital staff.” This would almost certainly lead to chaos in the event an attack took place (Scharoun, 2005).

Today’s bioterrorism planning is constricted through its conception of the world as a “Newtonian place,” leading to a conventional wisdom on how planning should be conducted and developed (McDaniel, 2004). This conventional wisdom comes to resemble traditional cost-benefit analysis. Alternative scenarios are put forward and then the probability of each scenario is determined. Each scenario has its cost computed and the following equation is used:

Probability X Cost = Seriousness of Threat

Of course, since not all threats can be addressed, they must be prioritized. Once prioritized with funding assigned, some sort of organizational structure is created to implement and execute a plan. This is followed by an assessment of readiness, usually through training exercises and the development of some sort of knowledge base for action. The end result is thought to be “preparedness” (McDaniel, 2004).

Complexity science teaches that the application of traditional reductionist, Newtonian scientific methodology to policy making is probably not the best way to cope with a bioterrorism environment. The characteristics of Complex Adaptive Systems show this system of thought inadequate, especially when considering health care systems (Bar-Yam, 2006; Clancy & Delaney, 2005; Tan et al, 2005). Terrorism itself "displays the highest level of uncertainty in terms of lack of information beforehand, and sometimes even afterward, on identifiable sources of the event, the time and place of happening, and the impact" (Begun & Jiang, 2002).

Bioterrorism preparedness for hospital administrators begins first with acknowledging that one is trying to prepare for the unpredictable. Some have suggested that executives adopt "preemptive strategies" emphasizing traditional organizational techniques such as coordination with stakeholder groups, an assessment of facility capabilities and source relationships, surge capacity capability, security, internal staffing, equipment stockpiling, surveillance capabilities, and readiness training (Zinkovich et al, 2005). Perry and Lindell (2006) analyze hospital planning for weapons of mass destruction incidents and put forward six main elements that are critical for hospital plans, including "incident command, hospital security, patient surge, decontamination, mental health consequences and communication." Many of these elements exist with the line of thinking of complexity theory.

Begun and Jiang (2002) establish a series of guidelines for leaders in preparing health care organizations for bioterrorism, shown below in Table 1. These guidelines have been constructed within the theoretical framework of complexity science, and show how bioterrorism planning is better suited within such a framework.

Table 1: Guidelines for Preparing Health Care Organizations for Bioterrorism

Guideline	Rationale
Develop leadership commitment to organizational resilience and learning	Change doesn’t occur without top commitment; change requires time and resources
Support conditions for self-organization --clear roles --training --seek out ideas --timely feedback --connections --communication --identify expertise	Plans will be incomplete in meeting bioterrorist events; anticipates complexity and unpredictability in responding to bioterrorism; distributes accountability and responsibility for response
Develop culture of resilience, learning, and social responsibility	Links bioterrorism to larger category of unpredictable events; avoids “flavor of the month” change
Connect and collaborate with the organizational field, including competitors	Competition is suspended in emergencies; bioterrorism response is interorganizational
Prepare individual organizational members and constituents for bioterrorism	Individuals need information and training; constituents need reasonable (vs. ideal) expectations
Contribute to and support governmental and professional association plans for preparedness	Enrolls organization as a participant in the prevention of bioterrorism; recognizes social responsibility and interconnectedness

Emphasized here is not that people should respond to “rules” but rather that they must be prepared for “unpredictable, dynamic situations.” Complexity science can focus attention on perspectives that might not be seen through traditional, reductionist thinking and planning. It requires that attention be paid to “nonlinear interdependencies among organizational elements.” It suggests that relationship ties, both in communication and reciprocity relationships enable organizations to better function when the unexpected occurs. Complex Adaptive Systems “are most effective when the members have attitudes that promote respectful interaction, mindfulness and the development of collective a collective mind and when leadership is participative and built on a bed of trust” (McDaniel, 2004). It generates the capacity for “sense making, learning and improvisation,” preparing leaders and the organization to cope with events that cannot be planned for in the traditional sense (McDaniel, 2004).

In fact, complexity theory teaches us that what traditional wisdom would suggest is a threat is in fact an opportunity for change and transformation. By strengthening a health care organization’s infrastructure to better deal with the unpredictable, it can better manage “surprises of all types” (Begun & Jiang, 2002). Doing so will hopefully enable health care organizations to better navigate the multiple issues affecting the entire system today, ensuring they not only survive, but thrive in today’s complex world.

Research Design

As noted earlier, computer simulation modeling fits neatly within the theoretical framework of complexity science. Modeling can serve as a useful decision-making tool, assisting in resolving problems, or at the very least, informing the decision. There are five levels, noted by Pritsker and O’Reilly (1999, pg. 1), at which simulation modeling can be employed:

- "As an explanatory device to define a system or problem;"
- "As analysis vehicles to determine critical elements, components and issues;"
- "As design assessors to synthesize and evaluate proposed solutions;"
- "As predictors to forecast and aid in planning future developments;"
- "As part of a system to provide on-line monitoring, status projections and decision support."

The use of computer simulation modeling as a tool has grown significantly as more powerful information technology and computers have become much cheaper and more widespread. Many industries are changing their design and evaluation process based on the use of simulation, and health care is no exception. Computer simulation modeling remains, however, a computerized mathematical tool, of which there are two basic types, according to Sinreich and Marmor (2003):

1. Prescriptive models: "These models provide a prescription for how to set the decision variables in order to achieve optimal performance of a predefined objective function."
2. Descriptive models: "These models provide a detailed report on the system's operational behavior based on its description."

Sinreich and Marmor, in their study of simulation technology being used to model emergency department operations, note that simulation can assist hospital management in the development and enhancement of their decision-making skills when evaluating different operational alternatives.

Regardless of the computer software program used, there is a general process by which simulation modeling is conducted. Here, we will briefly outline the process as discussed in Chapter 3 of Pritsker and O'Reilly (1999). The figure below helps us visualize this process.

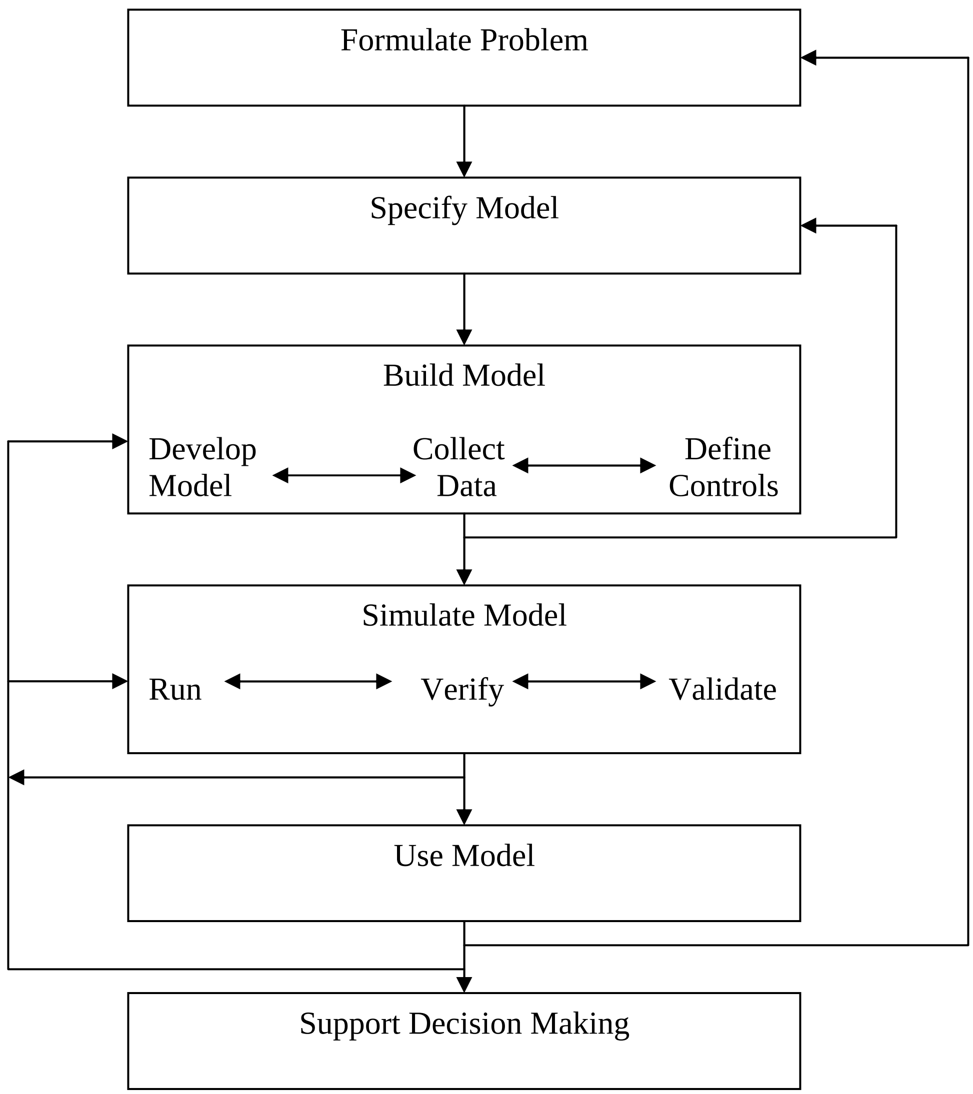

Figure 4: Modeling and Simulation Process, Adapted from Pritsker and O'Reilly (1999)

Formulating the problem will require us to understand the problem context, "identify project goals, specify system performance measures," set specific modeling objectives and define the system to be modeled. A series of questions are posed to help the researcher along in this process. These include: *"What operations and functions produce the systems output? What procedural elements exist in the systems operation? What interactions occur between functional units of the system? What information is available to characterize the operations, functions, and procedures of the system?"* (pg. 35). It is important to note that modeling objectives are "statements of desired results in terms of performance measures."

Specifying the model requires the researcher to use both art and science in conceptualizing. One must "extract the essence of the system without including unnecessary detail" (pg. 37). Good models have sufficient detail to be easily understood yet reflect in the most realistic sense the reality of the environment or organization being modeled.

Building the model is a three-step process: develop the simulation model, collect the data, and define the experimental controls. First, the model is developed with the structural and procedural elements that represent the system. Data is collected to add this to the system. Finally, experimental controls describe the procedures for performing a simulation and analysis of the model. These establish the initial state of the network.

To simulate the model, the build model step must have been completed at least once. A network simulation "advances time in accordance with the movement of entities through the nodes and activities of the model" (pg. 46). Before the model can be used to support decision-making, it must be shown to run in accordance with its own specifications. In other words, we attempt to ascertain whether the model is behaving as it is intended to. Finally, we seek validation that it is a reasonable representation of the system we are attempting to model. All of these sub-steps may be performed concurrently.

Using the model requires the making of run simulations and the subsequent interpretation and presentation of the output data. It may be used to draw inferences or test hypotheses, and therefore statistical methodology should be employed here. It should be noted that a simulation model "does not require a method for determining an optimal solution … [rather, it] specifies a means to obtain experimental data from which alternatives can be selected" (pg. 49).

Finally, modeling and simulation is used to *support* the decision-making process. We emphasize here that the model does not *make the decision*, but rather assists in informing the decision. It is important to remember throughout the process that communication of the research question and assumptions underlying the system and the model are clearly conveyed early on. A model is only as good as the data used to create it.

The author has met with the CEO of the hospital facility, and has had two subsequent meetings with the Emergency Department Medical Director and the Emergency Department Nurse Manager. They have already provided data on the emergency department patient flow process, daily patient flow data for the months of January 2006 and May 2006, staff schedules, architectural drawings and the bioterrorism response plan. Two recent studies commissioned by the facility will also provide useful data. The first was conducted a year ago for the purpose of system improvement. It specifically analyzed the patient throughput process, timing each step and made recommendations to the administration on how to reconfigure the patient flow process. The second study is an after-action report of a recent disaster preparedness drill conducted in February 2006. The author has been provided both of these studies.

The author has also had the opportunity to spend time in the emergency department, observing the normal activities. Based on these observations and on interviews with the Emergency Department Medical Director and the Emergency Department Nurse Manager, we can show the process by which patients enter the facility during an emergency. This flow chart will be used to assist in the model development, and is shown as Figure 5.

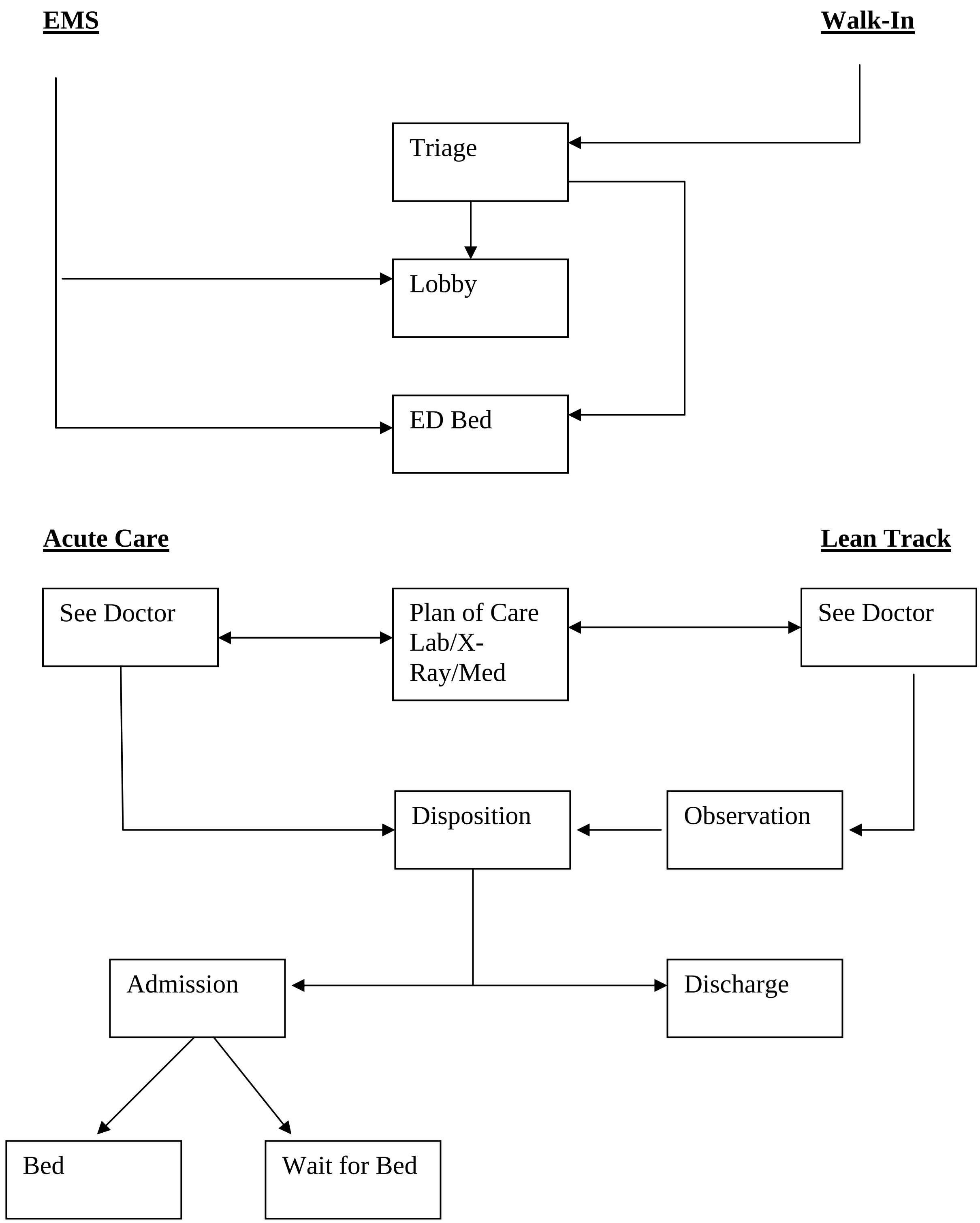

Figure 5: Emergency Department Process

Patients enter the emergency department one of two ways, either via ambulance or self-transport/walk-in. There is no helicopter facility. Once the patient enters the facility, he or she is triaged and given the initial screening for an emergency medical condition. In the case of EMS transport, this triage may already have occurred and the patient may be transported directly to a bed in the emergency department or to the lobby. Otherwise, the patient, if a self-transport, waits in the lobby for a bed. The patient is either assigned into the acute track or the lean track. The acute track is reserved for cases that seem to be more severe, while the lean track is for patient's whose condition does not warrant immediate treatment, and instead he or she is seen in turn, based on severity of the condition.

The emergency physician, who examines the patient and determines a plan of care, such as ordering lab test, x-rays or prescriptions, automatically sees acute care patients. Lean track patients may see either a physician or a physician-assistant (PA) to receive a plan of care. Lean track patients are then placed in an observation lounge to await disposition, while acute care patients have their disposition status determined immediately.

Disposition is either admission into the hospital or discharge. If the patient is admitted, he or she is moved to a bed on the appropriate floor. If no space is available, then the patient waits in a bed in the emergency department, a process called "boarding," until a bed is made available.

Winter Park Memorial Hospital: Bioterrorism Response Plan and Mass Casualty/Disaster Plan

In January 2002, the Florida Hospital system revised its Bioterrorism Response Plan (hereafter referred to as "the Plan"), noting that the "potential for a terrorist action has increased to the degree that calls for a comprehensive planning and preparation for all weapons of mass destruction (WMD) scenarios by healthcare facilities" (Hospital, 2002a). Later, its Mass Casualty/Disaster Plan was also updated to reflect the changing environment subsequent to the terrorist attacks of September 11th, 2001 and the follow-on anthrax attacks (Hospital, 2002b). What follows is a brief overview of the current plan. Later, this plan will be evaluated using computer simulation modeling of an inhalational anthrax release scenario.

The Plan notes that early identification of an outbreak of infection is critical to minimize casualties and deaths. Common features of an outbreak are outlined, including a rapid increase in the number of previously healthy patients with similar symptoms presenting to the Emergency Department, a cluster of previously healthy persons from a common geographic area, unusual clinical presentations, an increase in reports of dead animals and lower incidents of infection among those persons who are protected or potentially isolated from exposure (i.e., confined to home or no exposure to large crowds), an increase in the number of patients who expire within 72 hours and the presentation of patients who have recently traveled to foreign countries. Practitioners are encouraged to report any unusual symptoms to the local county health department or the Florida Department of Health (Hospital, 2002a).

The Plan briefly outlines the role of the various hospital departments (Security, Safety, and Engineering). The Security Department will work with local law enforcement on traffic control and perimeter security if necessary. It can even conscript staff from other hospital areas (non-healthcare practitioners) to assist. The Safety Department is responsible for setting up the decontamination site if needed and assure that enough supplies and personal protective equipment is available. The Engineering Department will provide manpower to set up decontamination equipment, ensure that necessary utility equipment is functioning and be prepared to respond if any critical devices shut down. All three departments are to have preplanned for these events. Healthcare workers are expected to report to their predetermined areas (personnel support, childcare, ancillary support to the Emergency Department) in the event of an attack (Hospital, 2002a).

Since the Plan is designed to respond to a terrorist attack, it may be necessary for the hospital to collect evidence for law enforcement to use in an investigation. The hospital must also be prepared to manage the psychological aspects of the event, and provide counseling if needed. It is important that information be conveyed in a clear, concise manner. The local or state health department will assume control over communication with the media (Hospital, 2002a).

It is likely that the hospital will need laboratory support, since most facilities are not equipped to identify bioterrorist pathogens. The laboratories will be responsible for collecting, packaging and transporting specimens to county or state laboratories for identification. The hospital pharmacy is expected to maintain a "reasonable, daily inventory" of common antibiotics used to treat victims, and should be prepared to acquire more from federal and state established pharmaceutical stockpiles. The hospital should also be prepared to stop the "non-essential use" of prophylactic and therapeutic antibiotics until the additional stockpiles arrive (Hospital, 2002a).

Being a hospital, any event which occurs will not happen in a vacuum. Patients and visitors will already be there receiving care. Those patients will have to be evaluated for quick discharge. Acute patients may have to be transported to other facilities such as other hospitals or skilled nursing facilities. Bioterrorism victims determined to be non-infectious can be sent home with antibiotics and home care instructions if maximum bed capacity or staffing levels are reached. The hospital should also realize that a large number of fatalities can occur, and in the event morgue capabilities are exceeded, short term arrangement of the use of refrigeration trucks should be made in conjunction with state and local coroner authorities (Hospital, 2002a).

Any bioterrorist event will almost certainly result in the facility implementing its Mass Casualty plan in conjunction with the Bioterrorism plan. The Mass Casualty plan is separate since other events, such as multi-car or school bus accidents, explosions or accidental chemical releases can occur which require the hospital to prepare for large numbers of victims. If information is received prior to patients arriving, then the hospital should attempt to verify the accuracy of the information. The Emergency Department Nurse Manager, Medical Director and Administrator will attempt to ascertain how many additional staff is required and contact Florida Emergency Physicians (FEP), the contract provider of emergency physicians and physician assistants, as well as Emergency Department Nursing in order to call in additional medical and nursing staff (Gabel & Sullivan, 2007; Hospital, 2002b).

Importantly, the hospital pharmacy is also contacted immediately and told to prepare for the medication contingencies that a bioterrorism attack may bring. If there is information on the nature of attack (whether it is anthrax, smallpox, etc.), then that information is provided so the pharmacy can begin to procure additional pharmaceuticals.

At most, Winter Park Memorial Hospital can expect an additional two emergency physicians and one additional physician’s assistant, ten additional nurses, three additional nurse technicians and one additional Health Unit Coordinator on top of its normal staffing level (Gabel & Sullivan, 2007).

The triage unit is moved outside of the emergency department to the front loading area. Two to three registered nurses (RNs) and one nurse technician will be out front to assess patients and code them as “Red,” “Yellow,” or “Green.” This code represents not only their acuity level, but also what area of the emergency department the patients will be sent to. In addition to the nurses and nurse technicians, two to three “runners” will be placed outside to escort patients to their various zones (Gabel & Sullivan, 2007).

The emergency department will be divided into zones that match the acuity level descriptions of “Red,” “Yellow,” and “Green.” The Red Zone will be located in the acute care area of the emergency department. It will have one dedicated emergency physician, up to two nurses and one nurse technician to provide patient assessment and care plan determination. Ideally, the nurse to patient ratio in the Red Zone is kept at three to one or four to one. The Yellow Zone will be located at Track 1, and the Green Zone is held in the PC 1 and EXT 1 and 2 rooms. Remaining physicians, physician assistants, nurses and nurse technicians will be floating between the Yellow and Green Zones providing assessments and care plan determination (Gabel & Sullivan, 2007).

Non-acute patients can be held in the Observation Room, while acute patients are admitted directly to the hospital. Theoretically, the hospital holds one hundred seventy-five beds upstairs. The hospital would begin discharging all elective surgeries, discharges and other patients able to be sent home to make additional room for acute patients moving from the emergency department to the hospital. The current wait time for a patient to be admitted to the hospital from the emergency department is ten and a half hours. We anticipate that would be streamlined to a point (Gabel & Sullivan, 2007).

This process is important to understand because in the event of a bioterrorist attack, it will be through the emergency department that the facility will be made aware that an event is in progress. For the purpose of our study, we can envision two different scenarios: one in which an attack occurs and patients begin presenting to the emergency department showing symptoms, but the facility does not have advance knowledge that the attack has occurred or that these patients are victims of a bioterrorist attack. In this scenario, the facility will "discover" the attack and implement its bioterrorist disaster response plan. The second scenario is that the facility is contacted by the appropriate authorities and informed that an attack has occurred and to prepare for incoming patients. This time, the facility is "warned" and can implement the plan *prior* to patients arriving.

To assist in the use of the computer software and model development, the author obtained agreement from Dr. Thomas Clarke, a senior scientist in mathematics at the University of Central Florida's Institute for Simulation and Training (IST) and from Carl M. Angelesea, MS CMSP C, a doctoral student in simulation and modeling at UCF IST. Also providing consultation is Dr. Duane Steward, a professor in the University of Central Florida's doctoral program in Health and Public Affairs, also an expert in computer simulation modeling and disaster planning.

This dissertation will use the ARENA computer simulation software program developed by Rockwell International. The program is a Windows-compatible software program.

Building a Model of the Winter Park Memorial Hospital Emergency Department

As explained earlier, a computer simulation model is composed of three basic elements: elements/units, resources, and processes. The first step in our model development was to construct a computer simulation model of the Emergency Department at Winter Park Memorial Hospital. The model would represent the Emergency Department in its "normal" state. To do this, the hospital provided us with Emergency Department patient load data for the months of January 2006 and May 2006, a process flow time study which had previously been conducted by the Lean Project Team at Winter Park Memorial Hospital in July of 2005, and the staff coverage schedule of emergency physicians, physicians' assistants, nurses, nurse technicians and health unit coordinators. Resources included available beds, stretchers, and chairs where patients could be kept for treatment or observation. The process was shown previously in Figure 5, Emergency Department Process.

A patient presents with symptoms. These were classified in the study by the Lean Project Team as chest pain, abdominal pain, urgent care (UC) or "other." After being triaged and seen by a physician or physician's assistant, the simulation models the patient's disposition as either "in patient" or "out patient." The model also shows the patients who are currently in the process of being seen or waiting to be seen.

We can show, step by step, how the model works.

The model logic sequence is as follows:

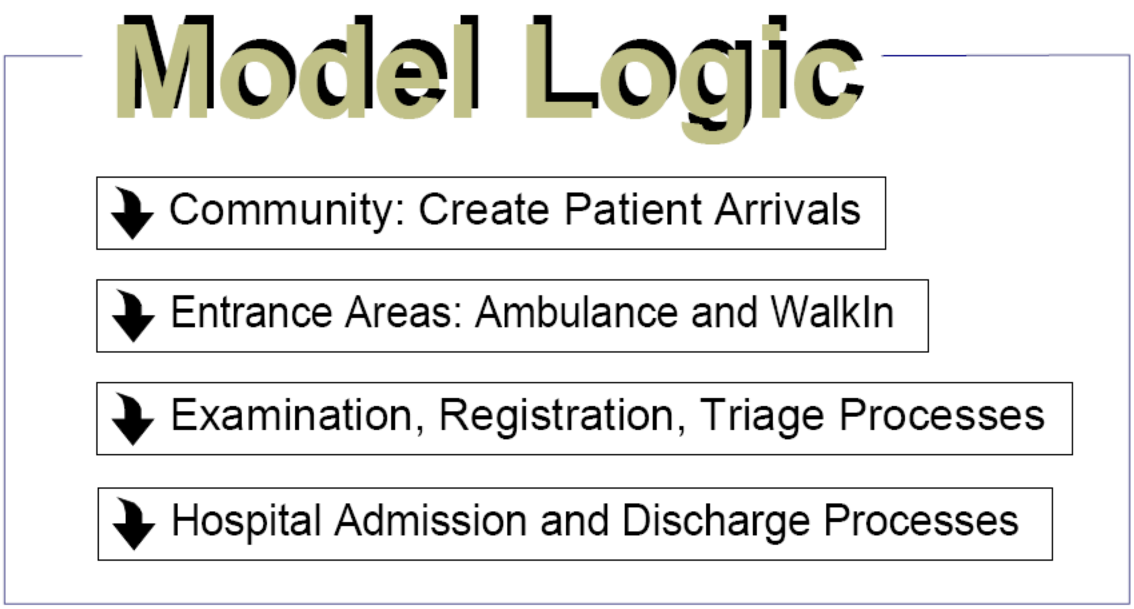

Figure 6: Model Logic

The community creates patient arrivals using data given to us by the hospital. The data is then used to generate patients using a Poisson probability distribution. This is the common, preferred methodology of generating an arrival process in computer simulation modeling. This methodology is useful for generating a number of arrivals when events occur over an interval of time at a constant rate, when there are a number of items in a batch of random size or a number of items required from an inventory (Law & Kelton, 2000).

Our model also accounts for resources utilized in the Emergency Department, including how they are generated, allocated and used. Staffing availability is based on the actual data provided by the facility, both in a typical day and during a bioterrorism attack. We have to account for processing time of the staff unit. For example, if additional physicians and nurses are called in during an emergency, it takes time for them to arrive. We can build in variables to account for that time, including transportation issues. Ultimately, these resources are finite. The facility cannot keep calling in additional staff. There may be none available as well as a diminishing utility. Beds as well are finite, and become an important indicator of performance, which we shall see later.

The Poisson probability distribution is used to create patients presenting with certain symptoms identified by the hospital as most common. These symptoms are also the same ones used in the July 2005 Lean Track Program Study. We chose to use these same symptoms for purposes of continuity with the real world events the hospital faces. Below, we can show how the Arena program simulates these patients using computer logic boxes.

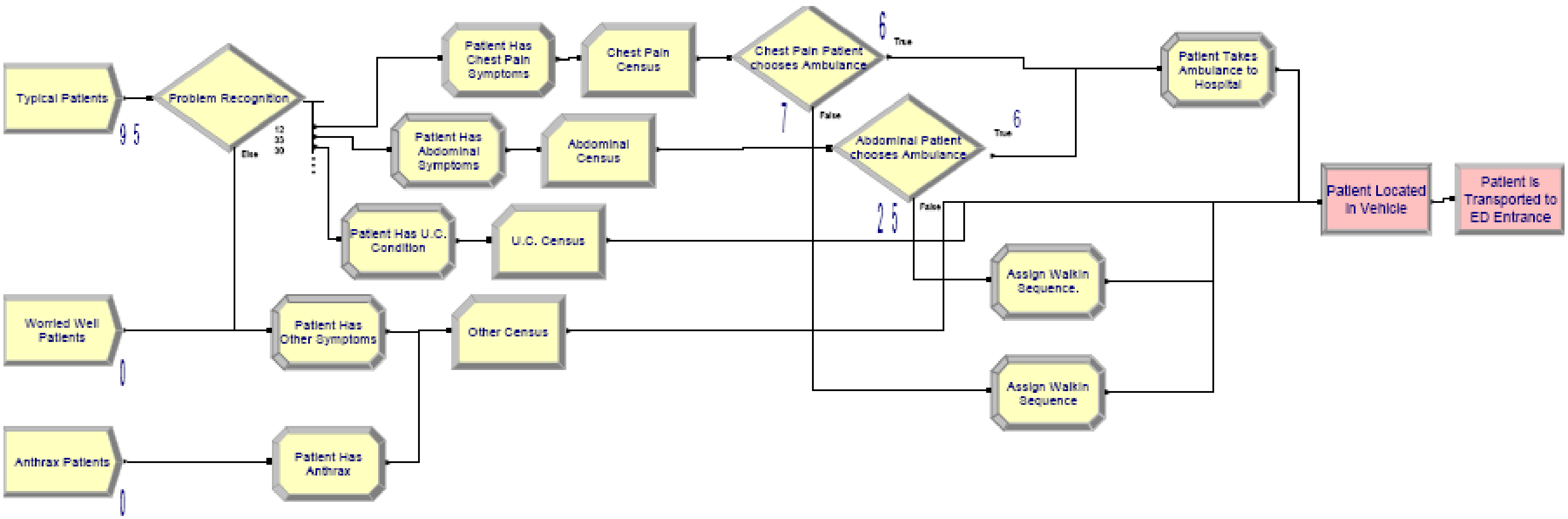

Figure 7: Patient Generation Process

The model shows “typical patients” arriving with basic problem recognitions of chest pains, abdominal pains, requiring urgent care or “other” conditions. These conditions are then distributed out to either ambulance mode of transport or walk-in/self-transport mode. The patient is “placed” in a vehicle and then “taken” to the Emergency Department.

Patients enter the Emergency Department in one of two ways: via ambulance or self-transport/walk-in. Again, this arrival method uses the Poisson probability distribution. Arena creates model logic boxes which show this process. The patient arrival process logic model is shown next.

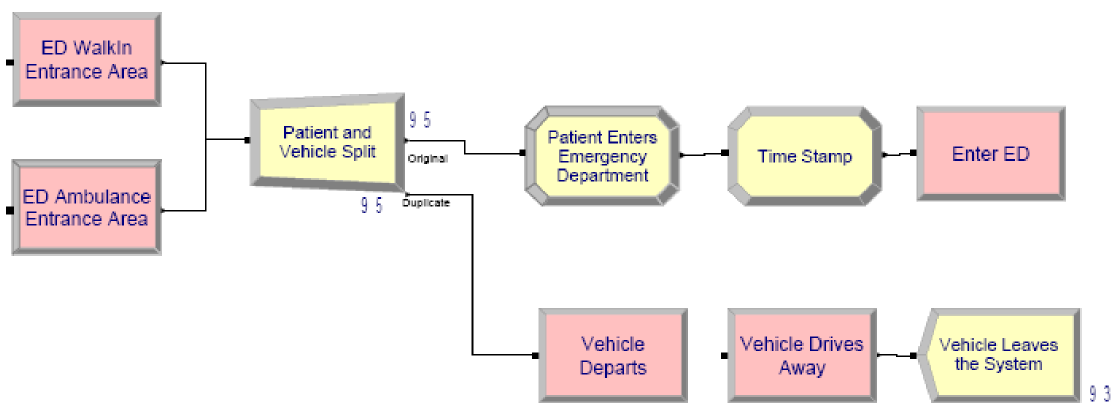

Figure 8: Patient Arrival Process

In the arrival logic, the patient arrives via a car or ambulance. The patient and vehicle “split” with the patient entering the Emergency Department and being “time stamped” for the simulation process. The vehicle is shown driving away, leaving the simulation system.

Now that the patient is in the Emergency Department, it goes through the normal series of events that a regular, real world patient would encounter. It is registered, triaged, examined, and processed based on its condition. The model logic below explains how this was built into Arena.

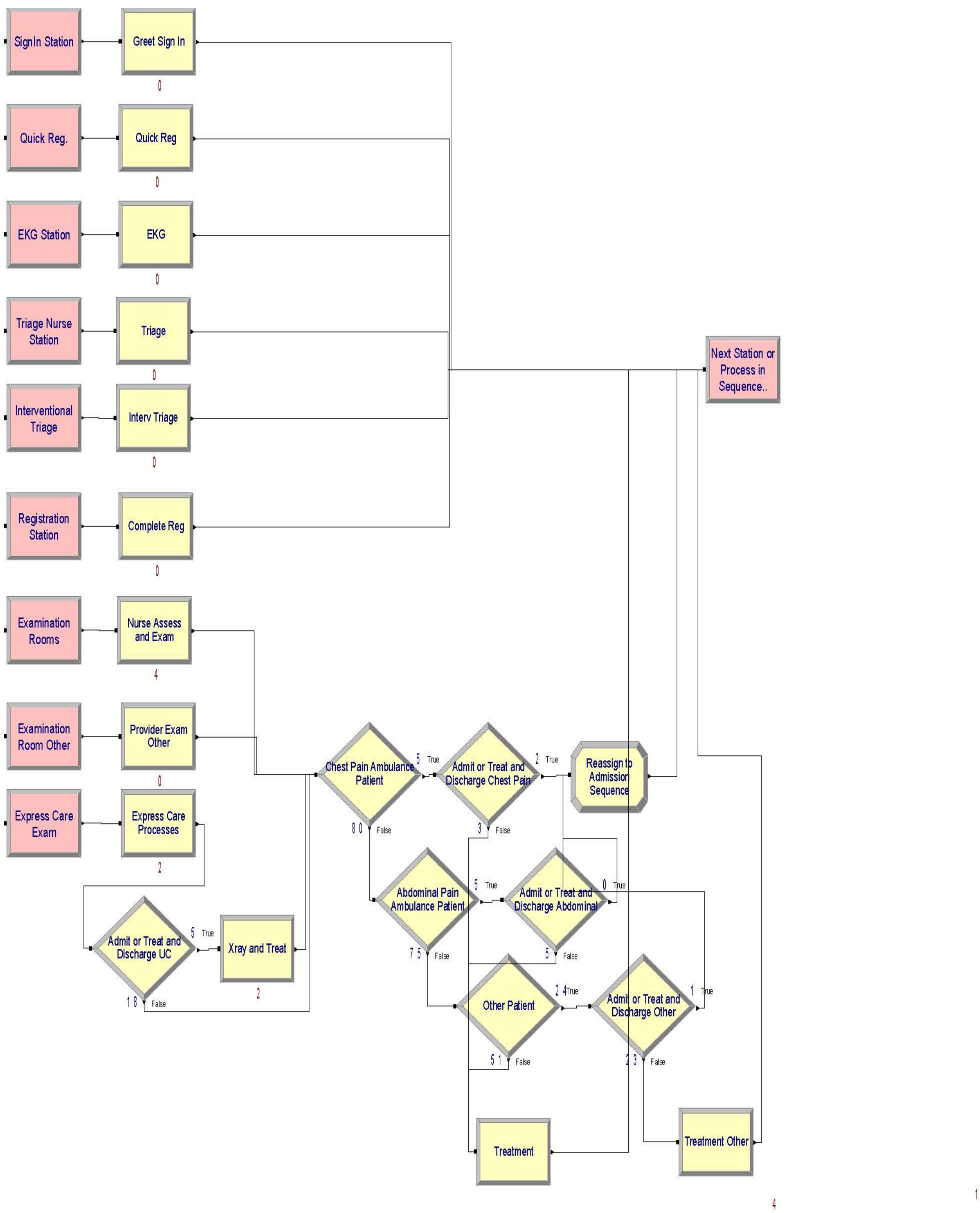

Figure 9: Patient Processing

Ultimately, two things are shown happening to the patient: it either is admitted into the hospital or it is discharged after receiving services. Arena is able to capture the time it takes for each patient to move through the process once it arrives at the Emergency Department, so our model will also show the amount of patients per hour per day   Below, the model logic is given for patient disposition.

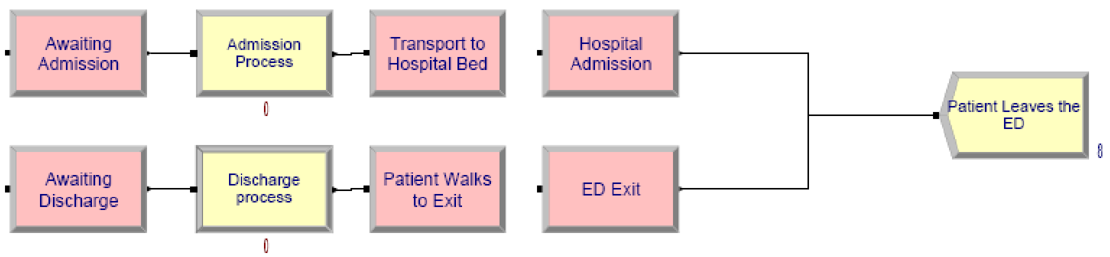

Figure 10: Patient Disposition

The logic boxes described represent the “behind the scenes” or “under the hood” calculations that the Arena software program is going through in order to simulate the processes and events at Winter Park Memorial Hospital. We can now see an example of the model process animation in the figure below.

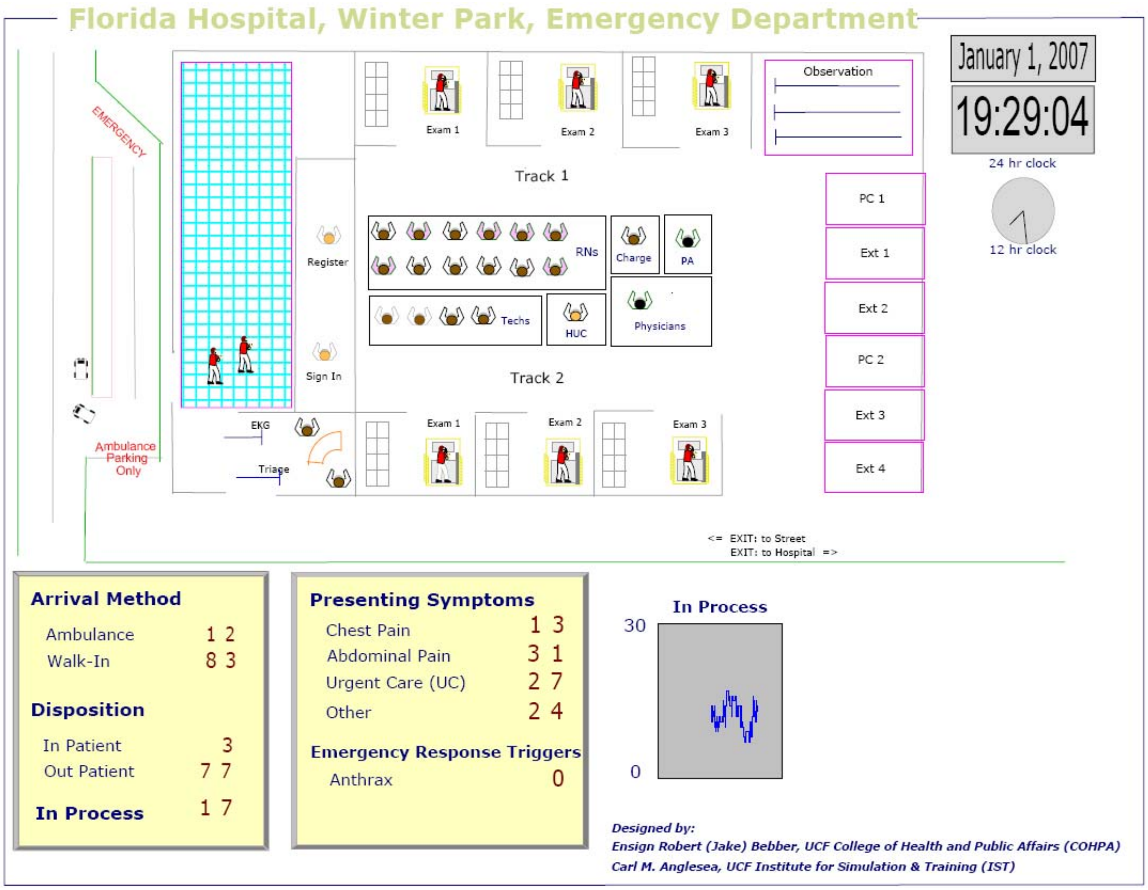

Figure 11: Emergency Department Animation

Validating the Model

Arena uses a Stochastic model of patient arrivals and processes once the patient is in the Emergency Department. This means that each time the model is run, it produces different results. It is validated by comparing the simulated results to the actual data provided by the hospital. In order to produce enough simulation data, it was decided to simulate a thirty day run length thirty times.

Our model is compared to actual data from January 2006 and May 2006. The table below looks at actual total volume data compared to the typical arrival data generated by our Arena model.

Table 2: Actual vs. Model Data

	Actual Volume	**Difference**	**Percent Difference**
January 2006 Typical January	3,627 3,517	110	3.03%
May 2006 Typical May	3,310 3.202	108	3.26%

Using the Emergency Department Summary Data for May and January 2006, we are also able to show the variation in patient arrivals by hour as well as patient visits by the day of the month for both months.

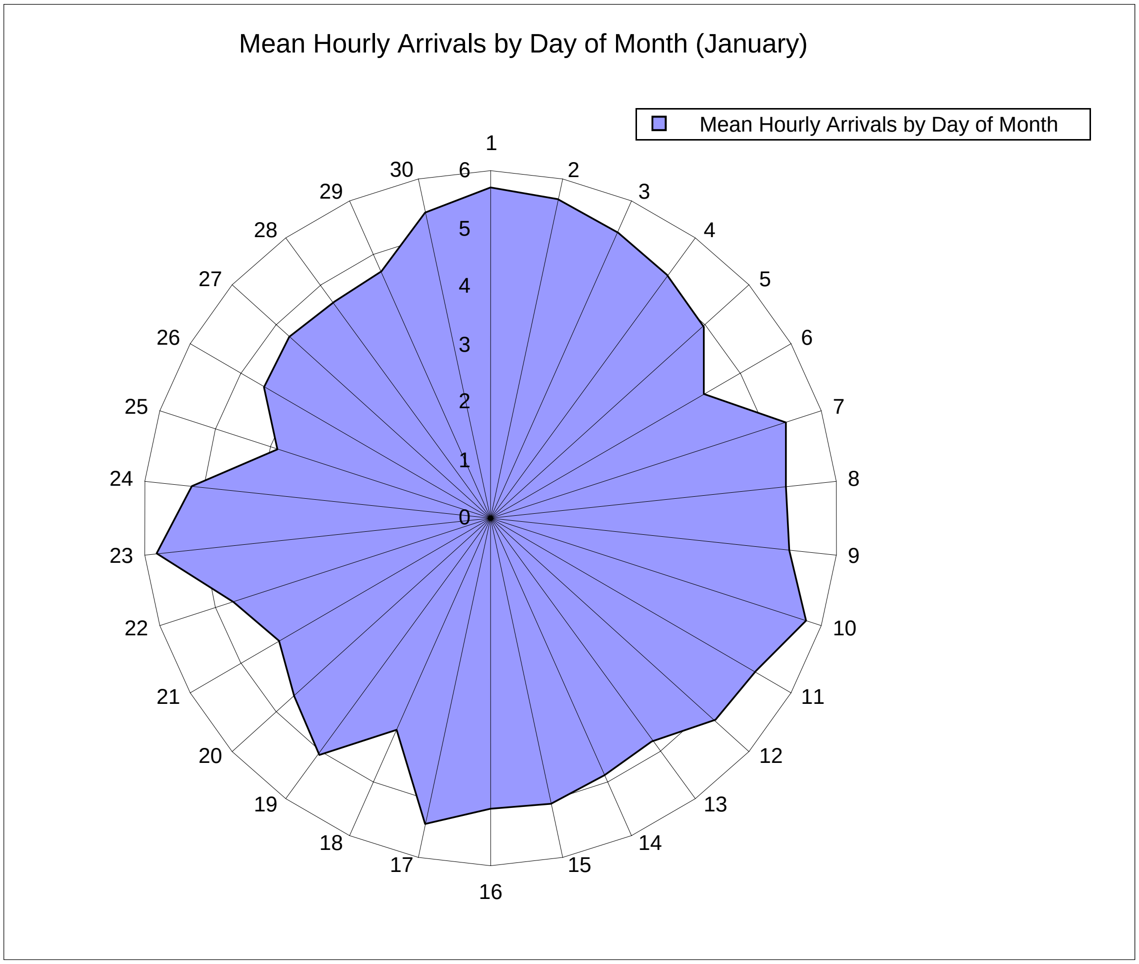

Figure 12: Mean Hourly Arrivals by Day of Month (January)

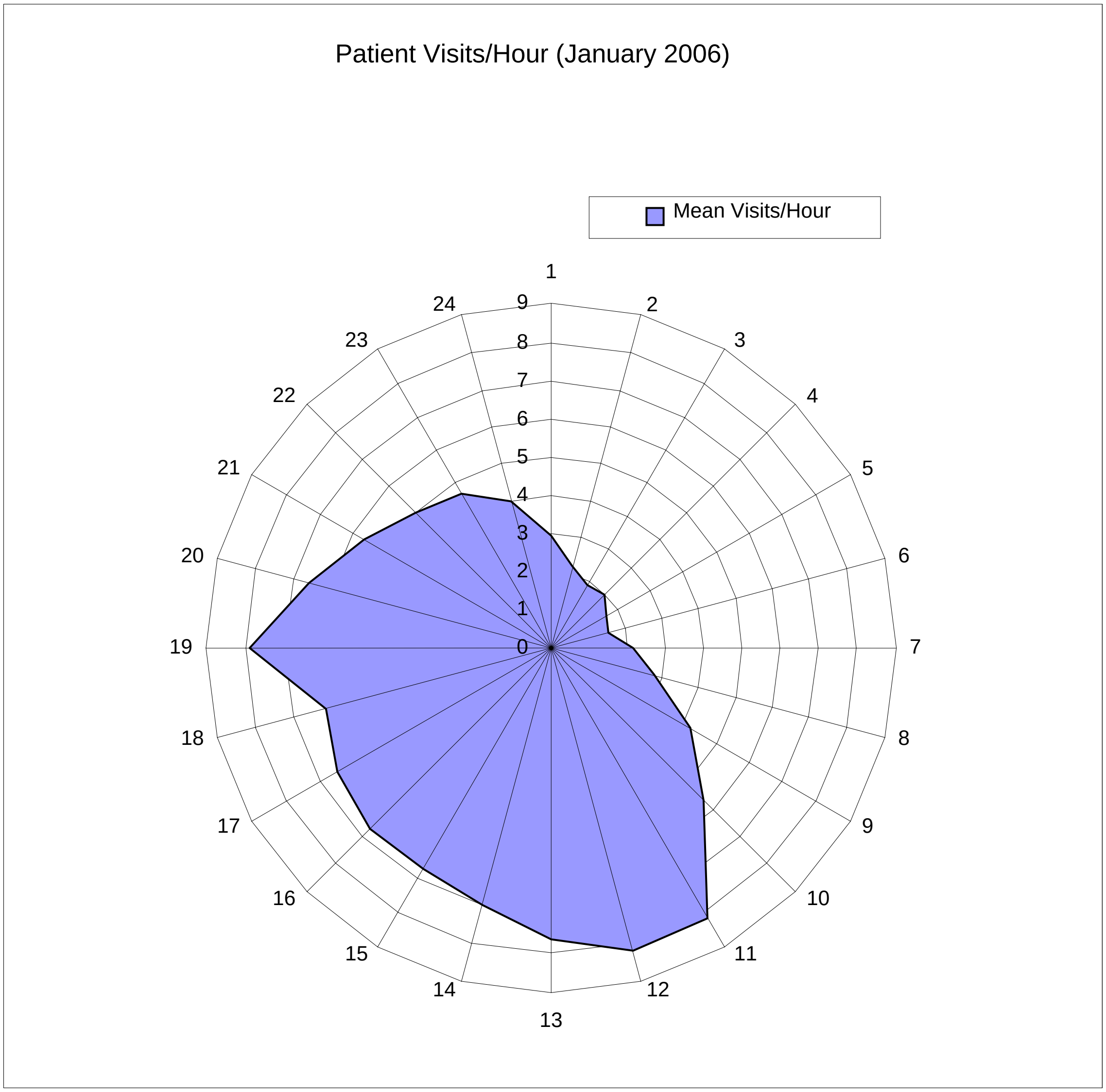

Figure 13: Patient Visits/Hour (January 2006)

Table 3: Modeled Typical January Arrivals

Time Interval	Day 01	Day 02	Day 03	Day 04	Day 05	Day 06	Day 07	Day 08	Day 09	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20	Day 21
00:00 - 01:00	0	5	2	8	2	5	2	4	0	4	3	2	2	4	2	2	2	3	3	1	1
01:00 - 02:00	3	2	3	3	1	2	5	2	3	2	1	1	4	1	4	1	5	2	0	3	5
02:00 - 03:00	5	3	4	1	2	0	5	1	1	1	0	0	4	4	2	5	1	1	1	1	2
03:00 - 04:00	2	1	0	2	0	0	5	1	3	3	4	1	1	1	4	1	0	2	6	0	0
04:00 - 05:00	3	0	2	3	2	1	3	2	5	1	3	2	0	1	1	0	1	0	2	1	2
05:00 - 06:00	4	1	1	0	2	1	3	2	1	1	1	2	0	1	2	2	0	5	1	1	3
06:00 - 07:00	5	4	2	1	3	3	2	0	1	6	4	4	0	2	2	2	1	1	0	3	0
07:00 - 08:00	3	7	5	3	4	0	3	4	2	4	5	4	2	8	1	6	3	0	1	1	4
08:00 - 09:00	3	5	3	7	4	2	3	5	2	7	5	3	5	3	3	3	3	6	6	4	7
09:00 - 10:00	4	5	3	4	4	7	5	6	7	6	9	7	3	5	5	8	5	6	8	10	3
10:00 - 11:00	11	9	7	7	11	9	7	8	8	8	10	10	7	5	4	7	6	8	7	7	3
11:00 - 12:00	7	9	9	6	15	6	10	16	11	7	5	11	5	9	7	4	15	4	9	6	5
12:00 - 13:00	6	11	7	10	9	10	6	6	8	12	5	6	12	4	6	7	9	3	8	9	10
13:00 - 14:00	13	8	6	9	6	6	6	10	5	5	6	5	6	9	5	16	3	5	4	11	6
14:00 - 15:00	14	12	4	4	6	8	6	8	6	11	4	9	7	6	6	7	6	7	4	6	8
15:00 - 16:00	3	9	13	7	6	7	6	4	5	7	5	7	5	6	6	6	7	8	7	5	4
16:00 - 17:00	5	8	5	7	7	5	6	7	9	8	6	8	10	9	10	0	6	5	9	2	2
17:00 - 18:00	10	8	6	12	8	5	2	5	6	4	4	4	5	9	11	6	4	3	6	5	7
18:00 - 19:00	8	9	12	9	8	10	9	8	10	14	12	6	9	3	8	8	4	5	3	5	4
19:00 - 20:00	4	7	7	6	4	5	9	6	6	5	8	8	3	7	10	7	11	4	8	5	5
20:00 - 21:00	7	5	4	7	4	6	2	4	5	4	8	10	9	8	7	6	11	5	8	8	4
21:00 - 22:00	6	3	8	6	5	3	6	3	7	1	3	3	4	4	6	4	12	2	9	5	7
22:00 - 23:00	2	0	8	4	2	0	6	2	4	7	6	4	3	3	6	7	8	7	6	4	5
23:00 - 24:00	3	3	5	1	1	2	8	8	4	8	7	5	5	3	0	2	3	3	3	3	1
Mean Arrivals	5.70	5.61	5.39	5.17	4.96	4.26	5.35	5.13	5.17	5.74	5.26	5.22	4.74	4.83	5.04	5.00	5.39	4.00	5.04	4.57	4.22
Total Arrivals	131.00	134.00	126.00	127.00	116.00	103.00	125.00	122.00	119.00	136.00	124.00	122.00	111.00	115.00	118.00	117.00	126.00	95.00	119.00	106.00	98.00

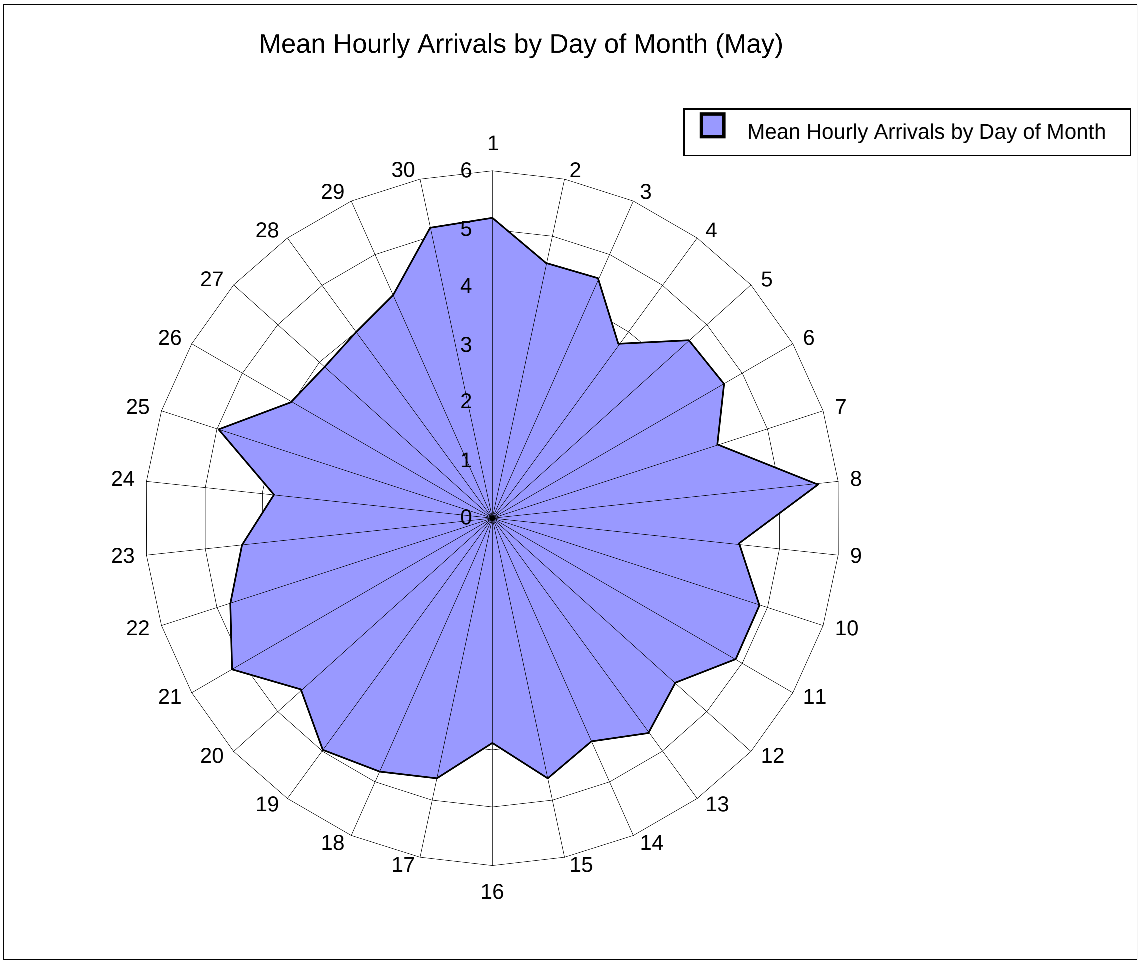

Figure 14: Mean Hourly Arrivals by Day of Month (May)

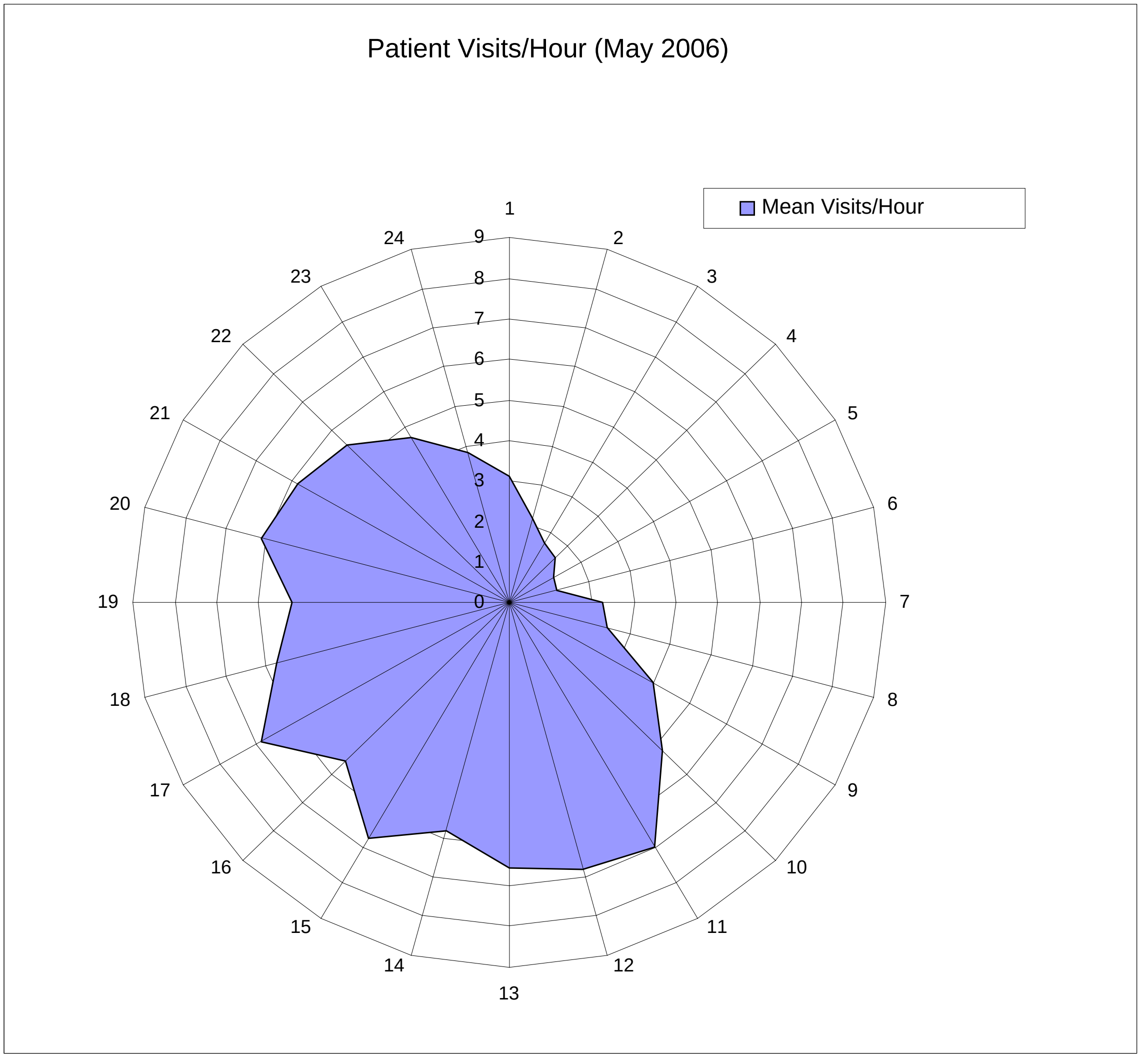

Figure 15: Patient Visits/Hour (May 2006)

Table 4: Modeled Typical May Arrivals

Time Interval	Day 01	Day 02	Day 03	Day 04	Day 05	Day 06	Day 07	Day 08	Day 09	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20	Day 21
00:00 - 01:00	6	2	3	3	2	6	3	4	6	4	1	2	4	4	5	3	0	3	6	2	1
01:00 - 02:00	2	1	3	4	2	2	1	2	3	2	4	3	2	2	0	1	1	2	4	3	3
02:00 - 03:00	1	0	1	2	3	1	2	3	0	0	2	0	4	4	1	1	2	0	1	3	4
03:00 - 04:00	0	1	2	1	0	0	0	1	2	2	0	2	6	1	2	1	2	2	1	3	3
04:00 - 05:00	2	1	1	1	2	4	3	0	0	3	0	2	4	3	0	0	1	1	0	1	1
05:00 - 06:00	3	1	1	1	0	1	2	2	0	1	0	1	1	1	1	0	2	0	4	2	0
06:00 - 07:00	4	6	0	1	2	2	2	0	2	2	6	3	1	2	1	0	1	0	3	3	2
07:00 - 08:00	4	3	0	1	4	4	1	2	1	3	1	6	1	1	2	1	2	3	1	4	5
08:00 - 09:00	3	5	4	2	5	6	4	9	3	4	4	4	7	3	8	5	3	2	5	3	5
09:00 - 10:00	3	4	6	4	4	6	4	12	9	4	7	4	5	5	4	1	3	9	4	4	1
10:00 - 11:00	12	11	7	6	7	7	11	7	12	8	5	4	7	5	8	8	4	8	7	4	9
11:00 - 12:00	5	8	4	2	9	7	6	8	8	6	9	5	6	2	13	5	7	4	11	8	11
12:00 - 13:00	8	6	10	6	5	9	4	7	6	5	11	7	8	8	6	4	6	9	5	7	11
13:00 - 14:00	7	5	7	8	2	9	3	6	2	8	6	7	3	4	6	4	6	8	9	4	7
14:00 - 15:00	7	6	9	3	6	9	7	8	6	4	7	4	7	13	7	9	7	5	7	6	4
15:00 - 16:00	6	1	6	6	4	2	1	10	4	9	3	7	7	6	4	5	7	5	7	5	7
16:00 - 17:00	7	4	8	2	5	5	9	8	4	10	7	9	9	2	8	3	10	10	7	7	8
17:00 - 18:00	9	4	7	5	8	4	4	9	5	6	4	8	5	6	5	7	5	4	9	3	6
18:00 - 19:00	6	10	6	3	4	4	3	7	4	11	9	3	7	3	5	13	6	6	6	1	5
19:00 - 20:00	5	6	4	8	10	5	7	5	8	6	5	3	3	4	5	8	6	7	9	6	7
20:00 - 21:00	6	7	6	3	6	6	3	8	7	7	5	3	5	1	7	1	8	9	8	7	10
21:00 - 22:00	9	5	6	7	5	5	7	6	6	3	9	3	6	3	4	6	4	8	2	4	3
22:00 - 23:00	5	5	5	6	8	5	7	6	5	2	2	1	0	10	6	4	4	5	3	7	4
23:00 - 24:00	5	3	1	3	4	3	3	4	2	5	6	8	1	8	2	2	8	3	1	7	3
Mean Arrivals	5.17	4.48	4.52	3.70	4.57	4.61	4.09	5.65	4.30	4.83	4.87	4.22	4.57	4.22	4.57	3.87	4.57	4.78	4.96	4.43	5.17
Total Arrivals	125.00	105.00	107.00	88.00	107.00	112.00	97.00	134.00	105.00	115.00	113.00	99.00	109.00	101.00	110.00	92.00	105.00	113.00	120.00	104.00	120.00

Through this comparison, we can see that patient volume, patient arrival times by day and patient visits by hour resemble both May 2006 and June 2006 data.

We also validate our model by comparing the arrival mode (ambulance versus walk-in) and the complaint (chest pain, abdominal pain, urgent care, and other) in our model with the actual data. In the logic display below, the problem recognition block (the diamond) sends 12 percent of patients down the chest pain path, 33 percent of patients down the abdominal pain path, 30 percent of patients down the urgent care path, and the remaining 25 percent down the "other" path. These percentages are determined by the real world hospital data provided by the hospital.

Patient arrival mode percentage is also broken down using real world data. We are given that 66 percent of chest pain patients arrive via ambulance, while 33 percent arrive via walk-in/self-transport. Similarly, 18.8 percent of abdominal pain patients call for EMS transport, while 81.82 percent come on their own.

Patient admission ratios are also determined in a similar way. Probability distributions are entered into the model based on real-world data provided by the hospital. Over a period of 30 runs of 30 days, we find the same percentages of patients are admitted and discharged in our model as reflected in the actual hospital data. These examples are shown below.

We can show how these percentages reflect the model process in the following two charts. Each one represents an actual run of the model. When converged over thirty runs, the model produces the same percentages as the actual hospital data.

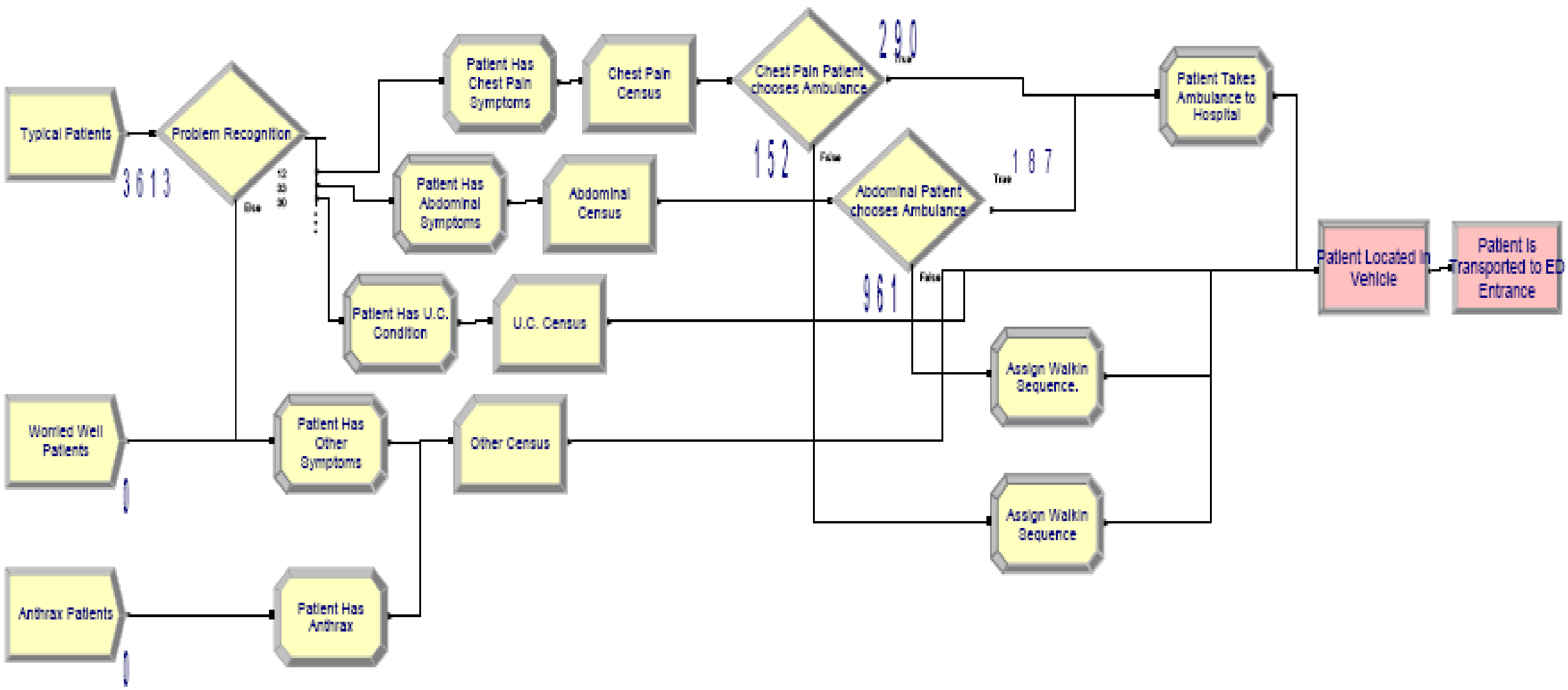

Figure 16: Model Patient Arrival Condition Example 1

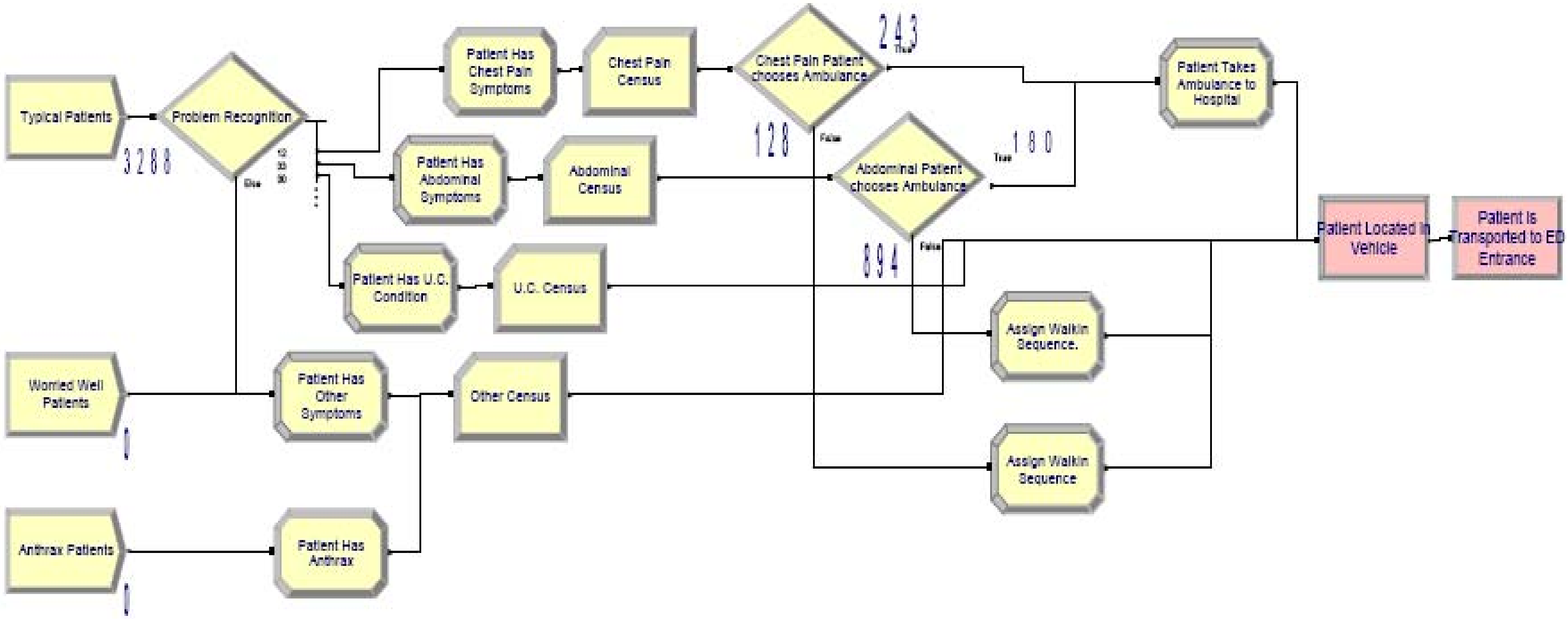

Figure 17: Model Patient Arrival Condition Example 2

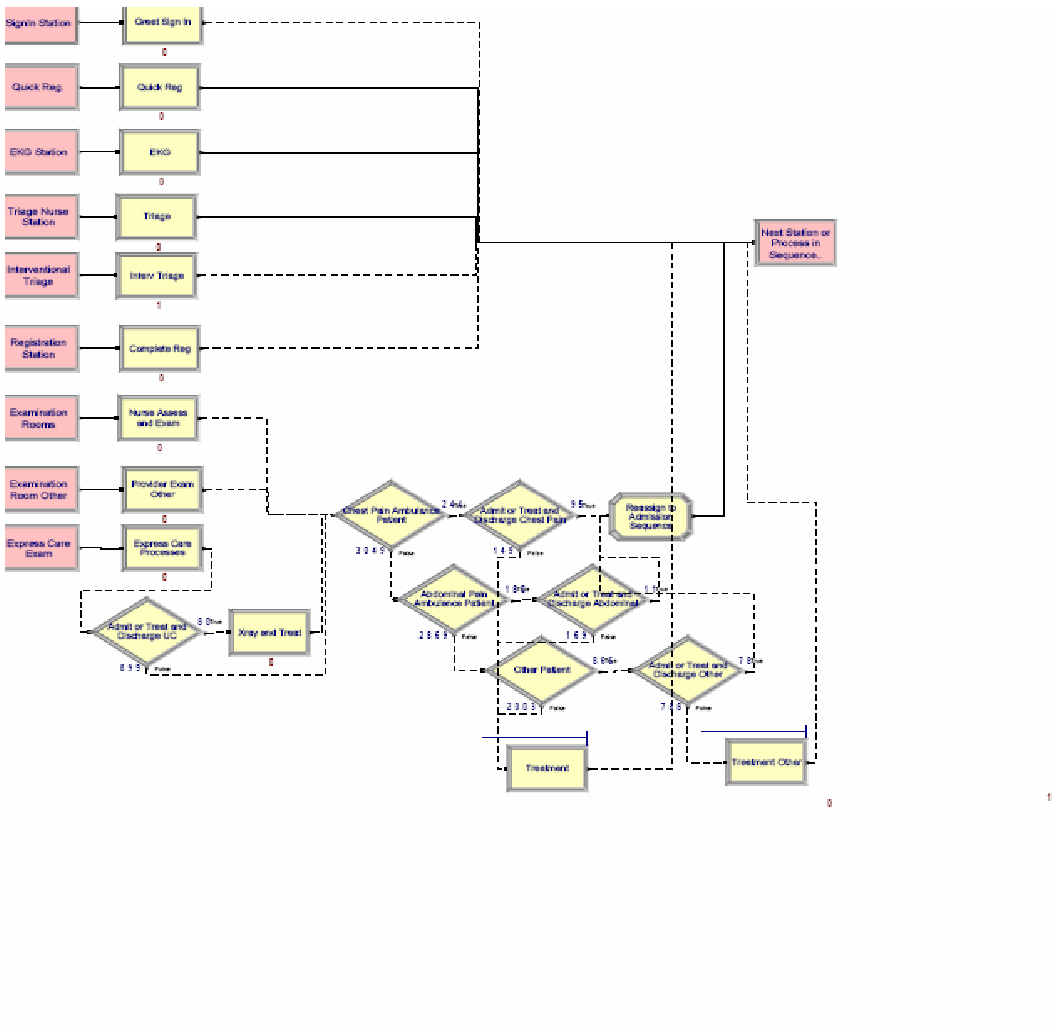

Figure 18: Patient Admission Example 1

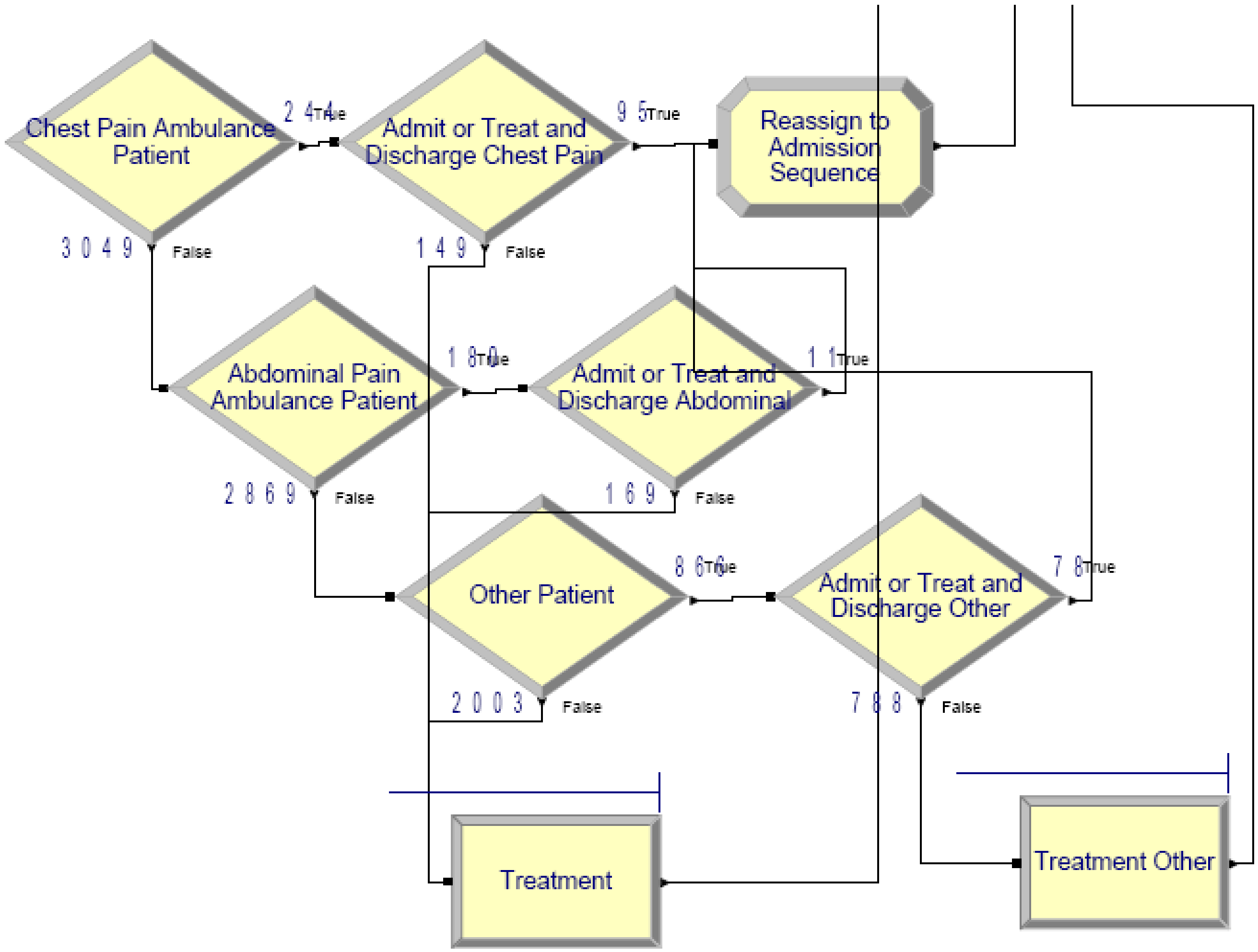

Figure 19: Patient Admission Example 1a (Magnified)

On May 22, 2007, we presented our model and tentative results to the staff members of the Emergency Department at Winter Park Memorial Hospital. Included in the staff present were Randal Poole, MD, and emergency physician and the Emergency Department Medical Director, Barbara Gabel, MA BSN CEN, Director of Emergency Services and Diane Sullivan, ANM BSN and the Disaster Response Coordinator for the Emergency Department. Based on their examination, our model was found to be representative of the Emergency Department.

CHAPTER FOUR: FINDINGS

Inhalational Anthrax Attack

Our results model what happens in the event of a biological attack using inhalational anthrax. We can assume that the attack was carried out using a crop dusting plane dispersing aerosolized anthrax spores over a population. We can envision two scenarios:

1. The attack is discovered immediately. The local county health department alerts Winter Park Memorial Hospital that patients will soon be arriving who are victims of a biological attack using inhalational anthrax. The Emergency Department has advanced warning to begin implementing its Biological Terrorism Response Plan.
2. The attack is not discovered. Patients begin arriving at the Winter Park Memorial Hospital Emergency Department with inhalational anthrax, but are not aware that they are victims. They present in various stages of the infection. It is not until patients begin entering into respiratory distress that facility staff suspects that inhalational anthrax may be the culprit. The local county health department is notified, and the facility transitions into their Response Plan mode.

In both cases, one of the critical problems faced by the facility will be the arrival of the so-called “worried well.” We assume that once information is made public that an attack has occurred, people who might otherwise be healthy or merely have flu-like symptoms unrelated to inhalational anthrax will begin to come to the hospital Emergency Department seeking treatment. This additional influx of patients, on top of actual anthrax victims as well as those patients who require emergency services and care unrelated to the biological terror attack will almost certainly place a great strain on the Emergency Department's capacity. An important part of simulation modeling is analyzing how the Emergency Department, once it has initiated its Biological Terrorism Response Plan, performs in the face of this new challenge.

The problems to be faced by the Emergency Department certainly are not limited to the influx of the "worried well" and the ability of the Emergency Department to handle the additional capacity. The facility must begin an expedited admissions and discharge process of patients in the Emergency Department who are not anthrax attack victims. Currently, the Emergency Department is showing an admissions time of a little over ten hours, from the time the physician orders the patient to be admitted to the facility to the time the patient is actually transported to a bed in the hospital. Discharge times can also be large. A backlog of patients will create a serious problem for the facility to be able to treat terror attack victims (Gabel & Sullivan, 2007).

Another issue will be the impact on patient length of stay (LOS) as "normal" patients seeking emergency services and care are joined by anthrax attack victims and the "worried well." There are many factors affecting length of stay, ranging from the ability of patients to be examined and seen by available staff, the time it takes for laboratory results to be ordered, completed, returned and reviewed by the clinician and admissions and discharge process time (Gabel & Sullivan, 2007).

Currently, the Emergency Department has to rely on clinical case findings in order to detect any sort of biological attack. We know from the literature that an outbreak of inhalational anthrax will not be discovered for approximately four days (Buckeridge et al, 2006). This means that the Emergency Department will be operating for several days in the midst of an attack without having implemented its Biological Terrorism Response Plan. We can anticipate that patient mortality will certainly be affected.

Once the plan is initiated, one of the first items to be addressed is staffing. The Emergency Department Charge Nurse, Emergency Department Medical Director and the hospital administrator on call will have to make an immediate determination of staffing needs. Additional emergency physicians, nurses, nurse technicians, and health unit coordinators can be called in. However, the staffing decision will be determined in a "fog of war" in an emergent discovery scenario. The number of potential victims would be unknown at that point, so additional staffing may not even be called in if the number of anthrax victims is only one or two at the time the decision is made. As additional staffing comes aboard, along with additional victims and potentially the "worried well," another unknown is how the impact of additional staff will affect patient flow, length of stay, mortality and the discharge/admissions process. It is conceivable that *too many* people can clog up the working of the Emergency Department, even in a disaster scenario, as well as *too few*.

Emergency Department Bed Capacity

A key indicator of the performance of the Biological Terrorism Response Plan will be how Emergency Department bed capacity is affected by the attack. Whether the scenario envisioned is an Advance Warning or an Emergent Discovery at the Emergency Department, we can anticipate that beds will begin filling up. The Response Plan calls for the Emergency Department to be divided into zones Red, Yellow, and Green, and patients are triaged to those zones based on their acuteness. This change in process flow should theoretically permit more patients to be seen by clinicians and for more patients to move through the Emergency

Department to either be discharged or admitted in a quicker fashion. Our model tested this by analyzing how bed usage was affected by the increase in patients, and most specifically, the influx of the “worried well.”

Our findings are able to be presented on the following charts.

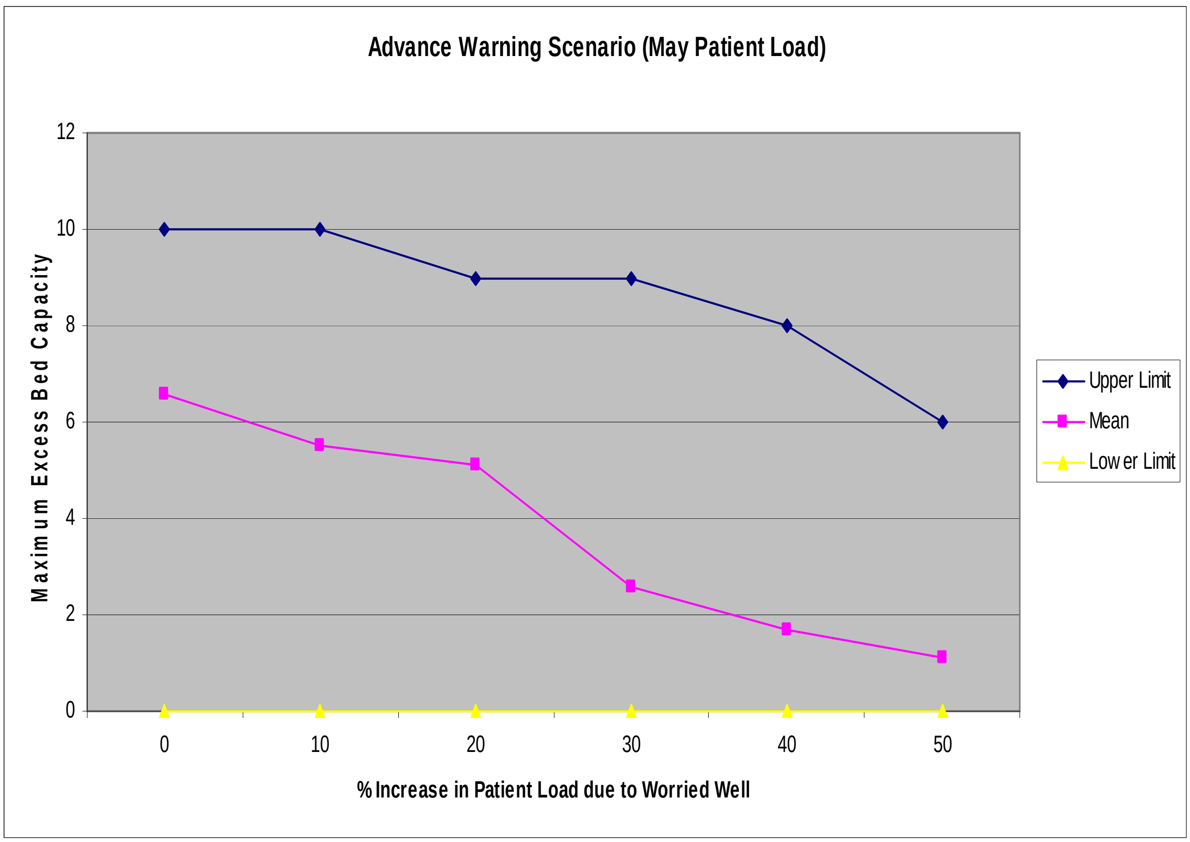

Figure 20: Advance Warning Scenario—May Patient Load

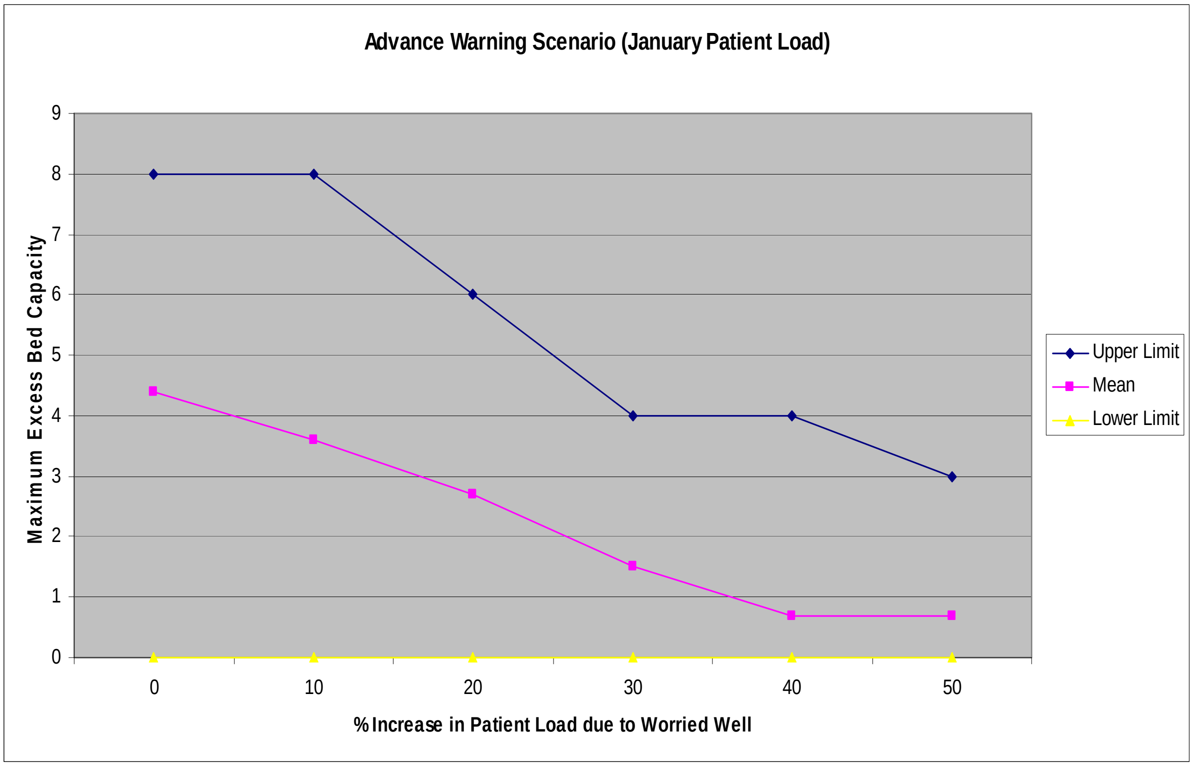

Figure 21: Advance Warning Scenario—January Patient Load

The data indicates that under the Advanced Warning scenario, Emergency Department bed capacity declines as expected, however beds continue to remain available at the mean and upper limits of patient volume. One point of caution should be made at this point. This data is not *predictive* in nature, it is *descriptive*. In other words, the model has generated results based on certain assumptions. This should not be taken to mean that with a twenty percent increase in patient load due to an influx of the "worried well" in a "January type" month (i.e., high patient volume), there will be two to three Emergency Department beds of capacity available on average.

The "upper limit" in both the typical May and January type months represents lighter patient volume days which tend to occur in those months. The "lower limit" obviously shows the impact on the Emergency Department when it is full or above-full capacity. (It is not uncommon for the Emergency Department to over 100 percent capacity.) As can be expected, when the Emergency Department is at or above capacity, no additional bed space is shown as being available under any scenario.

In our simulations of months with “May-like” patient loads, mean bed capacity does not become an issue until the patient load increase increases from twenty percent to thirty percent. At that point, we notice a precipitous drop in available Emergency Department beds, from just under six to barely over two. Up to that point, a twenty percent increase in patient load due to “worried well” only resulted in a loss of capacity from just over six beds to above five beds – an estimated one bed. Interestingly, at the upper limit level, bed capacity does not appear to drop off significantly until the patient load increases from forty percent to fifty percent.

A “January-like” month shows a steeper decline in mean available bed capacity as patient loads increase up to forty percent. At that point, the mean bed capacity actually levels off when the patient load rises from forty to fifty percent. At the upper limit of patient load increases, the bed capacity seems to step down dramatically as patient load increases from ten percent to thirty percent, levels off, and then steps down again.

When we look at the Emergent Discovery scenario—the one in which patients present to the Emergency Department not realizing they are victims of anthrax attack and the facility is unaware an attack occurred, we actually find that bed capacity remains the same in both “January-like” and “May-like” months.

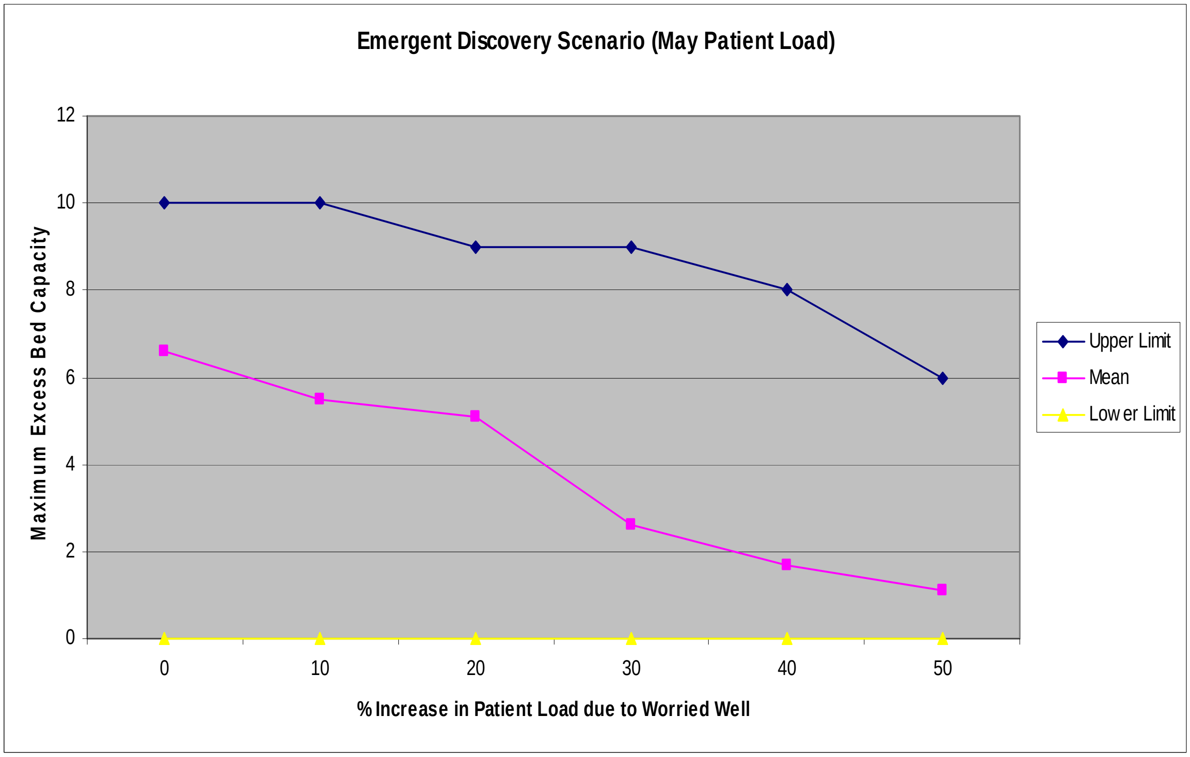

Figure 22: Emergent Discovery Scenario—May Patient Load

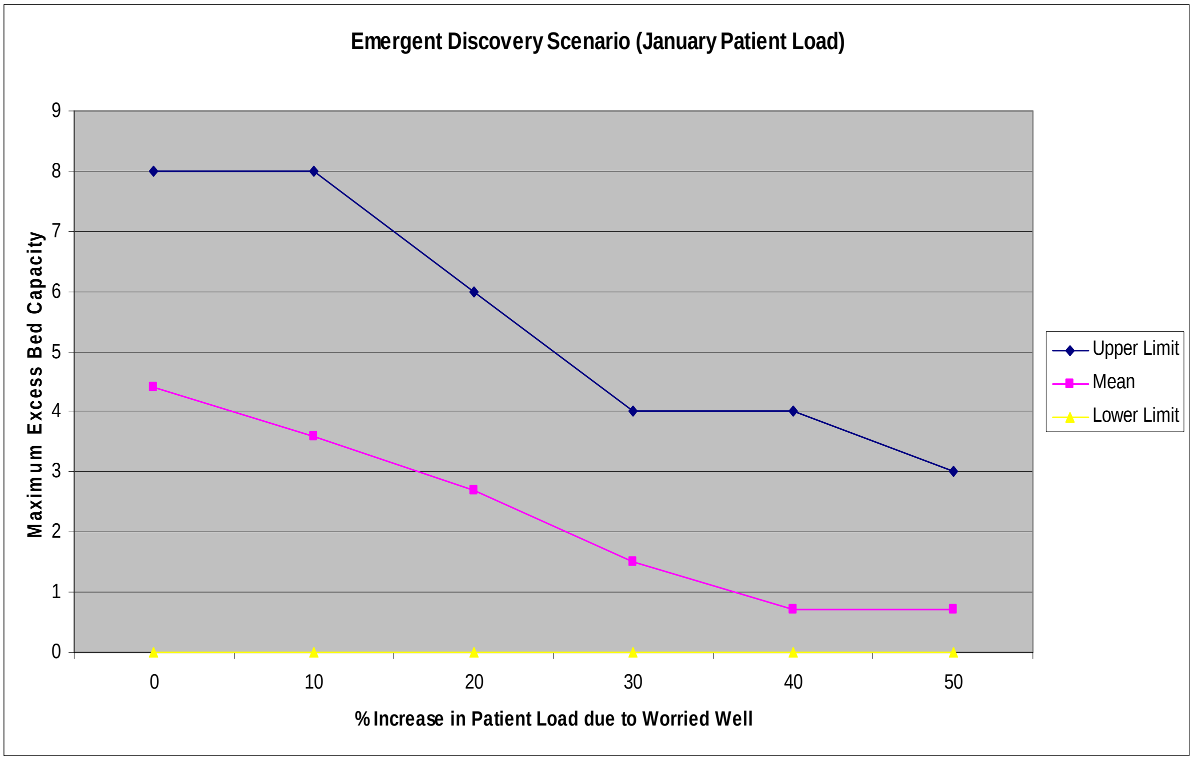

Figure 23: Emergent Discovery Scenario—January Patient Load

What sort of inferences can be drawn from the data? First, we see that regardless of the scenario, Emergency Department bed capacity remains available. It is important to remember that the actual capacity available shown is not *predictive* but *descriptive* based on the assumptions we used in developing the model, the Bioterrorism Response Plan, and the scenarios.

In general, the flexibility of the response plan to contingencies is what probably leads to additional capacity being available under the given scenario. Response plan flexibility is a key recommendation in bioterrorism planning literature (see McDaniel, 2004). It is also a good example of how Complexity Theory is the proper theoretical lens with which to view bioterrorism response. This ability to adapt and show flexibility may also be indicative of the organizational processes and staff mindset in the Emergency Department setting. Emergency care providers are used to dealing with providing care in an environment where information is limited or unknown, often having to make fast decisions and change processes and care based on the situation at hand.

As is often the case in computer simulation modeling, the results tend to beg more questions. For example, why does bad capacity drop precipitously between a 10 percent increase and 30 percent increase in patient load at the “upper limit” during a “January-type” high-volume month? We know that the upper limit of bed capacity represents the rosiest of days in a typical Emergency Department—i.e., a low patient volume. There is also a noticeable drop in mean bed capacity during “May-like,” low volume months as the mean patient load increases from 20 percent to 30 percent. Is this reflective of the effect of the marginal utility of additional staff, or the process of the Bioterrorism Response Plan beginning to wane in effectiveness? Perhaps it shows that the admissions process into the hospital or discharge process out shows dramatically, thereby leading to longer patient stays and subsequently, less bed capacity? Further analysis and data will be necessary to address these and other questions adequately.

Of course, the effectiveness of the Bioterrorism Response Plan cannot be measured by one indicator alone (Emergency Department bed capacity), albeit an important indicator we believe. System performance during a biological attack will be a function of multiple, interacting variables. Computer simulation modeling is a valuable tool in that these additional variables and scenarios can be added on to an existing model. Model results can then be used to evaluate how these input changes have affected our output in the safe, benign world of computer simulation rather than the time-consuming and less comprehensive process of running an actual disaster drill. Worse yet would be the onset of an actual attack and finding out the answer to questions both known and unknown “the hard way.”

CHAPTER FIVE: SUMMARY AND CONCLUSIONS

Summary

Using complexity theory as our structural framework, this dissertation used computer simulation modeling to attempt to test the effectiveness of the biological response plan at a local hospital facility. We chose Winter Park Memorial Hospital because its size and variation in patient volume is fairly representative of a typical hospital in America, and because it is located in an area of the United States that is considered a prime target for terrorist attack due to its popularity world wide.

We were provided data from the hospital on patient volume, length of stay, staffing, clinical care processes, changes in the process in the event of a known biological attack and other data to create a model. This model was validated by comparing results with the real world data and presenting it to the hospital staff, experts in how their system works. Once it was validated, we were able to proceed with introducing the various scenarios of an attack.

Two types of attack scenarios were imagined. In both cases, we assumed that the biological weapon of choice was inhalational anthrax dispersed in an aerosolized form. The Advance Warning scenario was based on the assumption that the local county health department notifies the hospital that an attack has occurred and to be prepared to receive patients infected with inhalational anthrax. The Emergent Discovery scenario assumes that neither the patients, facility, nor authorities know that an attack has occurred. Patients begin presenting to the Emergency Department showing flu-like symptoms. Patients then deteriorate into severe respiratory distress. Through clinical case findings the facility "discovers" that it has victims of inhalational anthrax, notifies local authorities, and initiates the response plan.

The effectiveness of the plan was evaluated based on its impact on Emergency Department bed capacity. In both scenarios, we anticipate that patient volume will begin to increase as both anthrax victims and the “worried well” come to the Emergency Department seeking treatment. Emergency Department bed capacity will give us some clue into how effective the plan is in managing this influx of victims and “worried well” while still having to deal with regular patients seeking emergency services and care.

Under both scenarios and in simulated high volume and low volume months, the Emergency Department showed resiliency in maintaining some bed capacity even when patient load increased by 50 percent. This suggests that the plan’s flexibility, and the ability of the Emergency Department to operate in a highly complex environment, is conducive to being prepared for a scenario involving a biological attack.

Limitations

We acknowledge that this study is limited in a number of respects. First, it is an attempt to utilize computer simulation modeling to evaluate a hospital facility’s bioterrorism response plan, which it appears to have never been done. Modeling is still not widely used in analysis of health care issues, certainly not to the extent that it has been used in other fields. Therefore, this research may be difficult to compare to previous efforts. No doubt future work will further improve and refine the techniques of applying modeling to bioterrorism preparedness by hospitals.

In choosing Winter Park Memorial Hospital as our unit of analysis, this work becomes a case study. Therefore, generalizing this work to other facilities is problematic at best. Winter Park Hospital is best described as a community hospital. What is necessary is to expand on this study, perhaps locally. We could analyze the response plans of the other campuses in the Florida Hospital system using this methodology. There is another hospital system in the Central Florida area which can also serve as a basis of comparison. From these additional units of analysis, we can perhaps begin to formulate a matrix of common indicators of preparedness. In any case, as a case study, we cannot expand upon these findings to other facilities, which limits this research's usefulness to a more qualitative nature.

Future Work

How can the effectiveness of a specific biological response plan be evaluated and what indicators should be used to measure that effectiveness? Computer simulation modeling in this dissertation has proven itself reliable and valid in creating a "working" Emergency Department based on the data from Winter Park Memorial Hospital. This model can then be subjected to any number of tests and scenarios, even those not necessarily related to biological terrorism response. Time constraints in producing this dissertation prevented further, in-depth analysis. However, future research is planned using the volumes of data already generated to explore the question of how effective the biological response plan is. Agreements have already been secured with Dr. Aaron Liberman and Carl Anglesea to write future articles to address several more points.

Future work can address several issues. We can briefly outline possible avenues of research. These can include:

- How does the implementation of the Biological Response Plan impact patient length-of-stay for both anthrax victims and regular emergency services patients? Length of stay remains an important indicator of Emergency Department performance.

- What is the optimal rate of staffing for the Emergency Department in the event of a biological attack? Staffing is built into the model by having a finite number of resource units available in the simulation program based on information provided by the facility. These units take time to arrive, provide care and cannot exist in the model indefinitely. Since they represent human beings, we have to account for humans needing rest for example, even in an emergency. These staff care "called in" in the case of an emergency, so that takes time. We wonder whether there is a diminishing marginal utility in the addition of staff. This can also be explored in the type of staff. Does the addition of one emergency physician improve clinical care timeliness? Would it be more advantageous to add more nurses or support personnel as opposed to physicians? What is the optimal staff mixture to patient?
- The Emergency Department currently relies on clinical case findings in order to "discover" an untoward event and lacks a standard syndrome surveillance program. In the event of an anthrax attack where the attack is unknown, what might the impact be on patient mortality and morbidity since the literature shows that the attack would likely remain undiscovered for three to four days? Would syndrome surveillance improve overall system performance in the event of an attack?
- The bed capacity in the Emergency Department shows varying rates of decline based on the increase in patient load. What factors influence the varying rate of that decline?
- How does the Emergency Department response plan fit within the entire hospital facility's plan? For example, other departments are "expected" to have developed their own plans in the event of a biological attack, including Hospital Security, Safety, Engineering, Housekeeping, Laboratory Services, and Pharmacy Services. This

dissertation separated the Emergency Department from the hospital and evaluated its plan only. How might the plan of the Safety Department impact the Emergency Department for example, as well as the overall ability of the hospital to respond to an event?

- The admissions process and the patient discharge process are a critical factor in patient length of stay and in bed capacity, both during typical days and during a response to a disaster. What factors drive the time it takes for a patient to be admitted or discharged? Can various processes be altered to expedite that process, or do common assumptions not stand the test of research?
- An attack using anthrax is just one of many types of potential attacks. As noted, inhalational anthrax is non-contagious and patients present with common flu-like symptoms. However, how does the Biological Response Plan perform in the case of a smallpox release, botulism, plague, tularemia, or viral hemorrhagic fever? Any number of biological agents will require radically different procedures, including contact precautions, isolation, and decontamination of patients. And what if the attack includes multiple releases of multiple types of agents, requiring the facility to adapt to different scenarios at the same time? This additional strain on resources may show the need for different response plans based on the nature of the attack.
- A number of community factors may play into a facility's ability to respond to an attack, many of which are outside of its control. One example might be the availability of public transportation. A large number of individuals may try to reach the hospital but do so through the local bus system, which is the only public transportation system available. How would interruptions on public transportation service affect patient arrivals, which in turn affects the facility's overall response effort?

- What indicators lend themselves to being useful measures of the effectiveness of a Biological Response Plan? Our model was able to evaluate one—Emergency Department bed capacity. We considered exploring in the future patient length of stay, staffing, mortality and the admission and discharge process. Are these indicators adequate or would others be necessary and more appropriate? Is it possible to create a standard evaluation matrix based on computer simulation modeling research by which we can measure the effectiveness of other hospital emergency response plans?
- Finally, what about the unknown "butterfly flap" in complexity theory? Random shocks built into the simulation may provide clues as to how much environmental complexity an organization can take.

Future work can center on these and other important questions. Because the initial model of the Emergency Department has largely been built and validated, we have an excellent starting point. We also have substantial data on our current scenario to continue to review and explore, so we can anticipate using this data for a long time. This promises to be valuable, ground-breaking work having its roots in theory but proving itself a practical tool for hospital administrators, clinicians, emergency managers and the public. In today's complex world full of potential terrorist threats, it can prove itself vital to emergency preparations.

APPENDIX A: EVALUATION OF BIOTERRORISM RESPONSE PLAN: DISCRETE EVENT MODEL DESCRIPTION AND VALIDATION

Florida Hospital, Winter Park Emergency Department

Evaluation of
Bioterrorism Response Plan

Discrete Event Model
Description and Validation

ENS Robert (Jake) Bebber, USN
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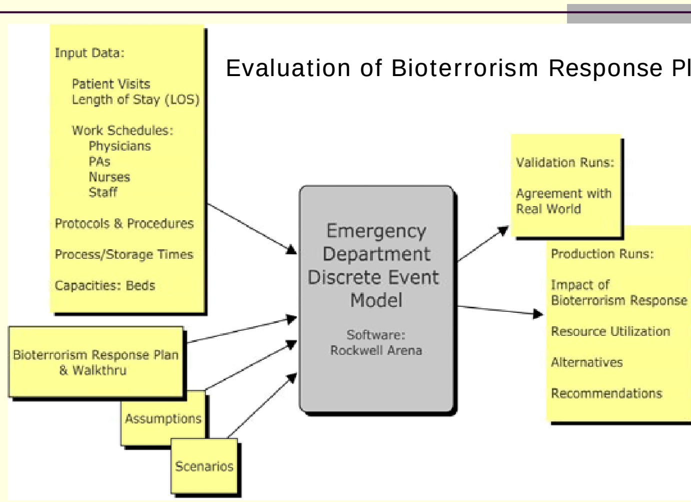
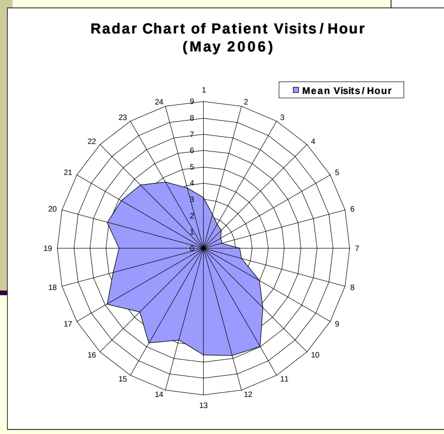
Carl M. Anglesea, M.S., CSMP
UCF Institute for Simulation & Training

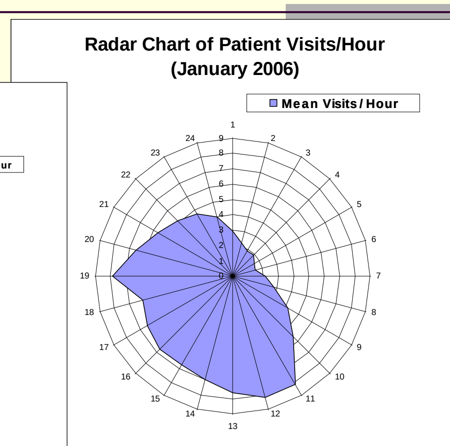
WPH Emergency Department



WPH Emergency Department

Patient Arrival Data:
Seasonal and Hourly Variation

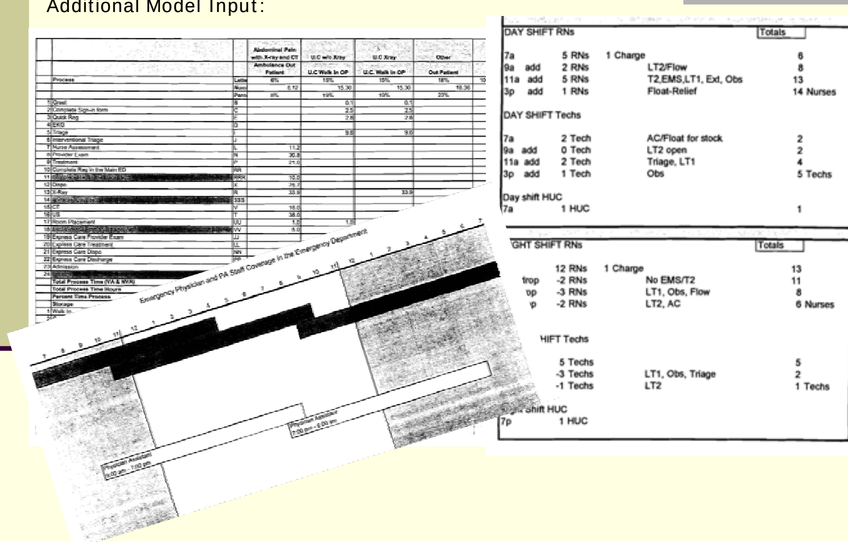




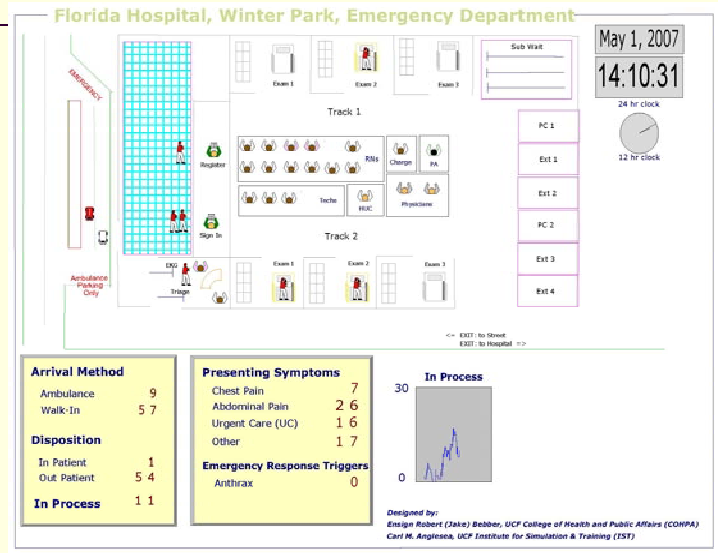
Source: ED Hourly Trend, Winter Park

WPH Emergency Department

Additional Model Input:



WPH Emergency Department



WPH ED Model Validation

- Stochastic model of patient arrival and processing sequences:
  - Run length: 30 days due to incubation period and public reaction
  - Replications: 30 runs for each set of monthly data (May and January)

- Model Validation: Comparison of simulated patients to real patients

  - Patient Arrivals:
    - Modeled using a Poisson probability distribution
    - Same mean arrival rates (hourly and seasonal variations)
    - Same arrival mode percentages (ambulance vs. walk-in)

  - Patient Processing Sequences:
    - Same patient complaint percentages (chest pain, abdominal, etc.)
    - Same patient processing and storage times
    - Same patient length of stay experienced
    - Same patient admission/discharge rates

Bioterrorism Response Plan Summary

- Infection Control Practitioner (ICP) identifies issue, notifies local health department
  - WPMH lacks ICP
- Contact precautions initiated (standard, enhanced)
- Local health department controls communication
- Hospital initiates Mass Casualty procedures
  - Charge Nurse, ED Physician, Administrator determine staff needs and resource needs

Bioterrorism Response Plan Summary

- Health Unit Coordinator (HUC) ensures stretchers and wheelchairs brought to ED
- ED is divided into Red, Yellow and Green areas
- Triage station outside at loading ramp directs patients based on condition to areas for treatment
- Expedited discharge procedures initiated to free beds in the hospital; non-critical patients are discharged from ED or moved to Observation

Inhalation Anthrax

- Symptoms
  - Non-specific flu like symptoms including fever, dyspnea, malaise, fatigue, headache, vomiting, chills and abdominal discomfort. Person may also have non-productive cough and mild chest discomfort.
  - These symptoms may be followed by a brief period (several hours to a couple days) of improvement followed by an abrupt onset of respiratory distress with dyspnea, diaphoresis, stridor (high pitched whistling respiration) and cyanosis. Septicemia, shock and death occur within 24-36 hours after onset of respiratory distress and mortality approaches 100%. Approximately 50% of cases develop hemorrhagic meningitis.

Inhalation Anthrax

- Diagnosis
  - Presumptive diagnosis based on respiratory failure with widening mediastinum. (Note – the onset of initial flu like symptoms will likely not be considered as anthrax when patients present to the ED. It will only be after patients begin to exhibit the effects of respiratory failure with widening mediastinum that anthrax becomes a suspect.)

Inhalation Anthrax

- Note also that the incubation period for inhaled anthrax is on average, 1-6 days, up to 6 weeks. Patients presenting with anthrax could come as late as a month away from exposure.
- Treatment
  - Early antibiotic treatment is critical to survival. Antibiotics include Ciprofloxacin, Penicillin G, Doxycycline.

Why Inhalation Anthrax?

- Common scenario found in the literature is mass exposure to inhalation anthrax dispersed in aerosol form via crop dusting plane
- Presents as flu-like symptoms, making diagnosis problematic if attack goes unnoticed
- Non-contagious; does not require isolation
- Treatable with antibiotics

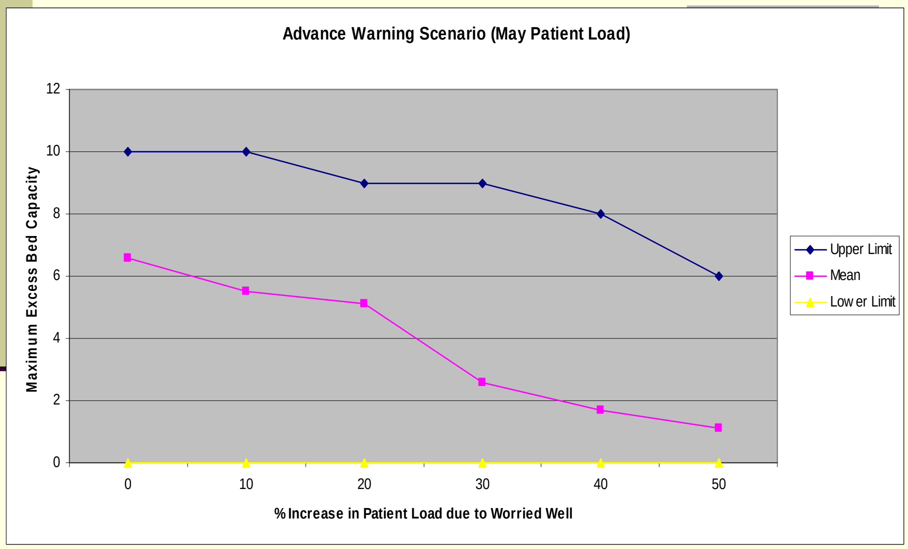
Data

- Emergency Department Summary Data for January 2006 and May 2006
  - January represents a “high volume” month
  - May represents a “low volume” month
- Staff data provided by Emergency Department Nurse Manager
  - Staff units include: ED Physician, ED PA, Nurse, Nurse Technician and Health Unit Coordinator
- Lean Track Program Study of July 2005
- Disaster Drill Assessments

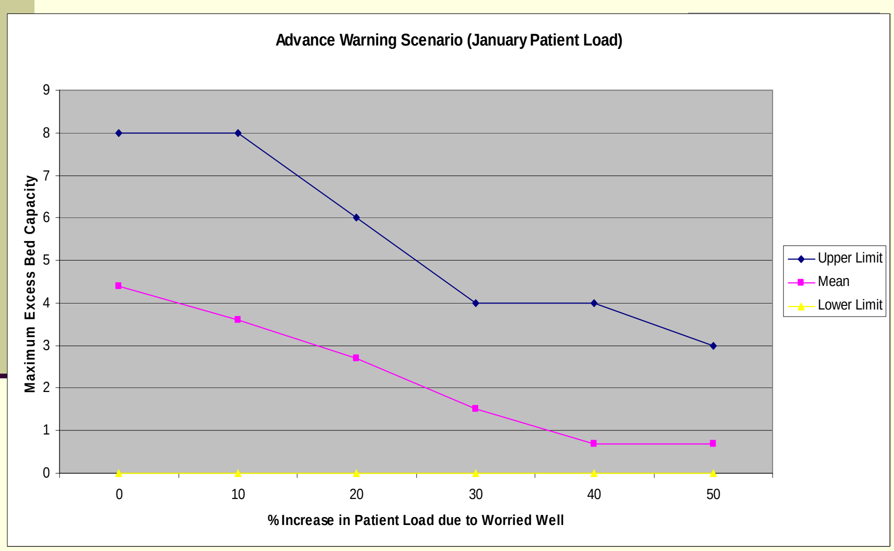
Scenarios

- Advance Warning
  - WPMH receives a warning from the local health department that there has been a bioterror attack using inhalational anthrax.
  - Emergency Department has approximately 30 minutes to prepare for incoming patients.
- Emergent Discovery
  - Patients who do not realize they have been exposed begin presenting to the ED with anthrax symptoms.
  - Discovery time can vary; mortality rate affected.

Advance Warning Scenario



Advance Warning Scenario



Emergent Discovery Scenario

- Bed capacity use is the same as the Advance Warning Scenario
- Based on the literature, we can anticipate that the lack of a syndrome surveillance monitoring program will mean that an anthrax outbreak will not be detected for 3.7 to 4.6 days after the release of spores[1]

1. Buckeridge, D. L., Owens, D. K., Switzer, P., Frank, J., & Musen, M. A. (2006). Evaluating detection of an inhalational anthrax outbreak. *Emerging Infectious Diseases, 12*(12), 1942-1949.

Discussion

- WPMH Bioterrorism Response Plan shows great flexibility
- In some cases, the facility is able to handle up to a 50% increase in patient flow due to the influx of "worried well"
  - Conversely, staff should monitor carefully and be prepared with contingencies
- Relying on clinical case findings rather than syndrome surveillance will likely delay discovery of an anthrax outbreak when attack is unknown. This will almost certainly lead to greater patient mortality.
- It is critical for WPMH to be able to manage the "worried well". Public response has to be communicated immediately and effectively through the Health Department.

Future Work

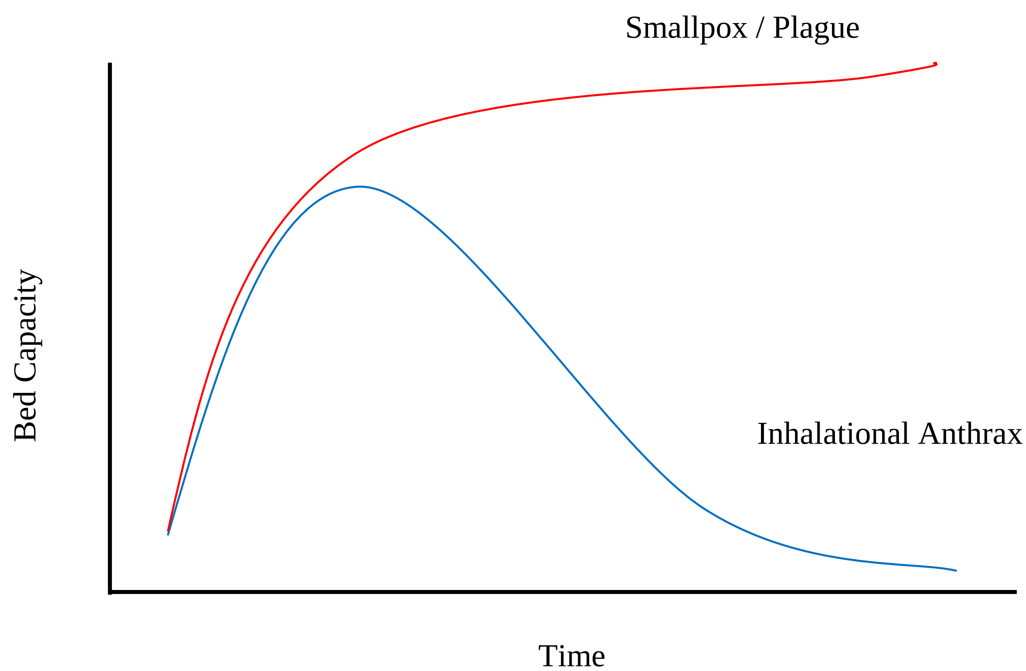
- Impact of Response Plan on Patient Length of Stay (LOS)
- Optimization of Emergency Staffing
- Patient mortality rates in the Emergent Discovery Scenario
- Analysis of the admissions process during emergencies

Questions?

Thank You!

APPENDIX B: ALTERNATIVE SCENARIO SPECULATION

Inhalational anthrax presents unique challenges to health care providers and administrators. Yet other potential contagions also represent significant obstacles to overcome. Smallpox has the ability to spread rapidly across a region, along with plague for example. This rapid spreading of infection would most certainly have significant consequences for health care facilities. We can suggest that many hospitals would become overwhelmed. Systems might not survive the additional shock regardless of their ability to withstand environmental shock.



Our data estimates that the Winter Park facility would be able to handle the additional patient load due to its ability to adapt to system shock. But we have to consider the possibility that some shocks cannot be withstood over time without additional capacity or diverting additional load to other sites.

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