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Emergency department capacity planning for a pandemic scenario: Nurse allocation

Florentino Antonio Rico
University of South Florida

Emergency Department Capacity Planning for a Pandemic Scenario:

Nurse Allocation

by

Florentino Antonio Rico

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Major Professor: Grisselle Centeno, Ph.D.
Ali Yalcin, Ph.D.
Kingsley Reeves, Ph.D.

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DEDICATION

To my loving parents Florentino Antonio and Martha Cecilia, my brother Jorge and his lovely wife Ximena, my dear sister Heidy, and my nephews Camilo and Alejandro. Last but not least, to Michael.

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ABSTRACT

The problem considered in this research is the efficient allocation of resources in an emergency department during a large flow of patient consequent to a pandemic influenza breakout. Predicting the impact of a Pandemic Influenza is very complex due to the many unknown variables that may play a role to how severe a pandemic can be. Scenario planning is considered in this research to forecast different potential outcomes and help decision makers better understand the role of uncertainties and become prepared to make important decisions.

The goal is to first create a forecast model to estimate the patient demand during the breakout period accessing an emergency department and employ it as input of a simulation model to replicate the dynamics of the system under a set of pandemic influenza scenarios. The results yielded by this approach will be used as decision tool for hospital managers to better utilize and allocate medical staff considering the fluctuant demand of the system on the zones of the emergency department: triage, red, yellow, green, and black.

Emergency departments are already overwhelmed during everyday operations; thus, it is expected in a case of pandemic influenza, their operations

will be challenged beyond their limits. Hospitals are the first responders in a case of pandemic influenza since they will admit and treat the first cases, also they will be the first to identify the new virus. It is critical for hospitals to plan and create strategies to more effectively face the large number of patients arriving, and the best use of the available resources.

Once the simulation model has been run and verified, and optimization procedure will be put in place to minimize the number of patients waiting in queue to be treated while maximizing flow of patients. The model is built using ARENA simulation software and OptQuest heuristic optimization to propose various combinations for the number of nurses needed for healthcare delivery. The proposed method significantly improves system efficiency by reducing the number of patients waiting in queue for health treatment and care, and also increases the total number of patients treated.

CHAPTER 1
INTRODUCTION

Pandemic Influenza Overview

Pandemic Influenza outbreak appears when a novel influenza virus emerges, it is able to cause illness in humans, and it can transmit from human to human easily. What makes these novel viruses a potential threat to the worldwide population is that human would have little o no immunity, and it is expected to be very deadly (CDC, 2009). To be better understand the intentions of this research, and what “Pandemic Influenza also known as “Pandemic Flu” implies, it is important to define the terms that will be used throughout this paper:

- *Seasonal Influenza* is a respiratory illness caused by both human influenza A and B viruses that can be transmitted person to person. Most people have some immunity and a vaccine is available.
- *Pandemic Influenza (or pandemic flu)* is virulent human influenza A virus that causes a global outbreak, or pandemic, of serious illness in humans. Because there is little natural immunity, the disease spreads easily and sustainably from person to person.
- *H1N1 Influenza* is a respiratory disease of pigs caused by type A influenza viruses that causes regular outbreaks in pigs. People do not normally get swine flu, but human infections can and do happen.

- *Avian (or bird) Influenza* is caused by influenza A viruses that occur naturally among wild birds. Low pathogenic avian influenza is common in birds and causes few problems. Highly pathogenic avian influenza A (H5N1), or HPAI H5N1, is deadly to domestic fowl and can be transmitted from birds to humans.

There is no human immunity and at this point in time only one Food and Drug Administration (FDA) approved human vaccine has been approved. The FDA has approved this vaccine for individuals who may be at increased risk of exposure to the HPAI H5N1 virus, but it is not commercially available. This vaccine has been included within the Strategic National Stockpile (SNS).

According to the National Strategy and Emergency Management Systems (EMS) Pandemic Management Systems Pandemic Influenza guidelines created in 2007, animals are the most likely reservoir for an emerging influenza virus. Avian influenza viruses played a role in the development of the human influenza viruses associated with the last three influenza pandemics. Two of these viruses remain in circulation among humans today and are responsible for the majority of seasonal influenza cases each year. There will be very little discussion of specifics regarding avian influenza epidemiology in this research as it is impossible to predict what kind of virus will in fact be the cause of a future pandemic.

Currently, there is concern with the current circulating H5N1 virus due to its high mortality among reported human cases and its broad geographic distribution. Most cases of H5N1 virus infection in humans have resulted from direct or close contact with infected poultry (e.g., domesticated chicken, ducks, and turkeys) or surfaces possibly contaminated from feces and/or respiratory secretions from infected birds. While there have been a few cases of probable person-to-person spread of H5N1, it has been limited, and inefficient as of this point in time.

Planners should be able to distinguish among the following:

- *Endemic Levels* is the constant presence of a disease or infectious agent in a certain geographic area or population group.
- *Epidemic* is the rapid spread of a disease in a specific area or among a certain population group.
- *Pandemic* is a worldwide epidemic - an epidemic occurring over a wide geographic area and affecting a large number of people.

For example, the Severe Acute Respiratory Syndrome (SARS) epidemic from 2002-2003 never progressed to a pandemic even though SARS moved to Canada from its origins in Asia. Although SARS covered a wide geographic area, the number of people affected by the disease was limited (EMS, and US Department of Transportation, 2007).

Pandemic Influenza Impact

The global impact of pandemic influenza could be severe in terms of lives lost and individual and community suffering, as well as severe negative impact upon social and economic systems. The following are potential impacts of pandemic influenza:

Rapid Worldwide Spread: When a pandemic influenza virus emerges, its global spread is likely inevitable. Preparedness activities should assume that the entire world population will be affected by the virus. Countries might, through measures such as border closures and travel restrictions, delay arrival of the virus, but would not be able to stop it.

Health Care Systems Overloaded: Most people have little or no immunity to a pandemic virus. Infection and illness rates will be very high.

Medical Supplies Inadequate: The need for vaccine and antiviral medications is likely to outstrip supply early in a pandemic period. In addition, a pandemic may create a shortage of hospital beds, ventilators and other supplies. Surge capacity at non-traditional sites such as schools may be created to cope with demand**.** Shortages may result in the need for difficult decisions regarding who should get antiviral drugs and vaccines.

Economic and Social Disruption: Travel bans, closings of schools and businesses and cancellations of events could have major impact on communities and citizens. Care for sick family members and fear of exposure can result in significant worker absenteeism.

The characteristics for today's society are not the same as it was during the pandemics in the last 100 years. The population has grown, and transportation systems are easier to get access to. This might affect how fast and virus can spread, and how severe it can be.   Society entities responding to this type of disasters are hospitals, transportation systems, and law enforcement agencies.

Public Health plays an important role in any case of kind of disaster that involves human causalities. Disaster have been defined as disruptions, or emergencies, of a severity and magnitude that results in deaths, injuries, illness, and/or property damage that cannot be effectively managed by the application of routine procedures or resources and that result in a call of outside assistance (Landesman, L., et al., 2000). The life cycle of a disaster event is typically known as the disaster continuum, or emergency management cycle. This cycle consists on the Pre-impact, during or Impact, and the after or Post-impact phase. The Basic phases of disaster management include mitigation or prevention, warning and preparedness, and response and recovery. The U.S. Department of Health and Human Services has been working actively on preparedness and response in a case of a Pandemic Influenza outbreak.

Planning is being carried out in different levels of society; that is, preparation in the Federal, State and Local, Workplace, Health care and Individual level. On the federal level The National Strategy for Pandemic Influenza, issued by President of the United States on November 1st 2005 guides our nation's preparedness and response for an influenza pandemic, with the intent of stopping, slowing or otherwise limiting the spread of a pandemic to the United States. By limiting the domestic spread of a pandemic, and mitigating disease, suffering and death, and sustaining infrastructure and mitigating impact to the economy and the functioning of society (Homeland Security Council, 2005).

State and Local Planning is very important also since a pandemic occurs in many localities. According to the U.S Department of Health and Human Services, much of the planning for a pandemic must be the responsibility of state and local governments. Community strategies that delay or reduce the impact of a pandemic (also called non-pharmaceutical interventions) may help reduce the spread of disease until a vaccine is available (CDC 2006). The Florida Department of Health has developed an emergency operation plan for an Influenza pandemic: this document contains detailed information on the risk assessment of the situation, assumptions, operations for notification, activation, and deactivation of the protocols, and finally it contains essential information about preparedness, response, recovery, and mitigation strategies.

Current Situation

June 11th 2009: "The world is now at the start of the 2009 influenza pandemic," WHO press conference. On the basis of available evidence and expert assessments of the evidence, the scientific criteria for an influenza pandemic have been met. The Director-General of WHO has therefore decided to raise the level of influenza pandemic alert from phase 5 to 6. A description for WHO the pandemic phases can be seen in Appendix A: World Health Organization Pandemic Phases

At this time, World Health Organization (WHO) considers the overall severity of the influenza pandemic to be moderate. This assessment is based on scientific evidence available to WHO, as well as input from its Member States on the pandemic's impact on their health systems, and their social and economic functioning.

The moderate assessment reflects that:

- Most people recover from infection without the need for hospitalization or medical care.
- Overall, national levels of severe illness from influenza A(H1N1) appear similar to levels seen during local seasonal influenza periods, although high levels of disease have occurred in some local areas and institutions.
- Overall, hospitals and health care systems in most countries have been able to cope with the numbers of people seeking care, although some facilities and systems have been stressed in some localities.

WHO is concerned about current patterns of serious cases and deaths that are occurring primarily among young persons, including the previously healthy and those with pre-existing medical conditions or pregnancy. Large outbreaks of disease have not yet been reported in many countries, and the full clinical spectrum of disease is not yet known.

Nursing Capacity Planning

Currently, there is being an increasing concern and appreciation of how important nurses are in healthcare systems. In a time where healthcare resources are becoming more overwhelmed, limited, and more expensive, concentrating efforts on increasing productivity and capacity planning is crucial. Therefore, one of the important operational issues in healthcare involves capacity planning such that the goals of high resource utilization and providing high quality service are met (Cote and Bretthauer, 1998). According to [Adenso et al., 2002], to design a model that permits the determination of the number of nurses required to cover minimum levels of quality, it is necessary to define several prior steps including :

- Patients must be classified (not all patients require the same nursing care), so as to subsequently identify the different tasks that nurses carry out in their work.
- Discover a way of determining the time taken to carry out each nursing task.
- Identify the desired levels of quality in the hospital.
- Establish the relationships between the theoretical staff and quality levels.
- Establish the procedure for calculating staff.

General Problem Description and Approach

- Forecasting a Pandemic Influenza: According to experts, Pandemic Influenza does not follow any periodicity, or epidemiological profile. It is not possible to know what the real impact of a novel influenza virus will have on the infrastructure of a country. But, it is necessary to plan for this event, and this research proposes a series of scenarios that will help decision makers create the capabilities in emergency department to improve care given to patient, and better allocate resources.
- Healthcare systems: During a Pandemic Influenza a substantial percentage of the world's population will require some form of medical care. Nations are unlikely to have the staff, facilities, equipment and

hospital beds needed to cope with large numbers of people who suddenly fall ill. Death rates may be high, depending on four factors: the number of people who become infected, the virulence of the virus, the underlying characteristics and vulnerability of affected populations and the effectiveness of preventive measures.

- Nursing Capacity Planning: Determining nursing staff levels in healthcare provider sites is a complex task because of the characteristics of staff management in any activity in the service sector and the social-economic importance of the work that nurses do. An urgent need exists to match patient needs with the health resources available. In recent years, demand for both medical and nursing staff has grown notably without these resources increasing to match demand (Cote and Bretthauer, 1998).

Figure 1 gives a global approach for the problem that is being analyzed in this thesis. The global objective is to study the nursing capacity planning under a high demand and overwhelming case of a Pandemic Influenza outbreak. To get this point, a forecast of potential demand and simulation model will be proposed. Making use of available academic tools as it can be seen in the figure, different models and scenarios will be tested and find which better fits the needs of this thesis' objectives.

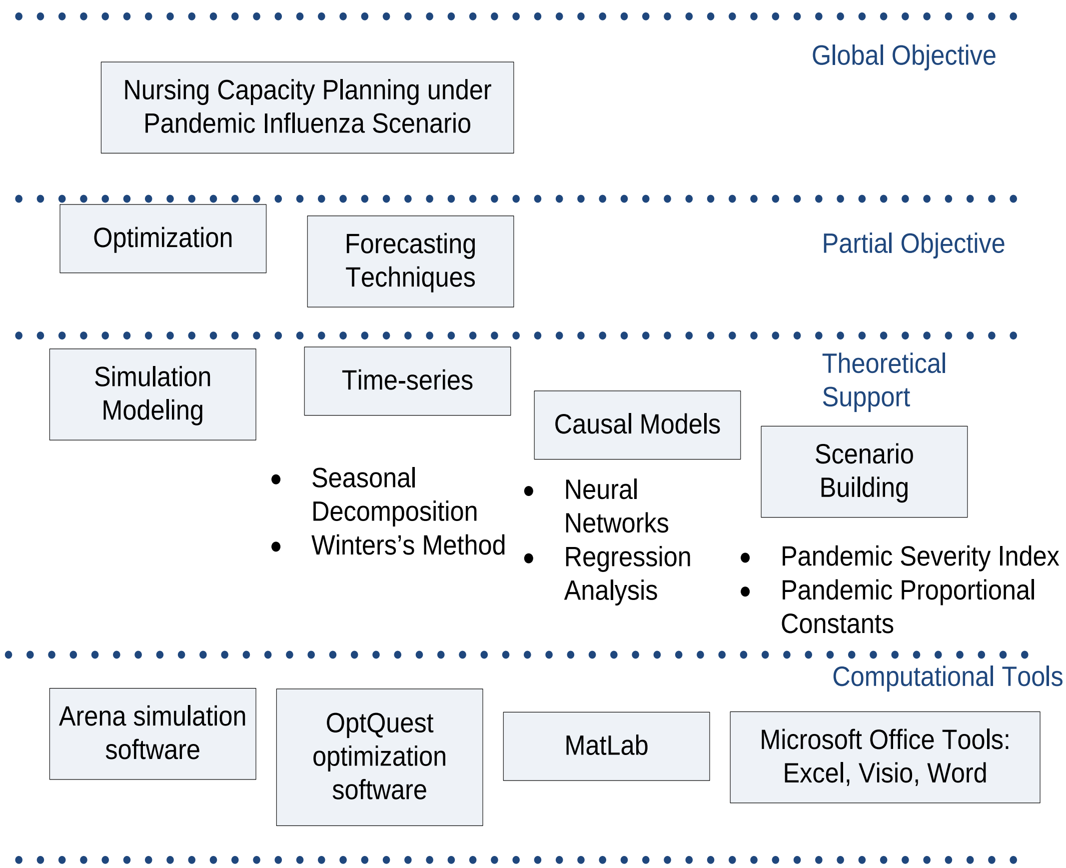


Figure 1: General Problem and Approach

Thesis Organization

This thesis is organized as follows: four more chapters follow after this point. Each chapter is organized in partial independent form, and at same time, they are cohesive, and necessary to reach the final objective (as it can be seen in Figure 3). The format used in the following chapters follows a scholarly journal format: each chapter contains an introduction, literature review, problem statement, research questions, methodology, results, and a discussion.

CHAPTER 2
PROBLEM STATEMENT

Introduction and Motivation

The problem considered in this research is originated due to the need for efficient methods to allocate resources in an emergency department during a large demand of patient following a pandemic influenza breakout. Due to the recent outbreaks of swine flu in 2009, it has become imminent for healthcare agencies managers to plan for this type of disaster. The first goal of this work is to develop a forecasting model that accurately estimates the patient demand for EDs during the breakout period. Results from the forecast will be used as input to a simulation model in charge of replicating the dynamics of healthcare providers under various pandemic influenza scenarios. The results yielded by these models will assist hospital managers in the decision making process to better utilize and allocate medical staff considering the fluctuant demand for the system and for the individual zones of the emergency department.

According to pandemic protocols from CDC and World Health Organization, once an outbreak occurs, hospitals must dedicate an exclusive area for patients with the pandemic virus. This area should be divided into five zones: triage, green, yellow, red and black [Davey et. al. 2006]. The model proposed aims to optimize the system by modifying the resource levels in the various zones of the ED to minimize the waiting time for the patients, and number of patients waiting to be treated while maximizing the flow of patients throughout the system. Special attention is given to those resources such as nurses and respiratory therapists who are essential for the delivery of care, and with the highest expected demand. According to [Toner, 2006], hospital preparedness for these types of events is not clearly defined, and should be revised to define specific, nationally sanctioned preparedness goals, priorities, and metrics

Emergency Departments are an essential element of healthcare systems because they provide immediate care for patients. However, they are also the most overwhelming component. According to the Institute of Medicine, EDs overcrowd represents an obstacle to the safe and timely delivery of health care. [Kellermann, 2008] exposes the worrying situation of EDs in the Unites States. Figure 2 illustrates how the number of emergencies departments have decreased from approximate 5000 to 4600 (about 8%) while the number of total emergency visits have increased from 90 to 110 million (about 18%) from 1994 to 2004.

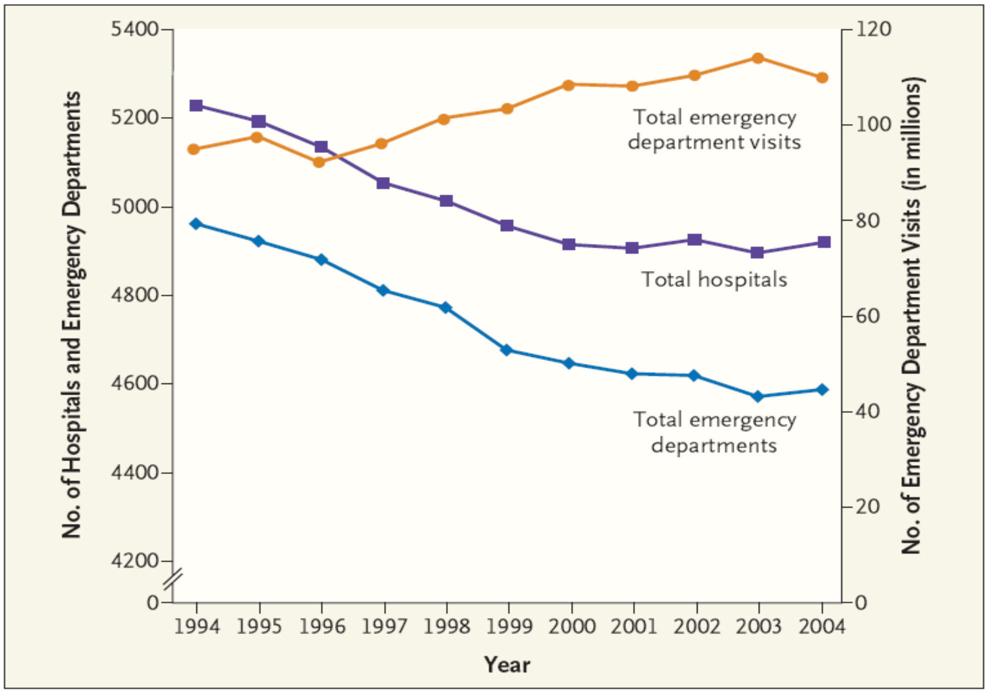


Figure 2: Trends in Emergency Department Visits, Number of Hospitals, and Number of Emergency Departments in the United States, 1994-2004

EDs are already overwhelmed during everyday operations; thus, it is expected that in a case of pandemic influenza, their operations will be challenged beyond their limits. Moreover, it is anticipated that these units will admit and treat the first cases, and also they will be the first to identify the presence of a new virus. For that reason, it is critical for hospitals to plan and create a robust plan to effectively process large number of patients arriving, and efficiently use of the limited available resources.

According to the Health and Human Services (HHS) planning assumptions and using the Center for Disease Control and Prevention (CDC) FluSurge 2.0 software assumptions, the availability of the hospital resources that would be needed for influenza patients alone are: 191% of actual non-ICU beds, 461% of actual ICU beds, and 198% of actual ventilators. Moreover [Toner, 2006] shows that there are shortages of healthcare workers of all kinds; for instance, 100,000 additional registered nurses (8% of current work-force) are needed under "normal" circumstances alone. Also, they reported that about 48% of emergency departments in the US are currently at or over capacity, which it is a problem that obstructs for the promptness and quality of care delivery.

Research Objectives

The specific objectives of this research are as follows:

- To create and validated a forecasting tool for the demand of patients assessing the ED during a pandemic influenza breakout.
- To explore and compare time series methods and causal models using nontraditional forecasting models to patient surge to the ED such as neural networks.
- To develop a simulation model that mimics the dynamics of the ED during the breakout.
- To analyze the system by changing the level of resources in the various zones and allocate resources in a way where waiting time and number of patients in queue are minimized.
- To determine the maximum capacity for an ED system.

Specifically, the following questions will be answered in this thesis:

- Is seasonal influenza data useful to predict pandemic influenza visits behavior?
- Which forecasting technique works better for seasonal influenza hospital demand?

- Does allocation of resources impact the efficiency in an ED? If so, which zones are more critical or need more resources?
- Is forecasting by scenario building a good option to predict the potential impact?
- What is the maximum capacity that a hospital can work?

Methodology

The final goal for this research is to design a nurse allocation policy, determine the maximum capacity, and give recommendations to improve the system studied. At this point, Chapter 1 and 2 have stated the “why, what, and how”: what the motivation to do this study is, what problem is being analyzed, and how is it going to be done. The way this thesis works is that each chapter is designed and studied in an independent way following a journal structure, but each chapter harmonizes with the rest because its output is the input of the next chapter as it is seen in Figure 3.

Chapter 3 makes use of various forecasting techniques both times-series and causal models for the demand of patient visits with influenza-like illness. These forecasting techniques are compared and evaluated using popular performance measures. Chapter 4 makes use of scenario building forecasting for a pandemic influenza using the forecasting model found in the previous chapter, and it proposes a Pandemic Proportional Constant to describe five levels of severity. Chapter five uses the five demand scenarios as input of a simulation model. This simulation model allows analysts to study what-if scenarios, and an optimized allocation of resources is proposed.

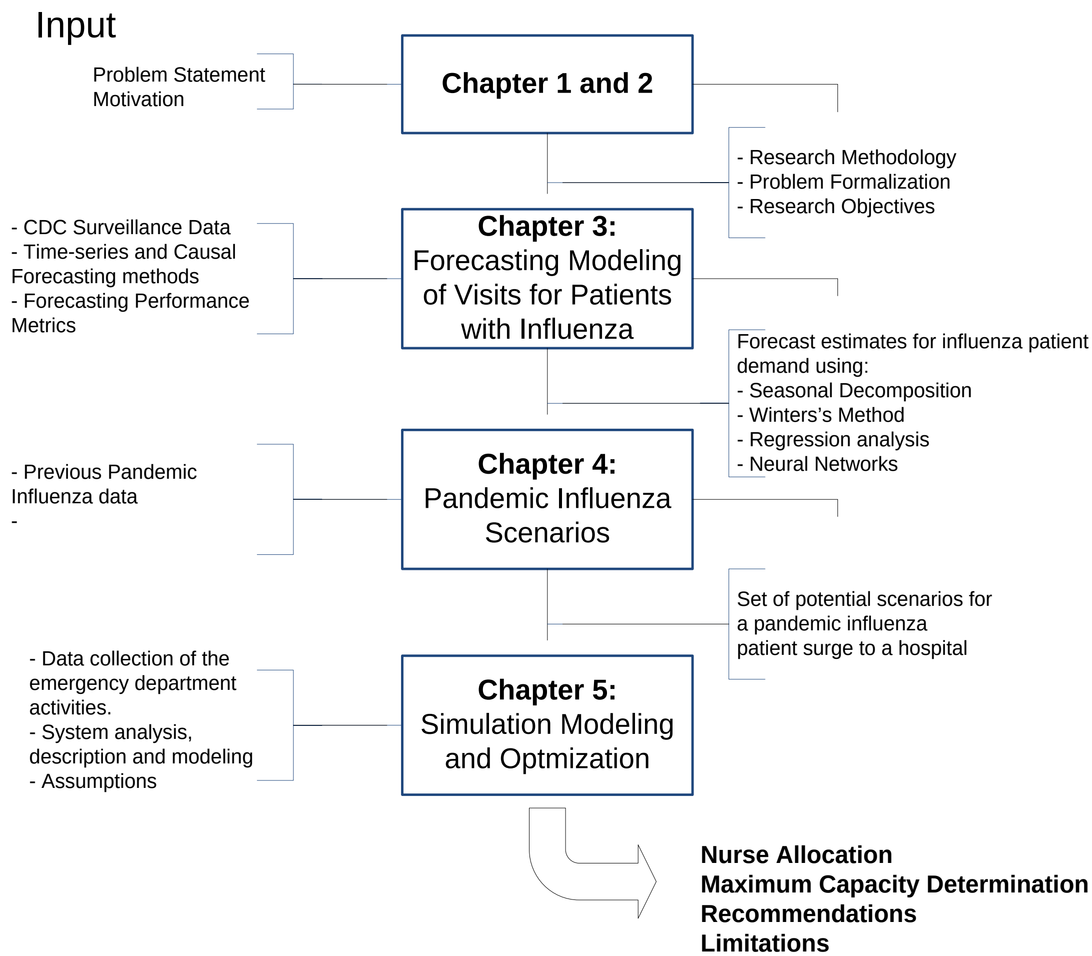


Figure 3: Thesis Methodology

CHAPTER 3
FORECASTING MODELING FOR VISITS TO ED UNITS FROM PATIENTS WITH INFLUENZA

Abstract

The challenge studied in this section is the determination of a forecasting model for the demand of patient that access hospital suffering from influenza. Current surveillance programs provide valuable information to help estimate the burden the disease has on the surge of patients assessing the emergency department. Four methods are implemented in this work with greater emphasis on Neural Networks and Fourier series regression. Results are compared using performance metrics such as MAD, MAPE, RMSE, TS, and ME. Performance results for the forecasting methods were compared using a t-test, and it was found that no method was statistically better than any other. Other criterion beyond accuracy needs to be considered.

Introduction

Forecasting is applied in a vast variety of fields, and its complexity level can range from very simple methods to very complicated algorithms (Nahmias, 2001). Forecasting and prediction is often performed by healthcare decision makers, practitioners, and researchers. Forecasting is often confused with planning. Planners can use forecasting methods to predict the outcomes for alternative plans, predict the number of patients that would access the system, how much medication should be kept in inventory, and so on. Forecasting serves many needs: It can help people and organization to plan better for the future and to make rational decisions. It can help in deliberations about policy variables (Armstrong, 2001). For example, how many resources will be used in the process? What work force do we need? Are there enough vaccines to fulfill the demand?

Forecasts can be either subjective or objective. Subjective forecasts are motivated by human judgment (i.e. Surveys, Delphi method, and expert opinions among others). Objective forecasting are those derived from analysis of data. They can be times series which uses only past values of the situation analyzed or Causal models that assume that there may be other variables related in some way to what is being forecasted. Figure 4 gives a list of some objective forecasting methods used in time Series analysis and Causal methods, as well as subjective methods. In the next sections, the forecasting method used to predict the seasonal influenza patient demand will be explained and expanded, and finally compared on how well they performed.

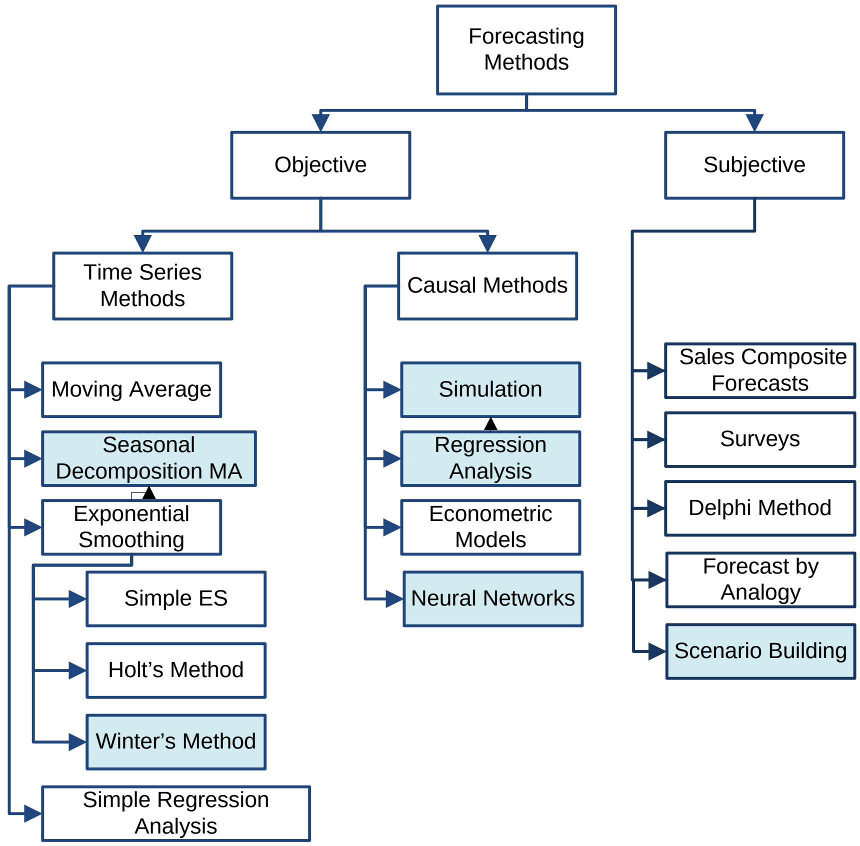


Figure 4: Forecasting Methods

Literature Review on Forecasting

This research will make use of different forecasting techniques to analyze the seasonal time series of the number of patients arriving to a Hospital with influenza-like symptoms. Data of seasonal influenza from national surveillance have been used in models to better understand the burden of the disease and its impact on all-cause deaths in the United States, and these data have contributed towards the development of statistical models to estimate the burden of epidemic diseases.

Influenza Mortality rates have been studied by different authors. [Serfling, 1963], and [Simonsen et al., 1997] used data from 108 US cities, and NCHS

(National Center for Health Statistics) weekly death data to implement linear regression models to estimate pneumonia and influenza related deaths trends. [Izurieta et al., 2000] used NCHS weekly death data to create baseline rate model for the summer and per-season to estimate hospitalizations, death rates, and outpatient visits. [Simonsen et al., 2005] used the data available to create a cyclical regression model to estimate excesses in pneumonia and influenza and all-cause mortality for each influenza season since 1972. Death rates also show a cyclical pattern. It is important to note that the regression models applied to death, can in similar ways apply to patient demand.

The studies mentioned above have used regression analysis to reach their goals, and they have been important to understand the impact of seasonal influenza on deaths, but they have not gone on analyzing on patient demand is impacted every year. Regression models such as Fourier series with the help of modern computer tools are able to capture the seasonality, trend, cycle, and residual error effect (Lim et al., 2000; Proietti, 2000).

Neural Networks is a causal forecasting model that is also able to forecast under the presence of seasonal effects. [Sharda et al., 1992] examined 88 seasonal time series and found that Neural Networks can model seasonality effectively and without seasonal decomposing the data, which can translate in time savings. [Gorr, 1994] found that Neural Networks are able to detect nonlinear trend and seasonality. Besides seasonality, other studies have found that Neural Networks are able to recognize patterns change in the data (Nam et al., 1995; Franses et al., 1997). Neural Networks are increasing in popularity since they provide a very good function approximation to model the trend and seasonality of the data (Zhang, 2005).

Forecasting is a tool used in this research to study emergency deparments. Other healthcare systems applications include: forecast the outcome for cancer treatment (Ohno-Machado L. et al., 1998), simulate physician behavior of Elastic Tissue (Radetzky et. al, 1998), Medical Image Analysis (Lasch et. al, 2000), and decision support in prescription and outcome prediction in drug therapy (Byrne et al., 2000). Others fields include: economy analysis and prediction (Grudnitski et al.,1993; Wong et al., 1995; Hann et al., 1996), ecosystems and meteorology forecasting (Atiya et al., 1999), power systems, manufacturing, optimization, signal processing, and social/psychological sciences (Kalogirou, 2000).

Research Methodology

The research procedure that is carried out through this research is depicted in Figure 5. After reviewing the literature available, it proceeds with problem statement formalization. Then, it is explained where the data used in this work comes from, and gives an overview of the forecasting models, and implementation. Finally, the results are compared and analyzed. This research aims to provide some empirical evidence on the effectiveness of time series forecasting methods and causal model such as Neural Networks on modeling and forecasting seasonal influenza and trend time series.

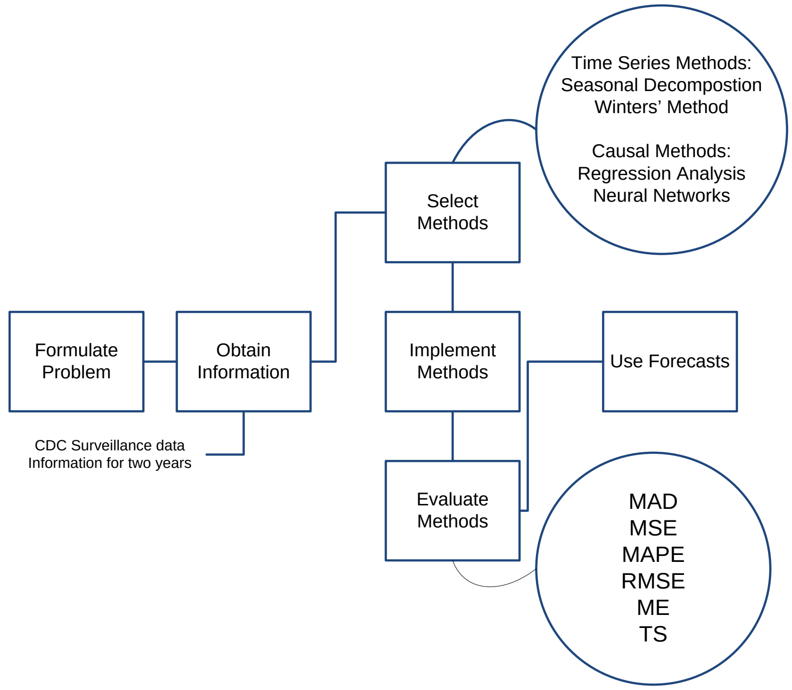


Figure 5: Forecasting Methodology

Problem Formulation

The problem considered in this chapter is the forecasting of the patient demand with influenza-like symptoms to EDs in a hospital. The objective is to find a model that represents the data seasonality and gives the best fit and generalization of its demand behavior.

Determining the burden of seasonal influenza is complicated. Influenza diagnosis is generally not laboratory confirmed and are attributed to pneumonia and other secondary complications (Simonsen et al., 1997). These secondary complications are referred as influenza-like-illnesses, and the data used in this investigation is using this information on patient visits to health care providers for influenza-like illness. Data is collected through the US Outpatient Influenza-like Illness Surveillance Network (ILINet).

Through the analysis provided in this chapter, it will be answered whether seasonal influenza surveillance data can be used to mimic the behavior of a pandemic influenza with a different severity level. Based on weekly historical data, various forecasting methods will be compared for accuracy of representation using a set performance metrics.

Data

The U.S. influenza surveillance system is a collaborative effort between CDC and its many partners in state and local health departments, public health and clinical laboratories, vital statistics offices, healthcare providers, clinics and emergency departments. Information in five categories is collected from nine different data sources that allow CDC to find out when and where influenza activity is occurring; track influenza-related illness, determine what influenza viruses are circulating; detect changes in influenza viruses, and measure the impact influenza is having on deaths in the United States. The outpatient Influenza-Like Illness Surveillance Network (ILINet) consists of about 2,400 healthcare providers in the 50 states reporting approximately 16 million patient visits each year. Each week, approximately 1,300 outpatient care sites around the country report data to CDC on the total number of patients seen and the number of those patients with influenza-like illness (ILI) by age group. This information is available in the Centers for Disease Control and Prevention's website and on Appendix B: Percentage of Visits for Influenza-like Illness Reported by Sentinel Providers, National Summary 2007-08 and Previous 2 Seasons.

Time Series Forecasting Models

The use at time *t* of available observations of the weekly number of emergency department patient visits from a time series to forecast its value at some future time $t + l$ can provide a basis for a variety of applications such as: customer demand, medications inventory control, economic and business planning, and general control of healthcare systems (Box et al., 2008).

We suppose that observations are available at discrete, equally spaced intervals of time (that is, the demand for patients d_t is the current demand in week *t* and the demand $D_{t-1}, D_{t-2}, D_{t-3},\ldots$ in previous weeks might be used to forecast demand for *l* number of periods in the future $l:1,2,3,\ldots,n$ weeks ahead. Let $z_t(l)$ be the forecast made at origin *t* of the demand z_{t+l} at some future time $t + l$. The function $z_t(l)$, which provides the forecasts at origin *t* for all future periods in the future, based on the available information from the current and previous values $D_{t-1}, D_{t-2}, D_{t-3},\ldots$through time *t*, will be called the forecast function at origin *t*. Our objective is to obtain a forecast function such that the average of the sum of the deviations $z_{t+l} – z_{t(l)}$ between the actual and forecasted values is as small as possible for each lead time *l*.

Time series forecasting methods assume that historical data is a good indicator of future demand. Before proceeding to the theory of the models, it is important to define the following terminology:

- Trend: It refers to the tendency for a decrease or increase in the data values over time. (i.e. the budgeted amount of money dedicated to the production of a vaccine for a pandemic influenza has increasing trend, and it can been seen in Figure 6.a)

- Seasonality**:** It is a repeating pattern in the data values over time: day of the week, hour of the day, month of the year, etc. (i.e. Pneumonia and influenza mortality rate shows a seasonal patter as seen in Figure 6.b)
- Cycles: It refers to a cyclic variation similar to seasonality, except that the length and the magnitude of the cycle may vary.
- Randomness: it refers to a series in which there is no recognizable pattern to the data.

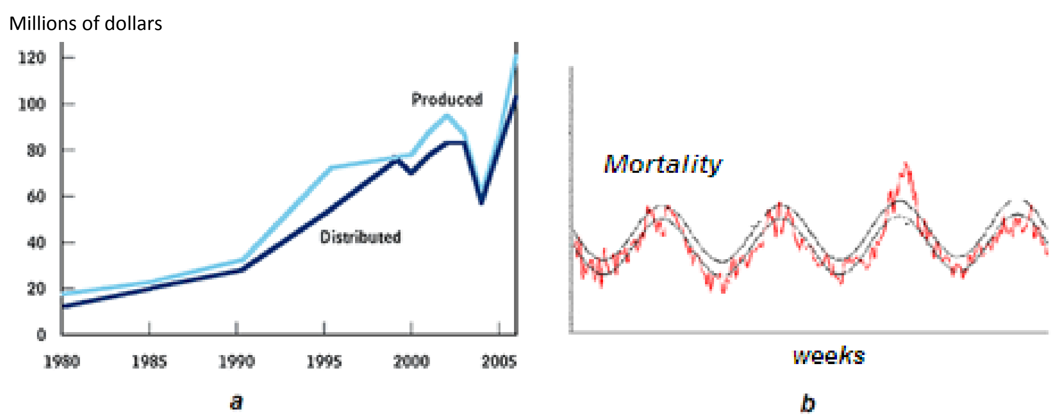


Figure 6: Examples of Trend and Seasonal Patterns in Healthcare

Seasonal Influenza visits showed a seasonal patterns as it can be graphically perceived in Figure 7 with period N = 52 weeks which is equivalent to a year. The time-series methods used in this studied were selected due to the capacity they have to recognize trend and seasonal patterns in the data.

Seasonal Decomposition Using Moving Averages

Moving average is the arithmetic average of the most recent *N* observations in a times series. Then z_t, the forecast made in period t – 1 for period t, is given by:

$$z_t = \left(\frac{1}{N}\right) \sum_{i=t-N}^{t-1} D_i = \left(\frac{1}{N}\right) (D_{t-1} + D_{t-2} + \cdots + D_{t-n})$$

To describe the seasonal pattern in a time series, it is assumed that there exists a set of multipliers c_t, for $1 \le t \le N$, with the property that $\sum c_t = N$. The multiplier c_t represents the average proportion amount that the demand in the t^{th} period of the season is above or below the overall average. *N* is referred to the number of periods before the pattern begins to repeat as the length of the season (as it is shown in Figure 7).

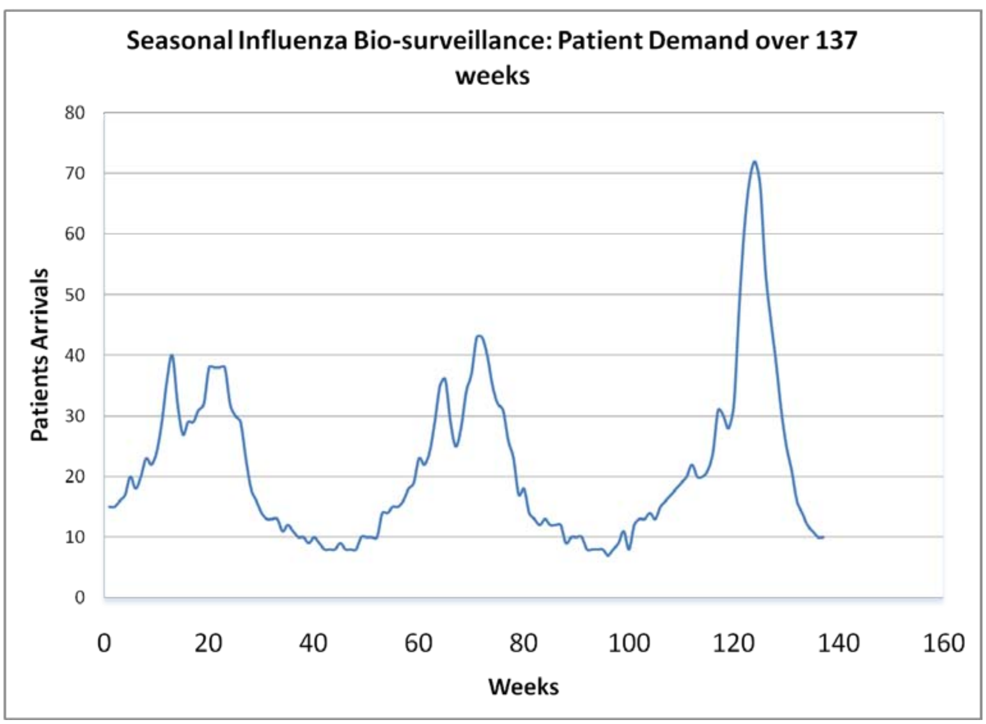


Figure 7: Seasonal Patient Demand Over 137 Weeks

Winters's Method

Winters' seasonal exponential smoothing method assumes that a time series is considered to consist of three components: level, trend and seasonality, and they change over time. In the additive version, a prediction is calculated by adding the components (Archibald, 2003).

Winters's method is a type of triple exponential smoothing, and this has the important advantage of being easy to update as new data become available. The model has the following form:

$$D_t = (\mu + G_t)c_t + \epsilon_t$$

Where μ is the base signal or intercept at time t = 0 excluding seasonality, G is the trend or slope component, c_t is the multiplicative seasonal component in period t, and ϵ as the error term.

This model also assumes that the season is exactly N periods and that the seasonal factors are the same each season and have the property that $\sum c_t = N$. Three exponential smoothing equations are used each period to update estimates of seasonal decomposed series, the seasonal factors, and the trend. These equations may have different smoothing constants, which we will label $\alpha, \beta, and\ \gamma$.

α = Smoothing constant for the level ($0 < \alpha < 1$)

β = Smoothing constant for the trend ($0 < \beta < 1$)

γ = Smoothing constant for the seasonal factor ($0 < \gamma < 1$)

- *The Series:*

$$S_t = \left(\frac{D_t}{c_{t-N}}\right) + (1-\alpha)(S_{t-1} + G_{t-1})$$

- *The Trend:*

$$G_t = \beta[S_t - S_{t-1}] + (1-\beta)G_{t-1}$$

- *The Seasonal Factors:*

$$c_t = \gamma\left(\frac{D_t}{S_t}\right) + (1-\gamma)c_{t-N}$$

Finally, the forecast made in period t for any future period t + τ is given by:

$$F_{t,t+\tau} = (S_t + \tau G_t)c_{t+\tau-N}$$

Causal Models

Causal models assume that forecasted data generating process can be explained by interaction of causal (cause-and-effect) independent variables in the environment. Determining how these variables are related to the output of a model or system can be a challenging problem, but the understanding of how variables are correlated can be very helpful. The causal models that are used for the seasonal patient demand in this research are Regression Analysis and Neural Networks.

Regression Analysis

A popular class of single-equation models to apply multivariate time-series data is the multiple regression models. This class of model is probably the most widely used in practice and feature prominently in many texts on forecasting for management science and business students (Chatfield, 2001). Let (x_1,y_1), (x_2,y_2),… (x_n,y_n) be n pair data points for the two variables X(weeks) and

Y(demand). Assume that y_i is the observed value of Y when x_i is the observed value of X. Refer to Y as the dependent variable and X as the independent variable. Data is a seasonal time series, which suggests that the relationship exists between X and Y that can be represented by a Fourier series. The Fourier series is a sum of sine and cosine functions that is used to describe a periodic signal. In this case, the Fourier series is used to find a function that is able to fit and describe the trend (if any) and seasonality pattern, and it is of the form:

$$y(x) = a_0 + \sum_{i=1}^{\infty} \left(a_i \cos\left(2\pi \frac{x}{c_i}\right) + b_i \sin\left(2\pi \frac{x}{c_i}\right) \right)$$

Where a_0 and b_0 represent the amplitudes, and c_i represents the periods. In order to find the Fourier series that fits the data well, it is necessary to determine how many cycles exist. MatLab 7.6.0 R2008a and the General Equations pane of the Create Custom Equation GUI (Graphic User Interface) was used to find the parameters that best described the seasonality of the data. For the first attempt, a c_1= 52±2 week cycle is assumed and fit the data using one sin term and one cosine term.

$$y_1(x) = a_0 + \left(a_1 \cos\left(2\pi \frac{x}{52}\right) + b_2 \sin\left(2\pi \frac{x}{52}\right) \right)$$

The "goodness" of the fit is evaluated using R-square, and residuals plot analysis. R-square statistical measure of how well a regression function approximates real data points. If the fit does not describe the data well, additional sine and cosine terms are added with unique period coefficients until a good fit is obtained.

$$y_2(x) = y_1(x) + \left(a_2 \cos\left(2\pi \frac{x}{c_2}\right) + b_2 \sin\left(2\pi \frac{x}{c_2}\right) \right)$$

The fit is an improvement over the previous fit, and appears to account for most of the cycles present in the seasonal influenza data set. The residuals appear random for most of the data as it appears is in Figure 8.

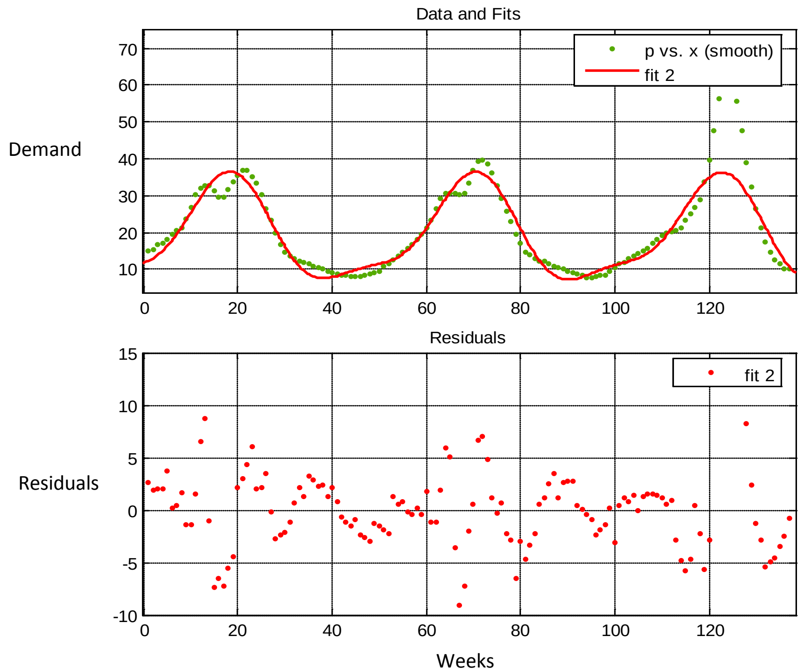


Figure 8: Fourier series Fitting and Residuals Plot

Neural Networks Overview

A Neural Network is a non-linear model whose structure is thought to mimic the design of the human brain. Neural Networks have been applied successfully to a wide variety of scientific problems, and increasingly to statistical applications, notably pattern recognition (Chatfield, 2001).

A Neural Network is a parallel, distributed information processing structure consisting of processing elements (which can possess a local memory and can carry out localized information processing operations) interconnected together with unidirectional signal channels called connections. Each processing element has a single output connection which branches into as many collateral connections as desired (each carrying the same signal: the processing element output signal). The processing element output signal can be of any mathematical type desired. All of the processing that goes on within each processing element must be completely local: i.e., it must depend only upon the current values of the input signals arriving at the processing element via impinging connections and upon values stored in the processing element's local memory (Hecht-Nielsen, 1989).

Neural Networks consist of an input layer, an output layer and one or more hidden layer as seen in Figure 9. The nodes or neurons of the network are arranged in consecutive layers (hidden layers) and the arcs are directed from one layer to the next from left to right.

This type of Neural Networks is called feed-forward networks or perceptrons. Basically, Neural Networks are built from simple units (neurons). These neurons are interlinked by a set of weighted connections (w). Each node or neuron is a processing unit that contains a weight and a summation function. A weight returns a mathematical value for the relative strength of connections to transfer data from one layer to the next. On the other hand, a summation function y computes the weighted sum of all input elements entering a neuron. In Figure 9, each neuron in the hidden layer computes the summation y_j using the following formula:

$$y_j = \sum_{i=1}^{2} x_i w_{ij} \quad j = 1,2,3$$

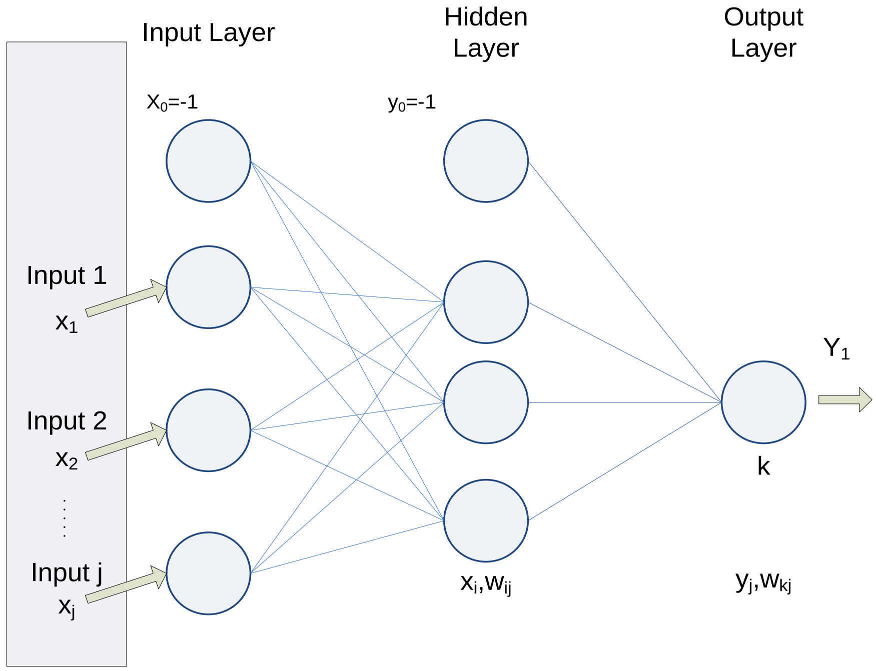


Figure 9: Neural Network Model

Furthermore, a sigmoid function y_T is used to transform the output so that it falls into an acceptable range (between 0 and 1). The objective is to prevent the output from being too large. The sigmoid function is of the following form:

$$y_T = \frac{1}{1 + e^{-y}}$$

As previously described, Neural Networks consist of neurons or nodes organized in different layers: input, hidden, and output. The input layer corresponds to the factors that would be "feed" into the Network. The information is propagated through the weighted connections to the hidden layers where it is analyzed. Then, the result of this processing is propagated to the next layer and eventually, to the output layer. The output is obtained by the following function:

$$\mathrm{Y} = \sum_{\mathrm{j}=1}^{3} \mathrm{y_j w_{kj}}$$

Once the network weights and biases are initialized, the network is ready for training. The network can be trained for function approximation (nonlinear regression), pattern association, or pattern classification. The training process requires a set of examples of proper network behavior: network inputs p and target outputs t. The back-propagation algorithm objective is to minimize the mean square error function:

$$E = \sum_i \left[y_i - F_{approx}(X_{i)}\right]^2$$

This error functions tells us how good an approximation to the real function F is. The idea of the back-propagation algorithm is to minimize this error (threshold) by adding for each training period, small changes in the directions that minimize the error function. This minimization method is called the steepest descent method. The general learning process is described in the following steps:

- Random numbers are assigned to the weights
- For all data points in the data set, calculate the output using the summation functions of each neuron.
- Compare estimated output with actual values
- If the results from 3 do not meet a threshold value, repeat steps 2 and 3.

A common problem that may occur when fitting the Neural Network to training data is over-fitting. Over-fitting occurs when the error of the training set is minimized to a very small value. As a result, when new data is introduced into the network the error becomes very large. In this situation the network has "memorized" the data set, and it is not able to "generalize" when new data is introduced into the network. Generalization refers to the ability of the model to perform well on data that has not been used to train the network.

There are two strategies that can be used to avoid over-fitting: regularization and early stopping. Regularization involves modifying the performance function. Early stopping involves dividing the data set into two subsets. The first subset is the training set and the second subset is the validation set. At the beginning of the training process the error for the validation and testing sets tends to decrease; however, when the network starts to over-fit the data both errors will increase. When the error for the validation set continues to increase for a specific number of iterations, then training is stopped.

This research applies Neural Network as a tool to forecast patient demand to EDs unit when suffering of seasonal influenza. The traditional back-propagation algorithm is used as the learning method for our network and early stopping criteria is used to avoid over-fitting.

Results

- *Seasonal Decomposition using Moving Averages:* by comparing different estimates for N, the one with the smallest average error (Forecasted estimate in time t minus actual demand in time t) was chosen. This method was implemented using N = 10. The forecasted estimates for the 137 weeks versus the actual demand are shown in Figure 10.

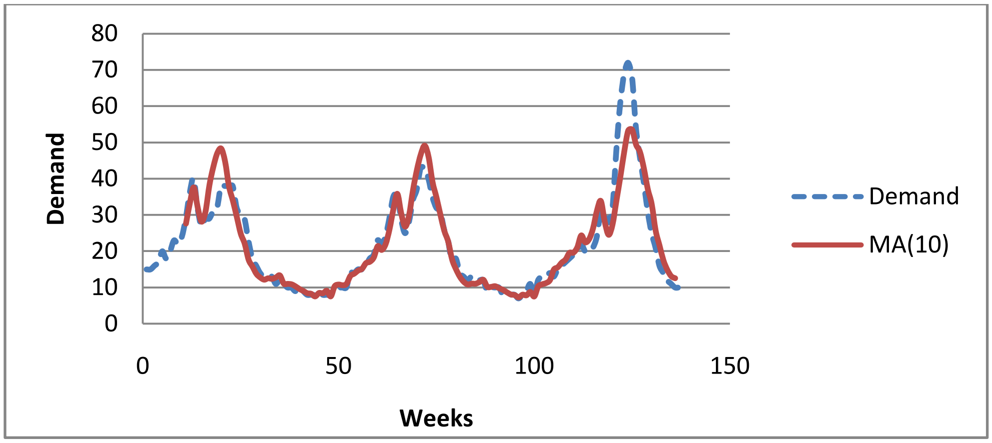


Figure 10: Moving Average Results

- *Winters's method:* after experimenting with various values of the parameters that would give the best fit of previous forecasts to the observed history of the series. The estimates $\alpha = 0.2, \beta = 0.1, and\ \gamma = 0.1$ were found to implement winters' method. According to [Nahmias, 2001], large values of the smoothing constant will result in more responsive but less stable forecasts The forecasted demand for the time series and real demand can be visualized for 137 weeks in Figure 11.

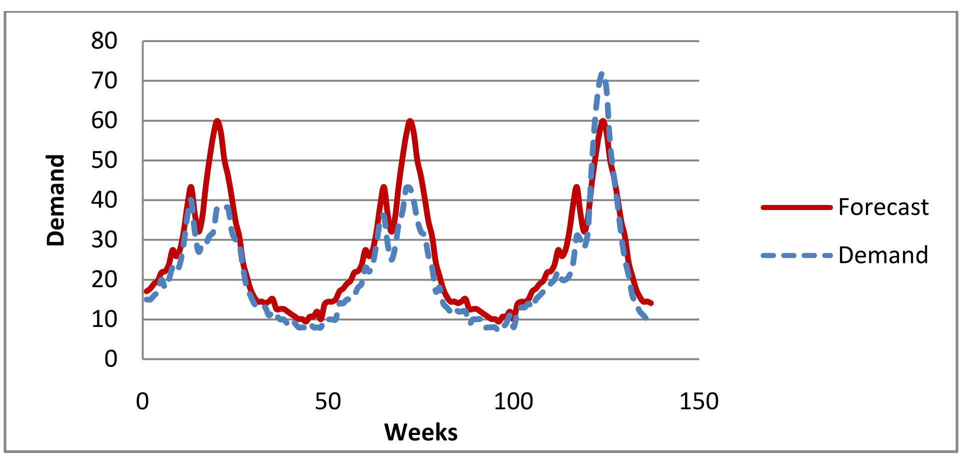


Figure 11: Winter's Method Results

- *Regression Analysis using Fourier series:* the function chosen to describe the time series for seasonal influenza visits to a hospital is a Fourier series since the data clearly behave in a periodic form. Using MatLab curve fitting tool (cvtool) the function of the form shown bellow is found:

$$f(x) = a_0 + \left(a_1 \cos\left(2\pi \frac{x}{52}\right) + b_1 \sin\left(2\pi \frac{x}{52}\right)\right) + \left(a_2 \cos\left(2\pi \frac{x}{c_2}\right) + b_2 \sin\left(2\pi \frac{x}{c_2}\right)\right)$$

With:

SSE: 1716, *R-square*: 0.8775, *adjusted R-square*: 0.8717, and *RMSE*: 3.705

And parameters:

Table 1: Fourier coefficients

Coefficients (with 95% confidence bounds):		
a_0 =	19.15	(18.5, 19.8)
a_1 =	-6.734	(-8.336, -5.132)
a_2 =	-0.5396	(-2.385, 1.305)
b_1 =	11.72	(10.54, 12.9)
b_2 =	-4.011	(-4.973, -3.048)
c_1 =	52	(51.29, 52.72)
c_2 =	26.19	(25.54, 26.84)

The function suggests that two cycles exist in the data, one (**c_1**) equal to 52 weeks which is yearly and another (**c_2**) of 26 weeks or bi-annually. The fitted function versus the historical data can be seen in Figure 12.

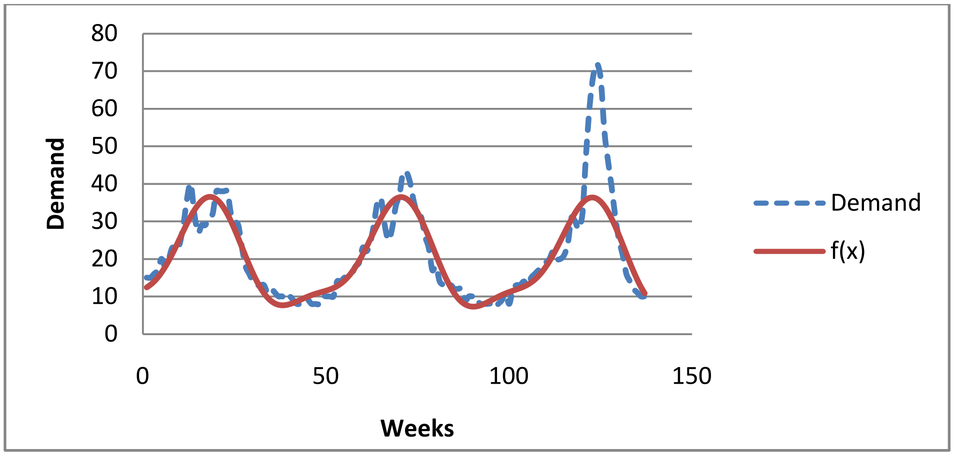
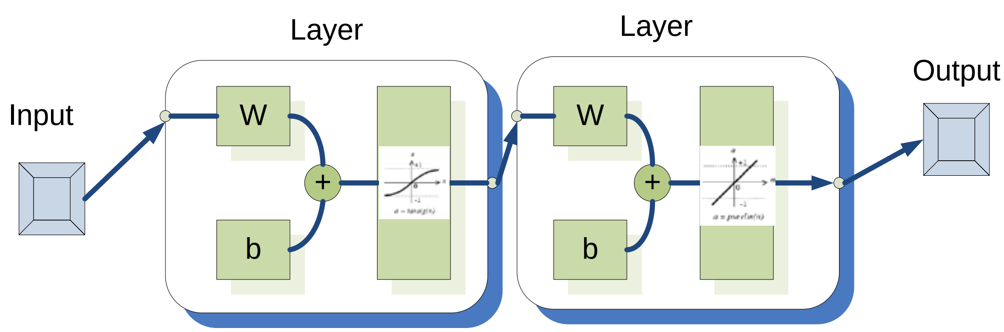


Figure 12: Regression Analysis Using Fourier Series

- *Neural Networks:* The architecture for the Neural Network used to predict the behavior of the time series is of the form:



MatLab 7.6.0 was used for the calculation of this Neural Network, the code used for this can be found in Appendix C: Neural Networks code. The data obtained were studied using the layered Neural Network with a back-propagation least mean square error learning algorithm. To predict patient demand, a Neural Network with 3 input nodes (year, month, and week), a single output node (number of patient that would asses a hospital suffering from influenza-like symptoms), and a one-layer back-propagation network has been used. There is no standard formula to calculate the number of nodes needed in the hidden layer (Wang, 1996). Basically, the number of hidden layers may be tested by trial and

error. Figure 13 show the Neural Network forecasted values and historical data during 137 weeks.

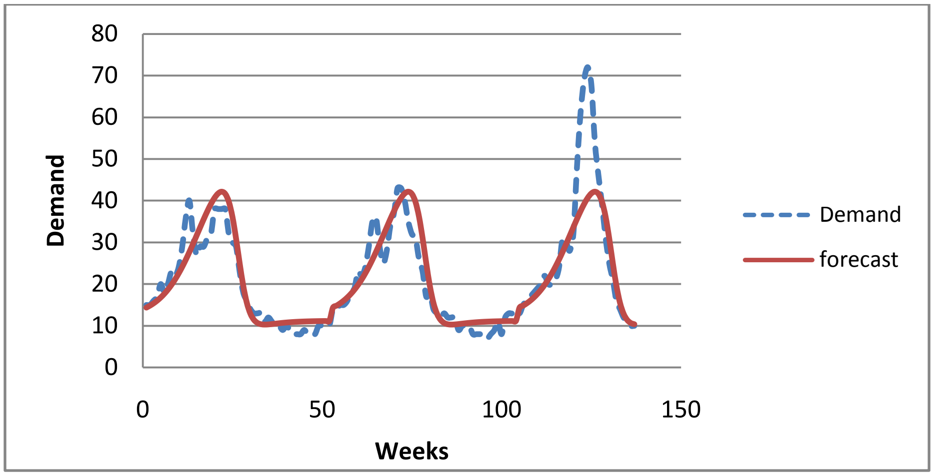


Figure 13: Neural Network Forecasting Results

Performance Metrics

The forecasting methods used in this research are evaluated by the calculation of different performance measures. That is, Mean Absolute Percentage Error (MAPE), Absolute Deviation (MAD), Mean Square Error (MSE), Root Mean Square Error (RMSE), Tracking Signal (TS), and the Mean Error. In the following sections, each one of these performance measures is described.

Mean Absolute Deviation (MAD): The mean absolute deviation (MAD) is the average of the absolute deviation over all periods. MAD measures the average distance of the sample errors from the error mean. If the value of MAD is large, it is reasonably to say that the errors in the data set are spread out (variable). In contrast to MSE, the MAD is very good at detecting overall performance of the model. It does not concentrate largely on the error of individual observations. The MAD is given by

$$MAD = \frac{1}{n}\sum_{t=1}^{n}|e_t|$$

MAD is appropriate to use when the numerical difference between the forecast value and the actual value is important.

Mean Square Error (MSE): The Mean Square Error (MSE) can be related to the variance of the forecast error. This is extremely useful since it can be used to measure the variability or dispersion of the error. The forecast error for a particular period *t* is given by:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}e_t^2$$

MSE penalizes large errors for a single observation, and it is very good at detecting if a few observations have large errors. The smaller the value of the MSE the closer the fit is to the data.

Mean Absolute Percentage Error (MAPE): The mean absolute percentage error (MAPE) is the average absolute error as a percentage of demand and is given by:

$$MAPE = \left(\frac{1}{n}\sum_{t=1}^{n}\frac{e_t}{D_t}\right) * 100$$

In practice a MAPE between 10% and 15% is excellent while a MAPE between 20% and 30% is average.

Root Mean Square Error (RMSE): The RMSE is the distance on average of a data point from the fitted line, measured along a vertical line. The RMSE is given by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2}$$

This statistic is easier to interpret since it has the same units as the values plotted in the vertical axis.

Mean Error: The mean error is an estimate of the forecast bias. The mean bias should converge to zero as *N* increases if the forecasting is not biased one way or the other. The mean squared error is defined as follows:

$$\bar{E}_N = \frac{1}{N}\sum_{t=0}^{N} e_t$$

Tracking Signal (TS): The tracking signal (TS) is used to monitor forecast bias. If the TS exceeds a predetermined bound, this indicates an alert that the forecast is being bias one way or the other. In general, the bound of the TS is between ±6 units from the mean. If the TS is below -6 then the model is under-forecasting. On the other hand, if the TS is above +6 then the model is over-forecasting. This would indicate an alert for analysts who may have to decide on using another model. The TS is defined as follows

$$TS_N = \frac{\sum_{t=0}^{N} e_t}{MAD_N}$$

Comparison of Techniques

The forecasting techniques used in this research: seasonal decomposition using moving averages (N=10), Winters's method ($\alpha = 0.2, \beta = 0.1, \gamma = 0.1$), regression analysis using a Fourier series, and Neural Network analysis (3 input nodes, one single output node: number of patient that would asses a hospital suffering from influenza-like symptoms). The performance metrics described in the last section are applied to the forecasting methods and the results are shown in Table 2:

Table 2: Comparison of Forecasting Techniques (note: all values are in generic units).

	MA(10)	Winters	Fourier	Neural Net
Mean Absolute Deviation (MAD)	2.88	5.18	3.66	3.56
Mean Square Error (MSE)	23.93	47.70	44.95	37.77
Mean Absolute Percentage Error (MAPE)	11.26%	24.70%	15.51%	15.43%
Root Mean Square Error (RMSE)	4.89	6.91	6.70	6.15
Mean Error	-0.03	-4.39	1.07	0.17
Tracking Signal (TS)	-0.10	-0.99	0.05	-0.14

Based on the results and its graphic representations Seasonal Decomposition using Moving Average and Neural Networks yielded the smallest error when compared to the influenza demand data for the seasons 2004-2005, 2005-2006, and 2007-2008. The reason why the fist method works relatively better than the others can be attributed to the small N = 10, which makes the model more sensitive to changes in levels but also more sensitive to noise that can be undesirable for future forecasts. Neural Networks and Fourier series also yielded similar errors estimates (being Neural Networks smaller), and both models give a smoother fitting and generalization of the data.

RMSE indicates on average what the distance of the forecasted value with respect to the actual values is. The RMSE is an excellent performance measure for the forecast since it provides information easy to interpret that can be used for managers that can take this error into account for planning purposes (Rojas, 2006). For the methods used in this work, it was shown that the RMSE vales vary from 4.89 and 6.91.

The mean error is an estimate of the forecast bias. If the forecasting model is not biased, the mean bias should converge to zero as *N* increases. Based on the results, Winters's method showed a tendency to under-forecast while Neural Networks method and Moving Average are close to zero, which leads to believe that they are unbiased.   Another metric to evaluate whether a method is under or over-forecasting is the TS. If the TS at any period is outside the range ± 6, this indicates a signal that the forecast is over-forecasting or under-forecasting. Figure 14 shows that none of the methods falls outside allowable limits in any period, but it can be seen a slight under-forecasting under the demand picks for Neural Networks and Regression analysis forecasts.

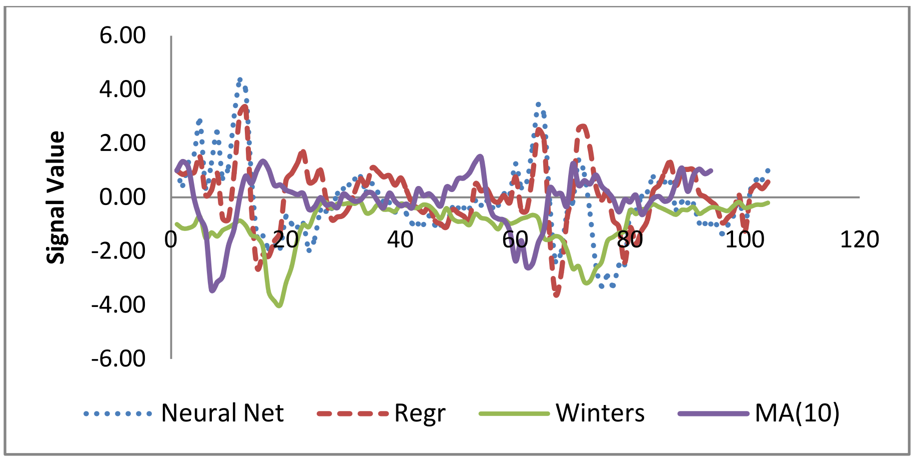


Figure 14: Tracking Signal for Forecasted Results

The forecasts were finally compared with the most current data available for ILI patients for the 2008-2209 seasons, the forecasts (red) and the current demand (blue) are shown in Figure 15. Seasonal Decomposition still demonstrated to be the most accurate representation. The forecasting methods estimates for the MAD are:

Winters	Fourier	MA(10)	NN
5.83	7.59	5.46	5.75

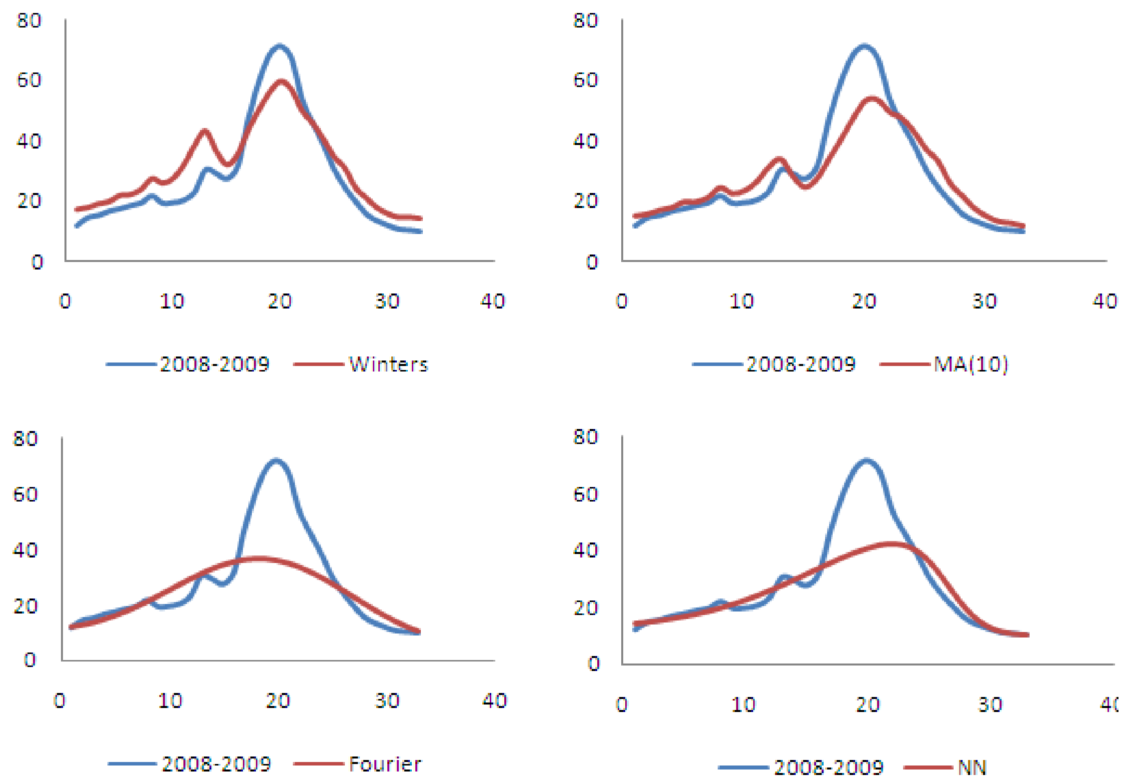


Figure 15: Current Season 2008-2009 ILI Visits versus Forecasts. (Vertical axes represent demand and horizontal axes represent weeks)

It was found that no method performed better than any other. Seasonal Decomposition using Moving Average appeared to be the most accurate representation based on the data. However, a paired t-test was conducted on the Mean Absolute Deviation (MAD) to determine if the performance difference between the utilized models was statistically considerable (Appendix E: Statistical Test of MAD). The test statistics revealed that the difference in performance between the Seasonal Decomposition model and the other models is not statically significant (large *p*-value) for this case.

Discussion

The time series methods were more sensitive to the data and demand changes (i.e. according to the CDC, during the weeks between Christmas holidays and New Years, the demand of patients going to a hospital decreases), but they fell short in providing a generalized behavior of the data which in some cases is more desirable. [Yokum, 1995] studied the criteria used to select a forecasting technique, and it was determined that other than accuracy, other factors including: ease of implementation, use and interpretation, theoretical relevance, and flexibility should be considered. This selection criterion is expanded in the next chapter.

Neural Networks does not require developing algorithms specific to problems and they can easily handle nonlinear functions. An advantage over other traditional methods: to analyze a non-linear relationship using linear regression analysis, it is necessary to first analyze the nonlinearity of the system and determine whether some input need to be squared or two input variables need to be combined. This analysis is overcome by the neural networks capabilities.

Another aspect that this comparison yielded is that there is no significant statistical difference on performance between regression analysis with Fourier series and Neural Networks, and there is no statistical evidence to suspect that one method performed better than the other as it is demonstrated with a paired t-test where the two methods were compared (Appendix E: Statistical Test of MAD).

CHAPTER 4
PANDEMIC INFLUENZA SCENARIOS

Abstract

Predicting the impact of a Pandemic Influenza is very complex due to the many unknown variables that may play a role to how severe a pandemic can be. Scenario planning is considered a type of forecasting that consider a set a different potential outcomes and help decision makers better understand the role of uncertainties and become prepared to make important decisions. This research considers five scenarios for the demand of patients to a hospital based on the severity levels, and proposes a Pandemic Proportion Constant (K_{PPC}) that helps determine how severe a Pandemic Influenza can be as a function of seasonal influenza forecasted demand.

Introduction

The Centers for Disease Control and Prevention has developed a surveillance system that collects and reports data concerning influenza activity with special focus on the months of October through May which represent the season where influenza-related cases are more frequent (Thompson, 2006). In the last years, this information has become more comprehensive and complex, and together with data on national hospitalization mortality rates, statistical models have been created to estimate the burden of the disease associated with influenza in the United States.

The previous chapter studied the most recent data for the influenza seasons (2004-2005, 2005-2006, 2006-2007, and 2008-2009), and made use of different forecasting methods both time-series and causal models. It was found that Seasonal Decomposition using Moving Averages yielded the best results or smallest estimates for every performance metric used (MAD, MAPE, MSE, RMSE,ME, and TS), and it was also very accurate when it was compared to the most recent data available (2008-2009) for influenza visits. Neural Networks and Regression Analysis came after Seasonal Decomposition (very close to each other) with still small forecasting errors and good description of the data.

One very important application of the implementation of surveillance is the estimation of the possible impact of future pandemic. According to the Centers for Disease Control and Prevention, examining demographic trends among the United States population and patters in influenza-associated mortality provides useful information concerning the future effects of seasonal and pandemic influenza. In this research, we use seasonal influenza data estimates to estimate the potential burden of a pandemic influenza to the flow and operations of EDs. Five different scenarios are evaluated depending on five different severity levels; thus, it ranges from the mildest severity levels that refers to the seasonal or inter-pandemic influenza behavior, to the most severe which it compares to the 1918 Spanish influenza that left an estimated of 548,000 deaths in the US. These scenarios and the demand model for the pandemic scenarios will be expanded in the subsequent sections of this chapter.

Motivation

There exists a widespread concern among policy makers and public health experts about the worldwide epidemic of influenza. Novel influenza A (H1N1) is a new flu virus of swine origin that was first detected in April, 2009. The virus, also referred as ‘swine flu’, is a type of influenza virus that causes respiratory disease. The virus is currently infecting people and is spreading from person-to-person, sparking a growing outbreak of illness in the United States. An increasing number of H1N1 cases are being reported internationally as well (CDC, 2009). The spread of the disease is thought to be in the same way that regular seasonal influenza viruses spread (coughs and sneezes). According to experts, it is uncertain at this time how severe this novel H1N1 outbreak will be in terms of illness and death compared with other influenza viruses. Because this is a new virus, most people will not have immunity to it, and illness may be more severe and widespread as a result. In addition, currently there is no vaccine to protect against this novel H1N1 virus. CDC anticipates that there will be more cases, more hospitalizations and more deaths associated with this new virus in the coming days and weeks.

The challenge of creating the public health infrastructure in the US that would be adequate to face a situation of this nature is of imminent need. The US Government has committed $3.8 billion toward planning and preparing for the next Pandemic Influenza, and Australia has also put AUD$555 million toward this initiative (Murray et al., 2006). These considerable efforts are in part due to the potential mortality and overall chaos. Mortality estimates that start from 2 to 360 million and even up to 1 billion have been proposed (WHO, 2005).

Background

Three mayor Pandemic Influenza outbreaks have emerged during the 20th Century: The 1918 “Spanish Influenza”, the 1957 “Asian Influenza”, and the 1968 “Hong Kong Influenza”. [Belshe, 2005] stated that pandemic influenza virus may originate through at least two mechanisms: the re-assortment between an animal influenza virus and a human influenza virus that yields a new virus, and direct spread and adaptation of a virus from an animal to a human. In 1918, an H1N1 virus closely related to avian viruses adapted to replicate efficiently in humans. In 1957 and in 1968, re-assortment events led to new viruses that resulted in pandemic influenza. The 1957 influenza virus acquired three genetic segments from an avian species, and the 1968 influenza virus (Hong Kong influenza, an H3N2 virus) acquired two genetic segments from an avian species. Future pandemic strains could arise through either mechanism (Belshe, 2005). In Appendix D: Mechanisms of Pandemic Virus Origination , analysis of virus origination is further explained.

The 1918-20 “Spanish Flu” Pandemic is considered the most mortal Pandemic Flu in History. Experts have estimated casualties of about 20 to 100 million deaths worldwide. These estimates are based on various historical documents, including national commission, eye-witness accounts, and local government reports (Murray et al., 2006). [Taubenberger, 2006] explains that the Spanish influenza caused approximately 50 million deaths worldwide out of almost 500 millions infected persons. The Spanish influenza appeared in three waves, being the second one the most lethal. In Figure 16 the three waves and the death rates for the United Kingdom case are shown.

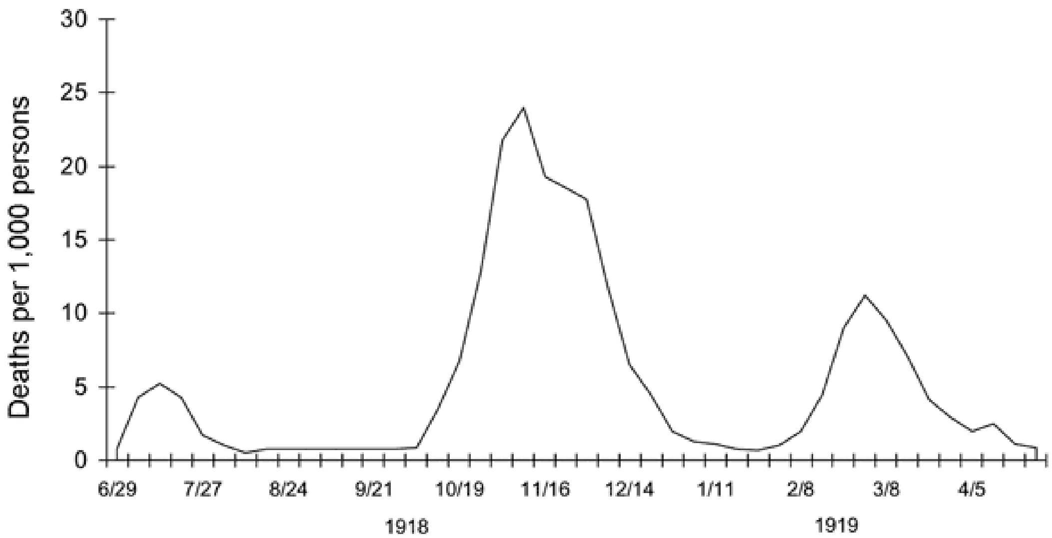


Figure 16: Three Pandemic Waves: Weekly Combined Influenza and Pneumonia Mortality, United Kingdom, 1918–1919.

Another interesting characteristic of this pandemic compared to historical data of previous influenza for the last 150 years, which show the highest mortality rates in the infants and very old, is that it also had a high mortality rate for the young adults (Taubenberger 2006). Figure 17 shows “U” and “W” shaped combined influenza and pneumonia mortality by age at death, per 100,000 persons in each age group, United States, 1911–1918. Influenza- and pneumonia-specific death rates are plotted for the inter-pandemic years 1911–1917 (dashed).

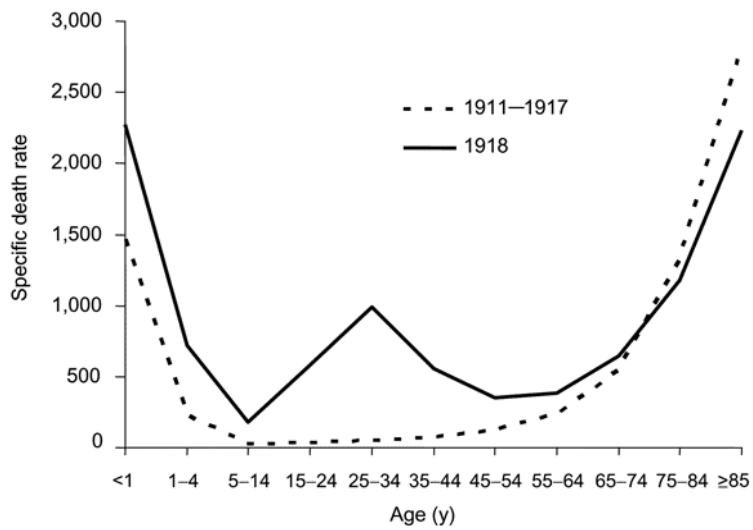


Figure 17: "U-" And "W-" Shaped Combined Influenza and Pneumonia Mortality

CDC expresses that even with the current method, planning, and preparations; the return of a pandemic virus equivalent in pathogenicity to the virus of 1918 would likely cause more than 100 million deaths worldwide. A pandemic virus with the pathogenic potential of some recent H5N1 outbreaks could cause substantially even more deaths.

The Influenza Virus is naturally carried by birds worldwide, and is very contagious among them. There are different types of influenza virus and all known viruses can be found in birds. There are only three known A subtypes of influenza virus (HIN1, H1N2, and H3N2) that are currently circulating among humans, and for which we have immunity. The main problem is that avian influenza viruses are constantly emerging and mutating; thus, they might become capable to spread among humans, leaving us exposed to a new deadly disease for which we might not have immunity (CDC, 2007)

Among the virus that have been able to cross the barrier from animal to human, H5N1 has been the most lethal with the largest number of detected cases. As of June 2009, the current situation for the novel “swine flu” H1N1 in the United States reports a total of 7927 confirmed or probable cases and 11 deaths (CDC, 2009).

Problem Formulation

A pandemic is caused by influenza A virus for which there is no preexisting immunity, facilitating the virus’s rapid spread throughout the world. During the past 120 years, 4 pandemics have occurred. Although some mortality surveillance has been in place in selected areas since the 1889 pandemic, new surveillance techniques have increased our understanding of features based on the past 3 pandemics (Monto et al., 2006). Pandemics do not follow a pattern, and data review of previous pandemic data suggests that no epidemiological profile, periodicity, origin, and timing between waves exist (Taubenberger, 2006).

The problem considered in this chapter is the estimation of the potential patient demand that an emergency department will have under a set of five levels of severity (scenarios) for a pandemic influenza breakout. The concept of severity levels has been adopted by information available from the CDC and WHO, and how they defined five Pandemic Severity Indexes (PSI). The objectives are as it follows:

- To develop a demand model that replicates a generalized behavior of the seasonal influenza. By a generalized behavior we mean one that shows the periodic, bell-shaped or sinuous behavior of the seasonal influenza visits to a hospital, and without the impact of undesired noise (i.e. decrease on demand due to New Year's holidays).

- To prove that there is a severity level such that a severe influenza season can be modeled as a proportion of another less severe.
- To explore and determine which seasonal influenza demand forecasting models is the most appropriate to represent the behavior of the data.
- To define a set of scenarios for the demand from a mild influenza season to a severe pandemic (1918 Spanish Influenza-like).

Specifically, the following questions will be answered in through this work:

- Can a seasonal influenza season patient demand be modeled by the product of a proportional estimate and another less or more severe season?
- Can a seasonal influenza based model be used to replicate a more severe pandemic influenza?
- What demand is calculated for each influenza demand scenario for every week?
- What is considered as an influenza season and what length of time should be used?

Methodology

Figure 18 depicts how this chapter interacts with the rest of this thesis. Based on the forecasting estimates from previous chapters, the model that best represents the seasonal influenza patient demand is chosen. Based on information available from the pandemic influenza that has appeared in the last hundred years, and the seasonal influenza forecasting model, a patient demand surge model is created to replicate five scenarios with different severity levels.

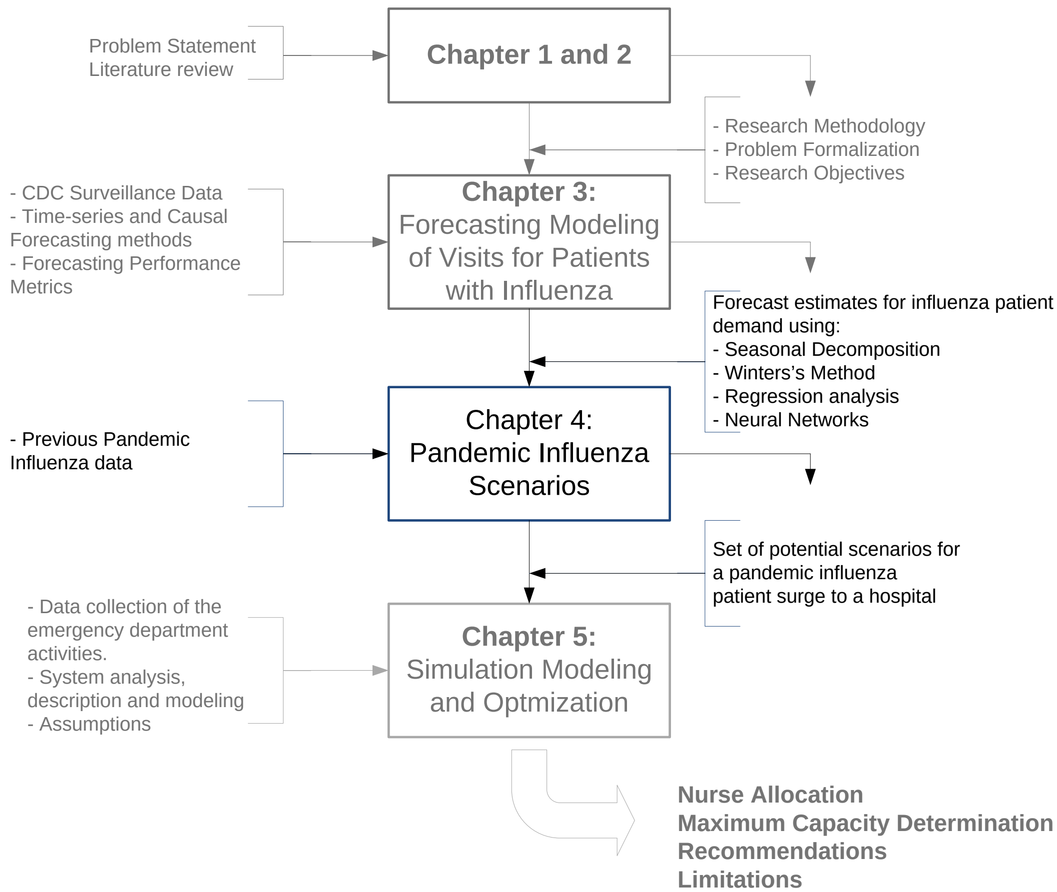


Figure 18: Thesis Flow for Chapter 4

Pandemic Influenza Model

In February 2007, the Unites States government released guidelines to help cities and states prepare for an Influenza Pandemic. The guidelines included a Pandemic Severity Index (PSI) designed to help officials predict the severity of an outbreak and put appropriate mitigation strategies in place. The PSI was developed by the Centers for Disease Control and Prevention, and the characteristics for every category in terms of case fatality (proportion of death among the critically ill), excess death rate (the rate of death per 10,000 persons compared to the normal seasonal baseline, and the equivalent influenza event in the United States experience are listed in Table 3.

Table 3: Pandemic Severity Index

PSI	Case fatality (%)	Excess death rate (%)	Potential no. of deaths (2006 population)	US Experience
1	< 0.1	< 30	< 90,000	Seasonal Influenza
2	[0.1, 0.5)	[30, 150)	[90,000, 450,000)	1957 and 1968 pandemics
3	[0.5, 1.0)	[150, 300)	[450,000, 900,000)	none
4	[1.0, 2.0)	[300, 600)	[900,000, 1.8 mil)	none
5	> 2.0	> 600	> 1.8 mil	1918 pandemic

From this point on, seasonal influenza is going to be considered as a Pandemic Influenza with and PSI equal to one. The objective is to determine which forecasting method implemented in Chapter 3 is more adequate to represent the demand during seasonal influenza.

Model Selection

Four forecasting methods were used to predict the demand of patient visits to hospitals, and a series of performance metrics were applied to measure accuracy (results can be obtained from Table 2). Seasonal Decomposition yielded the smallest errors at forecasting, but after comparing its performance using a paired t-test (α=0.05) with the other methods, it was found that there was no significant difference on their performance.

The selection criteria procedure used in this paper for the forecasting method (chapter 3) that would be more appropriate to describe the patient demand during a Pandemic Influenza with PSI equal to one is based on the study made by Thomas Yokum and Scott Armstrong: “Beyond Accuracy: Comparison of Criteria Used to Select Forecasting Methods”. According to

Yocum, research in forecasting has assumed that accuracy is the primary criterion in selecting among forecasting techniques in the past. It has been used as the only criterion in many studies. Moreover, in the 1992 International Journal of Forecasting papers that compared the results of different techniques and series, only one used criteria other than accuracy. In this paper we expanded the selection criteria based on sole accuracy to other important forecasting characteristics such as: ease of interpretation, use, implementation, and adaptation to conditions.

The procedure to select the appropriate method consists on rating each forecasting method in every criteria type. A scale ranging from 1 to 4 is used: 1 referring to the lowest ranking and 4 as the highest. Table 4 lists the forecasting criteria facets and the weight for each one. The weights are the average ranking (out of 7 points) of importance given by 322 experts from a total of 738 questionnaires sent to International Institute of Forecasting (IIF) members and nonmembers. For every forecasting method, the weighted total ranking is calculated as the sum of the product of the method rating and weight for every criteria facet.

Table 4: Forecasting Method Selection Criteria. (Note: All values are in generic units).

Criteria	Weight (out of 7)	Seasonal Decomposition	Neural Networks	Regression Analysis	Winters
Accuracy	6.2	4	3	3	2
Ease of interpretation	5.69	3	3	4	3
Adaptive to conditions	5.58	2	4	4	2
Ease of use	5.54	3	4	4	3
Ease of implementation	5.41	3	4	4	3
		85.88	101.79	107.48	73.48

It was found in chapter 3 that Seasonal Decomposition had the smallest performance error (MAD, MAPE, MSE, TS, ME), but it did not have a significant difference in performance when compared with the other methods. Therefore, accuracy cannot be the only selection parameter in this case. The introduction of other parameters is very important. The model to be used as the representation for the influenza patient demand is regression modeling with a Fourier series because it had the highest rating due to good interpretation capabilities, and it is a mathematical function that can be adapted to different conditions by varying the parameters (amplitude, period, level). The Fourier function with independent variable x= weeks and y=patient demand:

$$f(x) = a_0 + \left[a_1 \cos\left(2\pi \frac{x}{c_1}\right) + b_1 \sin\left(2\pi \frac{x}{c_1}\right)\right] + \left[a_2 \cos\left(2\pi \frac{x}{c_2}\right) + b_2 \sin\left(2\pi \frac{x}{c_2}\right)\right]$$

With:

SSE: 1716, *R-square*: 0.8775, *adjusted R-square*: 0.8717, *RMSE*: 3.705, and parameters:

Coefficients (with 95% confidence bounds)

a_0 =	19.15	(18.5, 19.8)
a_1 =	-6.734	(-8.336, -5.132)
a_2 =	-0.5396	(-2.385, 1.305)
b_1 =	11.72	(10.54, 12.9)
b_2 =	-4.011	(-4.973, -3.048)
c_1 =	52	(51.29, 52.72)
c_2 =	26.19	(25.54, 26.84)

Pandemic Influenza Severity Index Demand Models

Studies have been done to identify the length of an epidemic period, and it has been defined as those weeks when the observed number of deaths exceed the epidemic threshold defined by the CDC as the upper 95% confidence limit to the baseline (Simonsen, 1997). It has been found that the model for the pandemic season last for 12.5 weeks in average (range from 6 to 18 weeks), and this also coincides with the assumptions made by the CDC, and also the Influenza Pandemic Plans for the Veterans Hospitals assumptions (VA, 2006), and FluSurge: a pandemic patient demand estimator software available (Zhang, 2005). The model that this study will implement will assume outbreak duration of 12 weeks (x_1^{12}) in which the demand ($f(x)$) will vary following the Fourier function found in the last section.

It is intended to find the demand function of the expected Pandemic Influenza patient demand for five different severity scenarios: The most critical PSI proposed by the CDC is comparable to the "Spanish Flu" pandemic that occurred in 1918. Having already determined the demand function for the PSI 1, it is aimed to find the demand function for a PSI 5 scenario. The procedure to do so is explained as it follows:

- Define assumptions: according to the CDC propose pandemic planning assumptions, he clinical disease attack rate will likely be 30% or higher in the overall population during the pandemic. Illness rates will be highest among school-aged children (about 40%) and decline with age. Among working adults (ages from 18-65), an average of 20% will become ill during a community outbreak. Of those who become ill with influenza, 50% will seek outpatient medical care. Other assumptions made for the parameters used in CDC planning models model can be seen in Appendix F: Assumptions for Pandemic Influenza impact. This model takes into consideration the age distribution for the population that is being studied. The Hillsborough county population data used belongs to the 2007 census bureau:

Persons under 18 years old, percent, 2007	292,834.43
Persons between 18 and 65 years old, percent, 2007	749,797.84
Persons 65 years old and over, percent, 2007	138,151.73
Total	1,180,784.00

- Choose site for the model application: This study is intended to be applied to individual emergency departments. For practical purposes, a Hospital in the city of Tampa FL is chosen. The proportion of the total patient arrivals for a particular hospital is based on its capacity. For the city of Tampa, the list of emergency departments and capacity (expressed as number of beds) are shown in Appendix G: Number of beds per hospital in Tampa. *James A. Haley Veterans' Hospital* is used as example, and it is expected that 13.43% of the total patient cases will be seeking treatment in this facility.
- Estimate total demand: according to the CDC assumptions, it is expected that a total of 354,235 persons in the Hillsborough county will become ill, out which 177,117 (50%) will be seeking treatment in a hospital during the

12 week outbreak. 23,786 (13.43%) of those persons are expected to access to the *James A. Haley Veterans' Hospital*.

- Establish total demand function: Choosing a function $f(x)$ that is continuous through the interval $I = [x, x+h]$ posses a geometric motivation: the total demand over the time range (1-12) can be represented as the area of the region bounded by x and $x+h$. Figure 19 gives the graphical representation of the area by integrating:

$$\int_{x}^{x+h} f_1(x)dx = \int_{c}^{x+h} f_1(x)dx - \int_{c}^{x} f_1(x)dx = F_1(x+h) - F_1(x)$$

Where c is such that $a \leq c \leq b$, and h indicates an increment larger than 0.

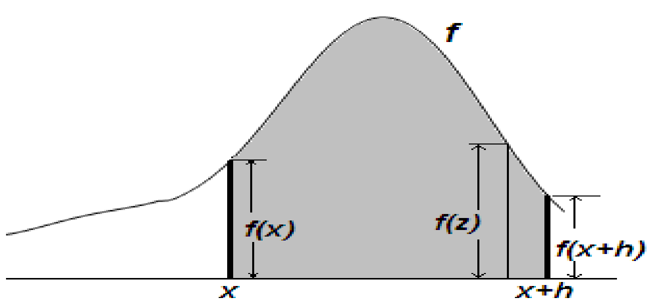


Figure 19: Integrals as the Area under a Function Curve

The results for the total demand (considered as $\int_{1}^{12} f_i(x)dx$, where $f_i(x)$ is the function for the Pandemic Severity Index $i = 1, \ldots, 5$). By integrating the Fourier series for the PSI 1 patient demand model is given by:

$$F_1(x) = \left| a_0 + \frac{c_1 a_1}{2\pi} \sin\left(\frac{2\pi x}{c_1}\right) - \frac{c_1 b_1}{2\pi} \cos\left(\frac{2\pi x}{c_1}\right) + \frac{c_2 a_2}{2\pi} \sin\left(\frac{2\pi x}{c_2}\right) \right.$$

$$\left. - \frac{c_2 b_2}{2\pi} \cos\left(\frac{2\pi x}{c_2}\right) \right|_1^{12}$$

- Estimation of a Pandemic Proportional Constant (K_{PPC}): This research aims to propose that the demand function for PSI 2,3,4,and 5 can be expressed a the demand function for PSI 1 multiplied by a constant named Pandemic Proportional Constant (K_{PPC}):

$$f_1(x) = K_{PPC} f_i(x)$$

The total demand is used to calculate K_{PPC} , and the estimates are shown in Table 5. The total demand for the severity levels between the mildest and the most severe was calculated by interpolating between the PSI 1 and PSI 5, using the same proportions implemented by the CDC guidelines as shown in Table 5: Total Demand for the PSITable 3.

Table 5: Total Demand for the PSI

Pandemic Severity Index	Demand (12 weeks)
1	438
2	2,973
3	5,947
4	11,893
5	23,786

Let $F(x) = \int_a^b f(x)\,dx$, Then the fundamental theorem of calculus says that the derivate $F^{'}(x)$ exists at each point in the open interval [a, b] where $f(x)$ is continuous and for each x we have $F^{'}(x) = f(x)$. Also, it has been proven that:

$$f_i(x) = K_{PPC_i} * f_1(x)$$

$$\int_a^b f_i(x)dx = K_{PPC_i} * \int_a^b f_1(x)dx$$

$$F_i(x) = K_{PPC_i} * F_1(x)$$

A list of the K_{ppc} constants found in this study for the five PSIs is show in Table 6. Finally, the demand functions for every scenario were found, and they are graphically represented in Figure 20.

Table 6: Pandemic Proportional Constants

Pandemic Severity Index	K_{PPC}
1	1
2	6.8
3	13.6
4	27.2
5	54.3

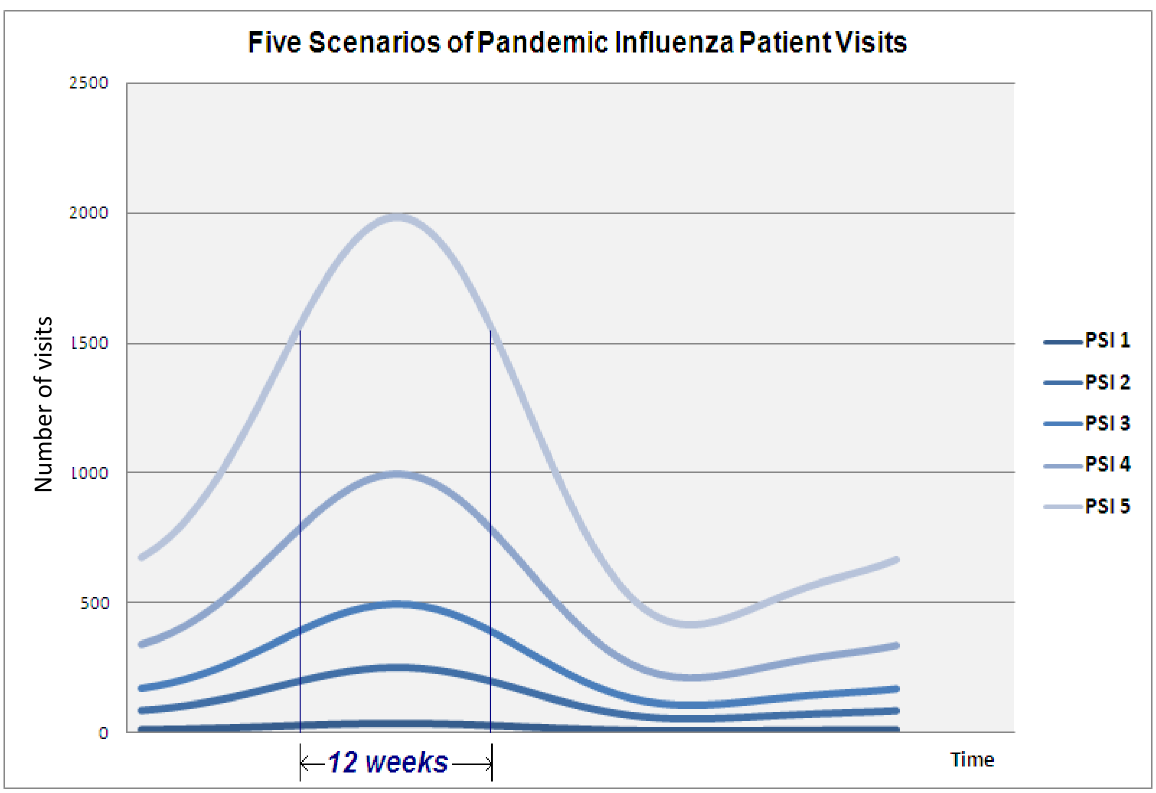


Figure 20: Five Pandemic Influenza Demand Scenarios

Discussion

Due to the uncertainty of how an Influenza Pandemic would impact society systems such as transportation, economy, healthcare systems, schools, and other social disruptions, this research considers that contemplating different scenarios from the most optimist to the worst case scenario. According to [Edmonston and Fost, 1998], an increasing number of analysts are using this technique, and that for some businesses have reacted faster and better than their rivals when the changes happened, because scenario planning exercises had prepared them to respond well to changes. Scenario building is another way of analyzing, and it is way of avoiding predicting the future wrong in fundamental and critical ways.

According to author John Petersen, president of the Arlington Institute, it is not possible to plan for all possible scenarios. It is preferable to consider some of them, and question what common elements exist across all of them?, What are the major threats?, and start building the system capability necessary to face the potential impact. These scenarios will be considered in chapter five, and they will be used as input to a simulation model that replicates the dynamics in a emergency department.

CHAPTER 5
EMERGENCY DEPARTMENT SIMULATION MODEL DURING A PANDEMIC INFLUENZA OUTBREAK

Abstract

This research proposes a nurse allocation policy to manage patient overflow by simulating five scenarios of different severity levels for a pandemic influenza outbreak. The objective is to minimize the number of patients waiting in queue to be treated by a nurse while maximizing patient flow. The model is built using ARENA simulation software and OptQuest heuristic optimization to propose various combinations for the number of nurses needed for healthcare delivery. Results are compared with a basic setting that closely emulates the resources and components in a Veteran's Hospital. The proposed method reduced patient average waiting of various activities held in the emergency department: baseline assessment, registration, and treatment by 90%, 93%, and 96% respectively. The average number of patients waiting for baseline assessment, registration, and treatment was reduced between 85% and 89 also.

Introduction

This chapter studies an emergency department system during a pandemic influenza outbreak. The results obtained from the previous chapters; specifically, the patient demand scenarios obtained from chapter 4 are used as input to a simulation model. To visualize how this chapter follows in this work, see Figure 22.

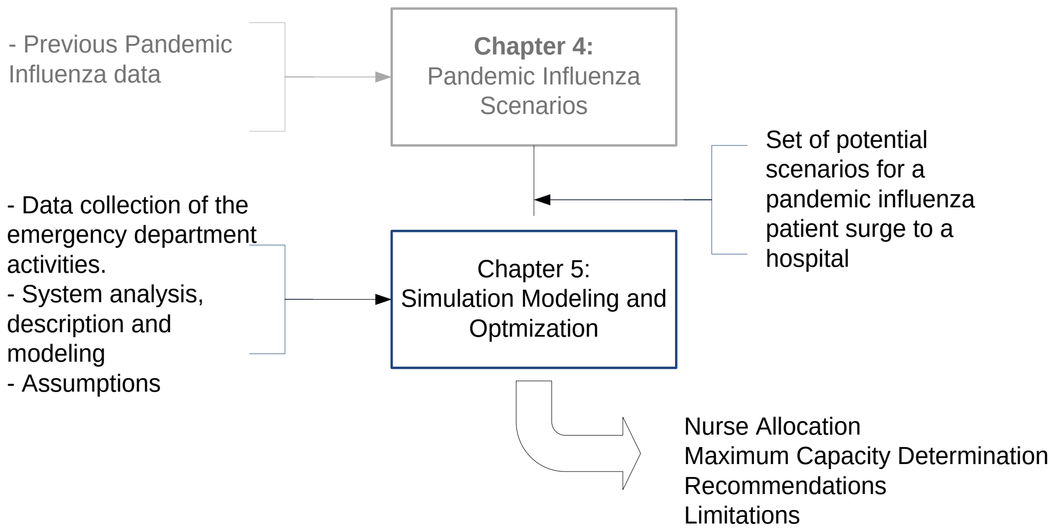


Figure 21: Thesis Flow for Chapter 5

According to many scientists and epidemiologists, a new Influenza Pandemic outbreak was unavoidable. Moreover, on June 11, 2009 the first pandemic outbreak of swine flu of this century has been confirmed by the WHO with a moderate severity. Experts agreed that it was not a matter of whether or not it would occur, but when (Roche, 2007). The word “pandemic” has been defined as a disease that emerges when a new virus appears, and then spreads easily from person to person worldwide. Pandemic occurs after three conditions are met: first, the emergence of a new flu strain; then, the ability of the strain to infect humans and cause serious illness; and finally, the easily human to human spread (DHHS, 2007).

Due to drastic increase in the number of patients assessing hospitals services during a severe pandemic influenza outbreak, it is vital for hospital management to develop a reliable plan to face events of this magnitude. Also, emergency department environments possess a limited number of resources (i.e., nurses, physicians, pharmacists) for the everyday routinely requirements. During and after an Influenza Pandemic incidence, the impact on patients' demand and the complexity of the cases could become overwhelming enough to result in a chaotic system impossible to operate. In this research, a simulation modeling approach is developed to enhance understanding of emergency department's intricacies, as well as nurse allocation and utilization. In general, simulation modeling is an adaptable and informative tool, and it can be used in assisting decision makers to better strategize when allocating limited staff personnel to critical tasks.

Literature Review

Simulation in Healthcare has grown in popularity because it can be used for dynamic as opposed to static analysis (Eldabi and Paul, 2001). Simulation has been used in emergency department for maximizing capacity (Baesler et al., 2003), assisting expansion plans (Wiinamaki and Dronzek, 2003), reducing length of stay (Samaha et al., 2003), and to assess indoor airborne infection risks (Liao et al., 2003).

To capture how emergency departments systems behave during normal conditions and how they react to unexpected situations, a variety of methods – ranging from simulation to optimization techniques – have been utilized in the literature. For example, ED systems analyzers have studied queuing systems complexities (Panayiotopoulos 1984); other analysts have used meta-models (a model of a set of related models) - a technique widely used in artificial neural networks. Meta-modeling is a good technique to explore when dealing with the stochastic nature and complex dynamics of the Hospital EDs (Kilmer, 1995); to reduce overcrowding and reduce the number of patients leaving without being treated (Hung et al., 2007); [Kolker, 2008] utilized principles of Operation Research to mimic different scenarios and propose solutions to reduce patient length of stay; to reduce overcrowding prediction in emergency departments (Hoot et al., 2008).

We present a computer simulation model that captures the dynamics on an ED during a drastic increase of patient demand over a short period of time (12 weeks). This research focuses on modeling the allocation of nurses. Because there is no way of know what the real impact of a new Pandemic Influenza outbreak would be, various scenarios are explored and a set of alternatives are generated to determine the maximum capacity and best combination of resources that increases patient flow and decreases the number of patients waiting.

Although simulation modeling has been widely used in various health care environments, it has not been used very extensively in the area of biological disease outbreaks or chemical attacks. A few of the models found in the literature include: a probabilistic transmission dynamic model created to assess indoor airborne infection risks considering various scenarios of exposure in a susceptible population for a range of R_0 (basic reproductive number) (Liao et al., 2005); a software called SEARUMS (Studying the Epidemiology of Avian influenza Rapidly Using Modeling and Simulation) which enables rapid scenario analysis to identify epicenters and timelines of outbreaks using existing statistical data (Rao et al., 2008); a simulation-based type of methodology developed to analyze the spread of H5N1 using stochastic interactions between waterfowl, poultry, and humans (Rao et al., 2008).

Problem Formulation

A large flow of patients is expected to access EDs during an outbreak. Thus, a pre-pandemic planning or a course of action is crucial to provide quality service, effective care to ill persons, and intelligent strategies that help prevent further spread of the infection. According to pandemic protocols, once the outbreak occurs, hospitals must dedicate an exclusive area for patients with the pandemic virus. This area will be divided into five zones: triage, green, yellow, red and black (Davey, et. al. 2006). Given the limited availability of nurses (even during normal daily operations), this study explores how to efficiently allocate nurses to the different zones for improved ED performance.

Nursing personnel are essential for an effective response to high patient demand, including patient care, patient tracking and information management, and logistical support. This study concentrates on this critical resource, by finding an optimal combination on levels of resources in the five zones with capacity and resource utilization objectives such as:

- Maximize patient throughput in the system: It is aimed to prove that by improving the efficiency of the system, more patients will be able to be treated during the breakout.

- Minimize number of patients transferred to other facilities: when the system reaches its maximum capacity, patients arriving will be sent to other facilities to be treated.
- Minimize average number of patients waiting to be treated: quality of service is measure by how many and how long patients are waiting for treatments.
- Resource utilization: the goal is to find the service levels in every area and find the combination that utilizes the resources in proportional levels; that is, resource utilization in any zone should not be significantly higher than in another zone.

Specifically, the following questions will be answered in through this work:

- How does the allocation of resources impact the efficiency of the system, in terms of queue length and waiting times?
- What are the most critical zones in the ED during the five Pandemic Influenza scenarios? What bottlenecks can be identified in the current system?
- What is the optimum nurse allocation during each of the five patient demand scenarios?
- How does the optimal proposed system impact resource utilization for the nurses in the different areas?
- Can assumptions made for this model be validated with current moderate “Swine Flu” pandemic outbreak?

Methodology

In this chapter a simulation model is created, and uses the arrival rates obtain in chapter five for five patient demand scenarios (the demand function curves can be seen in Figure 20 in Chapter 4). Besides the forecasting results from previous chapter, data collection from emergencies departments and other assumptions for the impact of a pandemic influenza outbreak are also implemented in the model. The first step towards the creation of the simulation model for this study is, as depicted in Figure 22, a problem formulation and defining the objectives and research questions.

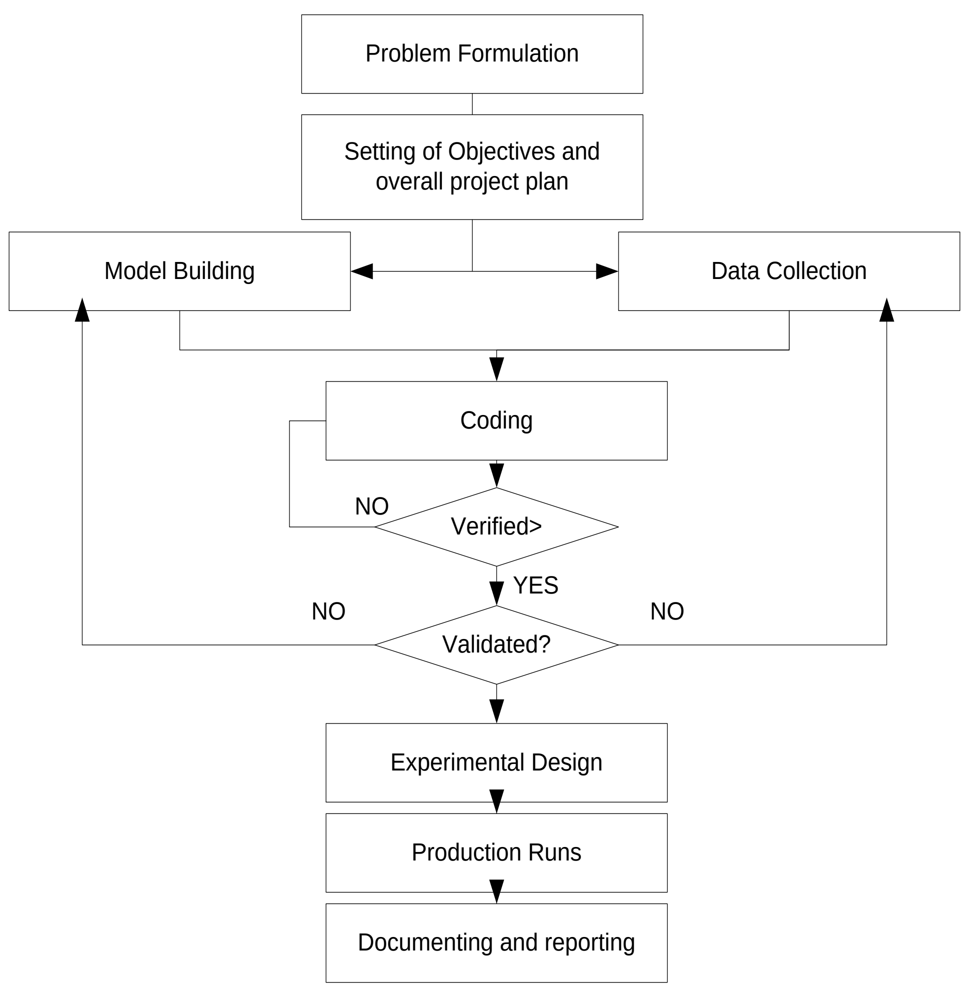


Figure 22: Steps in Simulation Study

A simulation model is created and is run for 5 replications, to better capture the behavior of the system and obtain better estimates. The verification process is iterative; the simulation model is verified to determine whether the computer implementation of the conceptual model is correct. The simulation model is also animated to visually verify the system is behaving properly; that is, it can be detected actions that might seem illogical. Results are analyzed, and by using OptQuest optimization tool of ARENA, a new allocation of resources is proposed in accordance with the chosen objective functions and performance measures. The final output of this is a new allocation model for nurses levels in the different zones of the ED, limitations of the model are explained, and recommendations are given to face the situation under study.

Model Description

This simulation model is developed using Arena 10.0 simulation software. The initial objective is to evaluate the system performance during different levels of demand. Then, OptQuest for Arena is used to find the optimal allocation of resources in the different areas of the hospital. The simulation model is divided into five zones. These five zones include:

- Triage Process
- Green Zone
- Yellow Zone
- Red Zone
- Black Zone

Every patient is considered an entity entering the model. A patient accesses the triage zone where he/she is processed by a nurse. In the next section, a more detailed description of the processes that occur in the system is given.

Conceptual Model

Potential infected patients arrive to triage process. Triage is a sorting process where nurses determine how critical a patient's illness is. The patient is tagged with a color that represent one of the different zones where he or she can receive a proper treatment (these categories are red, yellow, green, and black). The criterion of sorting a patient to the different areas depends on the severity of the symptoms that the patient exhibits, and the complexity or number of medical procedures that might be required (Vance and Sprivulis, 2005). A patient accesses the triage zone where he is processed by a nurse. The estimated time for the triage process is based on a triangular distribution with parameters 1.42, 2.75, and 4.5 minutes (Hupert et al., 2003).

Patients with the mildest symptoms are considered an outpatient visit, and these patients go the green zone, where they will be registered, receive a health condition assessment and medical tests, and finally treatment. Patients with the most severe symptoms go to the yellow and red zone. In the red zone, patient with the most severe symptoms are present, and they need ICU treatment. Patients in less advanced stage of the illness go to the yellow area and use ventilator and recurrent treatment. Patients that are beyond any medical help are taken to the black zone. Figure 23 gives a graphic representation of the process that is being described here.

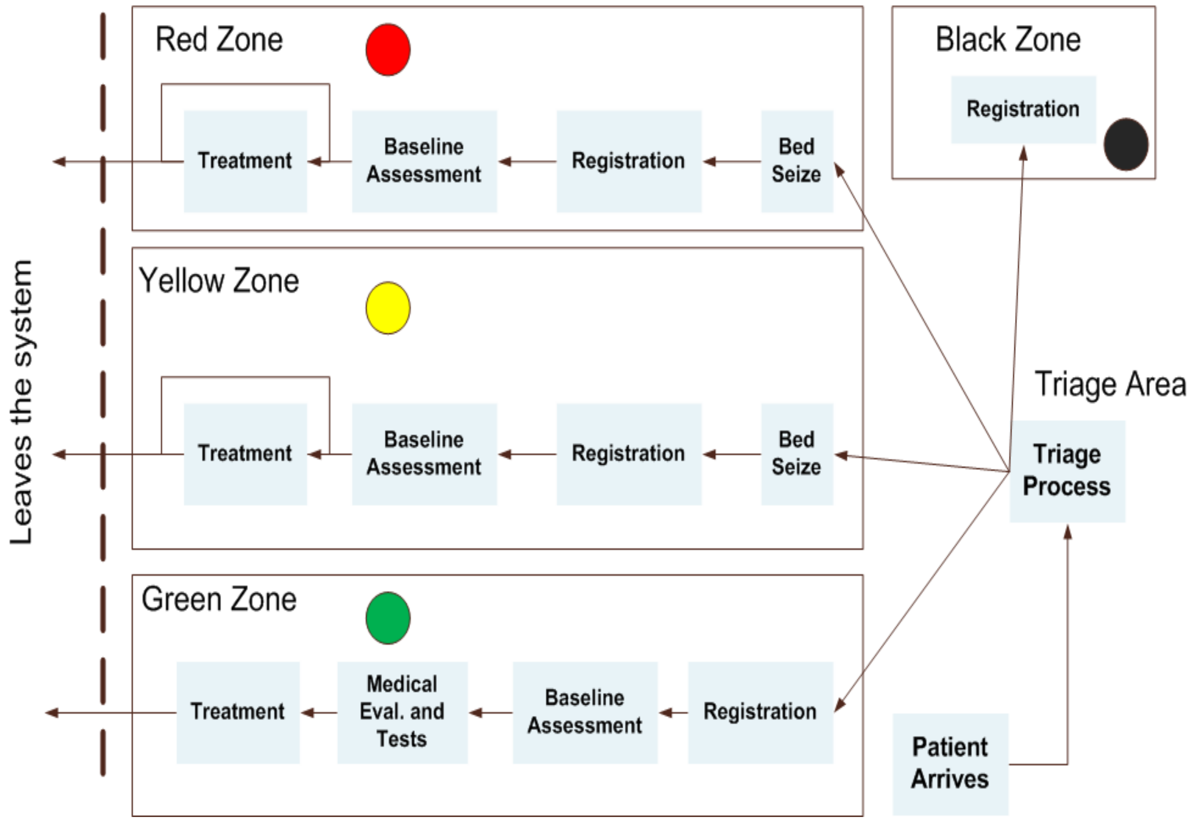


Figure 23: Process Flow for the EDs during a Pandemic Influenza

After the triage process, the processes performed by nurses for the red and yellow zones are similar: the registration is performed, and baseline assessment while the patient waits to be treated. The patient seizes a bed and waits to be seen by a nurse. The nurse decides if a consultant should be called to conduct a more detailed examination of the patient. The physician might order more tests for the patient if needed (this process is represented in the simulation as delay). The consultant could also discharge the patient based on his expertise. If the consultant orders tests, the patient will continue through the process of testing. The consultant or an authorized member of the staff can decide which type of treatment should be provided. If there is no need for a consultant, the patient is treated by the nurse who performs the first examination. Once the tests have been completed, there is a delay until a clinical decision can be made by the attending physician. The clinical decision determines illness level of severity and the treatment to be used. The patient will stay in the systems while receiving treatment. After a period of time, the patient should improve and go home. Time estimates for the processes can be retrieved from Appendix I: Time estimates for the processes held in the ED.

Assumptions

- The clinical disease attack rate will likely be 30% or higher in the overall population during the pandemic (CDC Pandemic Planning Assumptions, 2009).
- The number of hospitalizations and deaths will depend on the virulence of the pandemic virus. The number of Number of episodes of illness, healthcare utilization, and death associated with moderate and severe pandemic Influenza scenarios. (CDC Pandemic Planning Assumptions, 2009). Estimates on impact of virulence of a pandemic on healthcare can be seen in Table 7 and are based on extrapolation from past pandemics in the United States.
- Rates of absenteeism will depend on the severity of the pandemic. The simulation model in this study assumes that the number of nurses will decrease 5% weekly for the first 5 weeks of the outbreak.
- Average length of non-ICU hospital stay (yellow zone) for influenza-related illness is 5- 6 days (CDC FluSurge, 2005).

- Average length of ICU stay and ventilator usage (red zone) for influenza-related illness is 10 days (CDC FluSurge, 2005).
- Patients in the yellow zone will require receiving treatment every 6 hours from the nurses during the length of stay. For the red zone, the frequency of treatments is every 3 hours.

Table 7: Estimates for Rate of Illness, Outpatient Visits, Resources Utilization, and Deaths for Pandemic Assumptions. Estimates Are Based On 2006 Population

Characteristic	Moderate 1958/68-like (number of persons)	Severe 1918-like (number of persons)
Illness	90,000,000	90,000,000
Outpatient medical care	45,000,000	45,000,000
Hospitalization	865,000	9,900,000
ICU care	128,750	1,485,000
Mechanical ventilation	64,875	742,500
Deaths	209,000	1,903,000

- This simulation models uses the CDC pandemic planning assumptions on the virulence of the virus. The triage sorting process that takes place in the ED determines what proportion of visits goes to the green, red, yellow, and black zone. Based on the estimates from Table 7, this study assumes that out all visits to the ED, 22% of visits will be needing hospitalization, recurrent treatment, and they go to the yellow zone, 5% percent of visits requires more intensive treatment (ICU and ventilators) and goes to the red zone, 68% of visits will not require to be hospitalized but will go through the process once to receive treatment, and the other 4.2 percent of visits will be those who are beyond medical help, and are sent to the black zone.

- If an influenza pandemic progresses to the point where thousands of people are ill at the same time, most cases will be clinically diagnosed and treated empirically without laboratory confirmation (Association of State and Territorial Health Officials, 2002).
- The Hospital chosen as prototype for the implementation of the simulation is the James A. Haley Veterans Hospital, and estimates for the resources available according to the VA Respiratory Infectious Diseases Emergency Plan (Farley, 2006) is depicted in Table 8 .

Table 8: Estimates for the resources available according to the VA Respiratory Infectious Diseases Emergency Plan

Resources available	
Nurses	30
Non-ICU Beds	111
ICU Beds	40
Number of Ventilators	84

Verification

The checking process is iterative. In the process of building the simulation model, when discrepancies among the conceptual and operational model appeared, the model was checked for errors. The verification process in this study included the examination of the simulation program SIMAN to insure that the operational model accurately reflects the conceptual model.

The verification procedure also included checking that the input data (arrival times, processing time, and decision modules) were being used appropriately (i.e. Make sure that times units concord throughout the model and results were reasonable). Finally, the simulation model was animated to detect actions that were behaving wrongly or resource utilization levels during the run of the simulation. A snapshot of the simulation model for week 7 of the outbreak animation can be seen in Appendix J: Snapshot of simulation animation.

Validation

Validation refers to the variety of subjective and objective techniques used to validate the conceptual model. A conceptual model of a real world system must appear reasonable to those that are knowledgeable about the real system. To achieve this, the conceptual model was designed together with the emergency management program coordinator from the James Haley VA hospital. Also, we were able to be part of the 2007 pandemic influenza drill where many the tasks that nurses perform and protocols used could be documented and implemented in the conceptual model.

Other than opinions of expert personnel in the area, the simulation assumptions validity is enhanced by the use of assumption from institutions specialized in the area of study; that is, the Center for Disease Control and Prevention (CDC), the World Health Organization, and UD Homeland Security assumptions.

Results

The model was run for 5 replications of 2016 hours (~12 weeks). A SIMAN summary of results can be seen in Appendix K: SIMAN simulation summary report. The current system allocation model assumes distribute the number available of nurses (30) as it follows:

Green Zone	7
Yellow Zone	7
Red Zone	7
Triage Zone	7
Black Zone	2

Resource utilization: It is observed that the utilization for the nurses in the yellow zone is considerable higher than in the other zones. Even though the yellow zone receives 22% of patients visits compared to the green zone which receive 68% of patient demand, patients in the yellow and red do need recurrent treatment from the nurses. A 3D surface comparing resource utilization for nurses in the various zones for the five severity levels is depicted in Figure 24, and estimates used for this graph can be obtained from

.

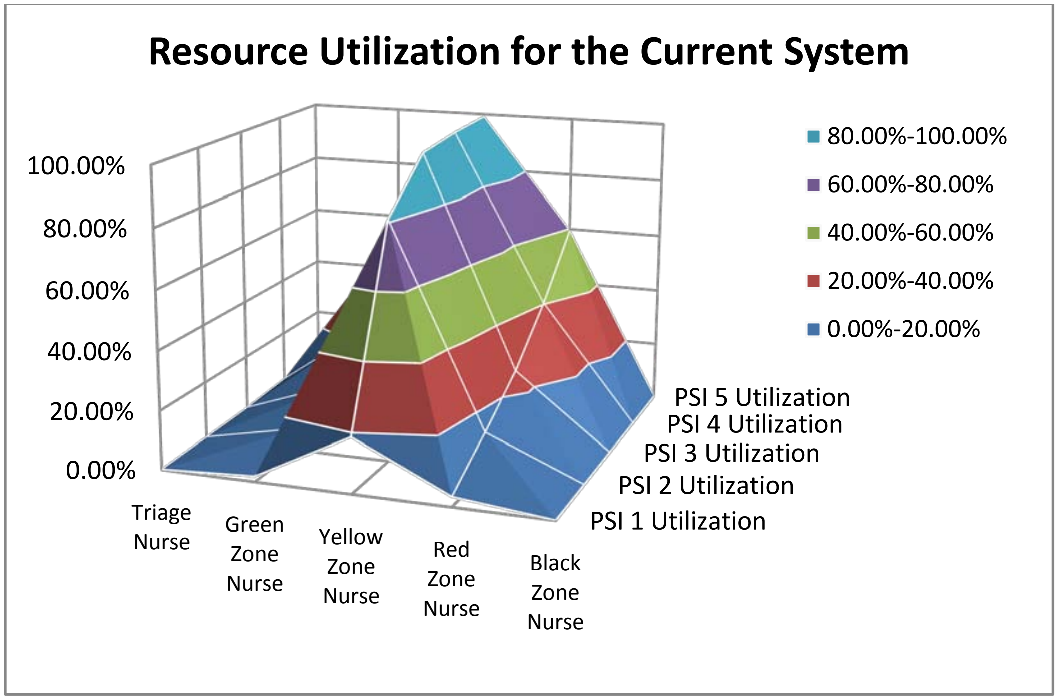


Figure 24: Nurse Utilization of the Various Zones for the Five Severity Scenarios with the Current System Allocation Policy

Table 9: Resource Utilization Estimates for the Nurses in the Various Zones with the Current Allocation Policy

	Triage Nurse	Green Zone Nurse	Yellow Zone Nurse	Red Zone Nurse	Black Zone Nurse
PSI 1	0.17%	1.85%	18.82%	3.44%	0.08%
PSI 2	0.71%	7.32%	80.91%	13.72%	0.07%
PSI 3	1.24%	12.73%	96.85%	24.99%	0.10%
PSI 4	2.44%	25.18%	98.49%	40.34%	0.17%
PSI 5	5.27%	54.05%	99.16%	59.43%	0.20%

Figure 24 clearly shows that the current system workload is not balanced; while some resources are under-utilized (i.e. triage nurse utilization ranges from 0.17% to 5.2%), other resources are over utilized (yellow zone nurse utilization). This translates is a poor quality of healthcare and working conditions for the Medical personnel. In the next section, three optimization criteria is evaluated to find a new allocation policy that addresses the issues regarding resource utilization and queue length.

Queue length and waiting times: as the utilization peaked for the nurses in the yellow zone, the same happened for the queue waiting times and length in the yellow zone. Waiting time also peaked to an average of 20-30 patients waiting for a bed in average in the red zone for the scenario with PSI 5. A graphical representation for the average number of patients and time waiting in the difference phases of the process for each zone is given in Figure 25 and Figure 26. The estimates for the queue length and waiting times can be obtained in appendix L.

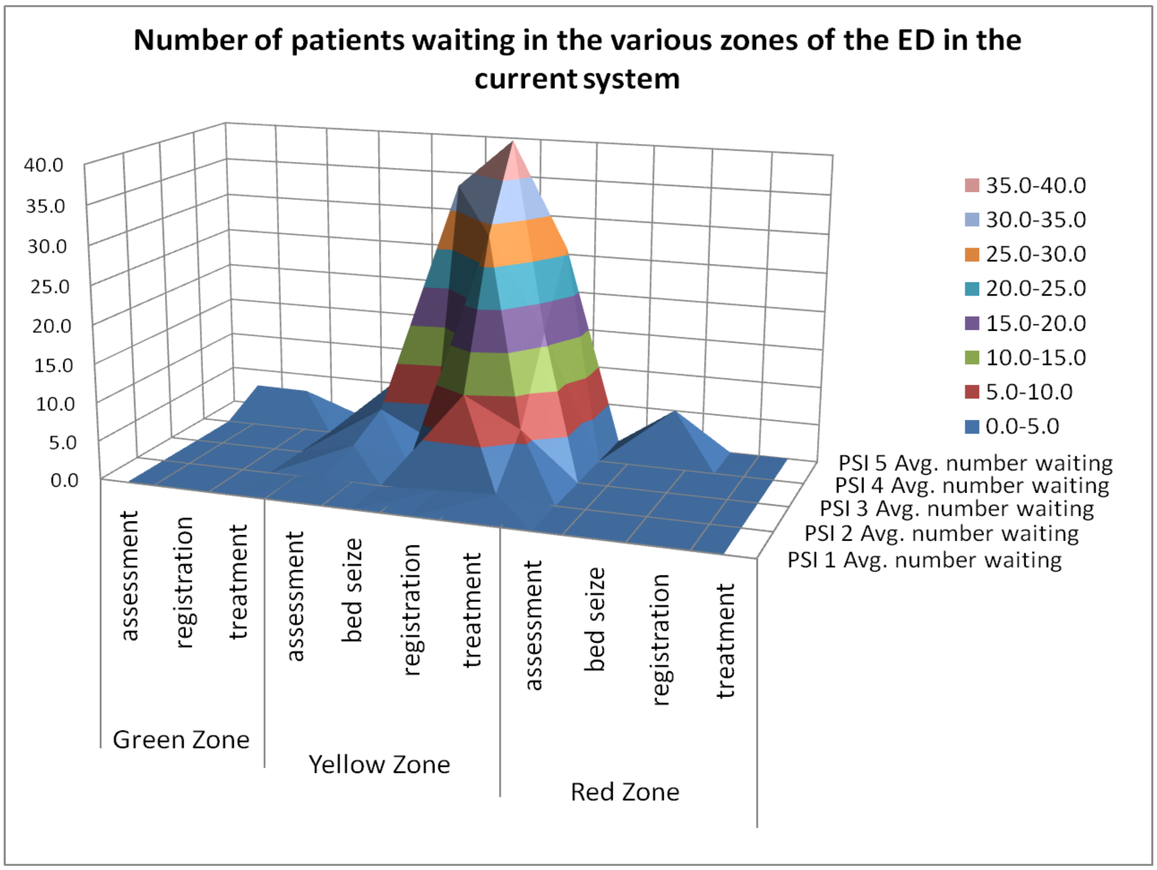


Figure 25: Number of Patients Waiting in each Zone of the ED

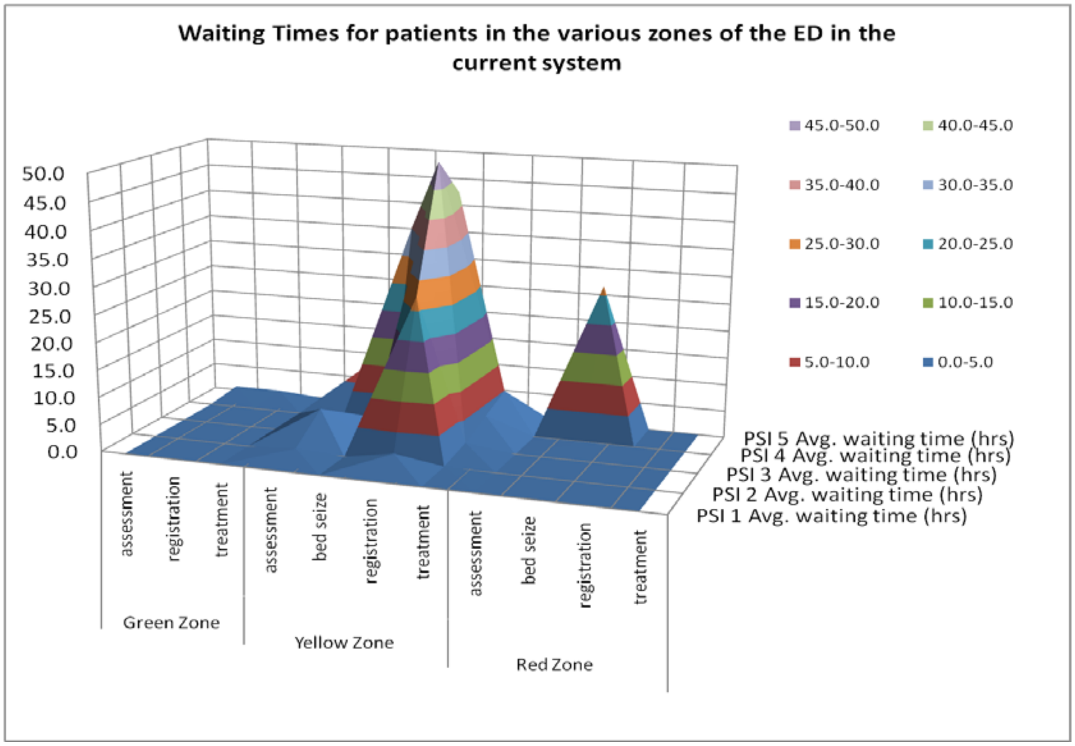


Figure 26: Queue Waiting Times (Hrs) for the Current System

Optimization

The design follow to apply this optimization procedure is divided into the following elements:

- Controls: these are the variables or resources in the model that you can manipulate, such as the number of nurses of each zone. After you define the controls in your simulation model, you can select which controls to optimize in OptQuest. OptQuest will change the values of these controls with each simulation until OptQuest finds values that yield the best objective.

The controls are defined in the following way:

$$\text{T\_Nurse} = \text{number of nurses in the triage zone}$$

$$\text{G\_Nurse} = \text{number of nurses in the green zone}$$

R_Nurse = number of nurses in the red zone

Y_Nurse = number of nurses in the yellow zone

B_Nurse = number of nurses in the black zone

- Responses: these are the outputs of the simulation you are interested on measuring. For this simulation model, the responses used in the analysis are: patient flow in the green, red, and yellow zones, number of patients transferred to other facilities because of system too full, and queue length for the various zones, and per process type. The list of responses as used in the OptQuest is listed on table 10.
- Constraints: these define a relationship among controls and/or responses, and set the limits on which variables can vary. For the system, the capacity used is of 30 nurses, thus the total number of nurses in the ED (for all the zones) should be equal to this amount.

Table 10: List Of Responses For The Optimization Procedure In Optquest

yellow_patient_out
red_patient_out
green_patient_out
Transferred patients
G_assessment.Queue.NumberInQueue
G_registration.Queue.NumberInQueue
G_Treatment_Seize.Queue.NumberInQueue
R_assessment.Queue.NumberInQueue
R_Bed_Seize.Queue.NumberInQueue
R_registration.Queue.NumberInQueue
R_Treatment_Seize.Queue.NumberInQueue
Triage Process.Queue.NumberInQueue
Y_assessment.Queue.NumberInQueue
Y_Bed_Seize.Queue.NumberInQueue
Y_registration.Queue.NumberInQueue
Y_Treatment_Seize.Queue.NumberInQueue

- Objective: This function defines the goal of the optimization. OptQuest for Arena allows you to define more than one objective, but only one objective can be used for an optimization. Three objectives were defined for this model:

Objective 1 = Maximize patient throughput in the system:

$$Max\ z = [green\_patient\_out] + [red\_patient\_out] + [yellow\_patient\_out]$$

Objective 2 = Minimize number of patients transferred to other facilities:

$$Min\ z = [transferred\ patients]$$

Objective 3 = Minimize average number of patients waiting to be treated:

$$\begin{aligned} Min\ z = {} & [G\_assessment.Queue.NumberInQueue] \\ & + [G\_registration.Queue.NumberInQueue] \\ & + [G\_Treatment\_Seize.Queue.NumberInQueue] \\ & + [R\_assessment.Queue.NumberInQueue] \\ & + [R\_Bed\_Seize.Queue.NumberInQueue] \\ & + [R\_registration.Queue.NumberInQueue] \\ & + [R\_Treatment\_Seize.Queue.NumberInQueue] \\ & + [Triage\ Process.Queue.NumberInQueue] \\ & + [Y\_assessment.Queue.NumberInQueue] \\ & + [Y\_Bed\_Seize.Queue.NumberInQueue] \\ & + [Y\_registration.Queue.NumberInQueue] \\ & + [Y\_Treatment\_Seize.Queue.NumberInQueue] \end{aligned}$$

- Run: The optimization model was run for every scenario, and the results for the allocation of nurses is expressed in percentages of total available nurses to give a more general representation on how workforce levels in each zone should be allocated. As it was observed in the results sections, the response values (Queue length and waiting times) in the PSI1 and PSI 2 were equal to zero. For this reason, no optimization was applied to these scenarios; results for the optimization are summarized in the next section.

Allocation of Resources

Objective 1 = Maximize patient throughput in the system:

Table 11: Resource Allocation as a Percentage of Total Number of Nurses for Objective 1

	PSI 3	PSI 4	PSI 5
Black	3.33%	3.33%	6.67%
Green	16.67%	16.67%	23.33%
Red	10.00%	10.00%	10.00%
Triage	13.33%	13.33%	6.67%
Yellow	56.67%	56.67%	53.33%

Objective 2 = Minimize number of patients transferred to other facilities:

Table 12: Resource Allocation as a Percentage of Total Number of Nurses for Objective 2

	PSI 3	PSI 4	PSI 5
Black	3.33%	3.33%	3.33%
Green	13.33%	13.33%	23.33%
Red	10.00%	10.00%	10.00%
Triage	6.67%	6.67%	3.33%
Yellow	66.67%	66.67%	60.00%

Objective 1 and 2 suggest that approximately from 53% to 66% of the workforce should be concentrated on the yellow zone, and it becomes in the most critical zone in the ED. In the optimization model it was found that the system was able to process more patients: 10% more patients under the PSI 5, 80% more under the PSI 4, and 100% more patients during the PSI 3. The number of patient that had to be transferred to other facilities also decreased 90% (from 1704 to 165) under the PSI 5, and100% for the other severity scenarios. The optimized allocation policy also had a positive impact on the utilization of nurses throughout the ED in the sense that it made the utilization more balanced as it can be seen in Figure 27 compared with resource utilization in current system shown in Figure 24.

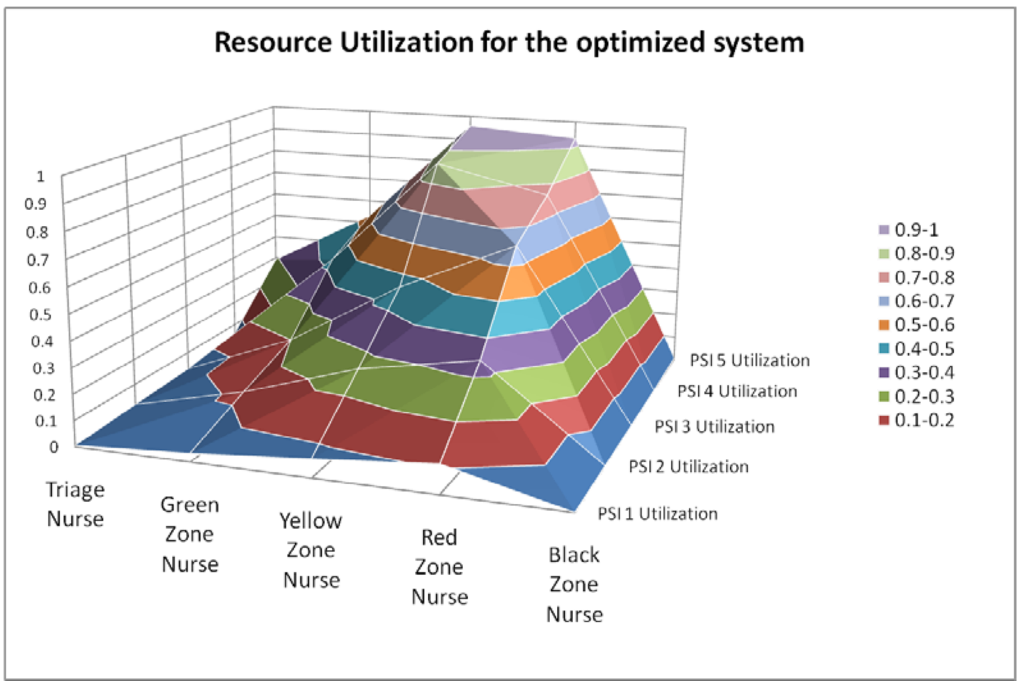


Figure 27: Resource Utilization after Optimization

Objective 3 = Minimize average number of patients waiting to be treated:

Table 13: Resource Allocation as a Percentage of Total Number of Nurses for Objective 3

	PSI 3	PSI 4	PSI 5
Black	3.33%	3.33%	13.33%
Green	13.33%	13.33%	33.33%
Red	13.33%	13.33%	16.67%
Triage	3.33%	3.33%	6.67%
Yellow	66.67%	66.67%	30.00%

Table 13 presents the allocation policy obtained after optimizing the system with the objective of minimizing the number of patients waiting the various queues for beds, baseline assessment, registration, and treatment. Results were obtained for the queue waiting times and length, and it was found good improvement for the number of patients waiting for nurses yellow zone. The average waiting to times baseline assessment, registration, and treatment was reduced by 90%, 93%, and 96% respectively. The average number of patients waiting for baseline assessment, registration, and treatment was reduced by 85%, 89%, 86% respectively. Figure 28 depicts the resource utilization for the nurses in the various zones for the processes that nurses are involved and beds utilization. It can be seen in Figure 28 that after optimizing and finding a better allocation of nurses where queue and waiting times have improved, and patient flow increased, beds have become the new bottleneck in the system.

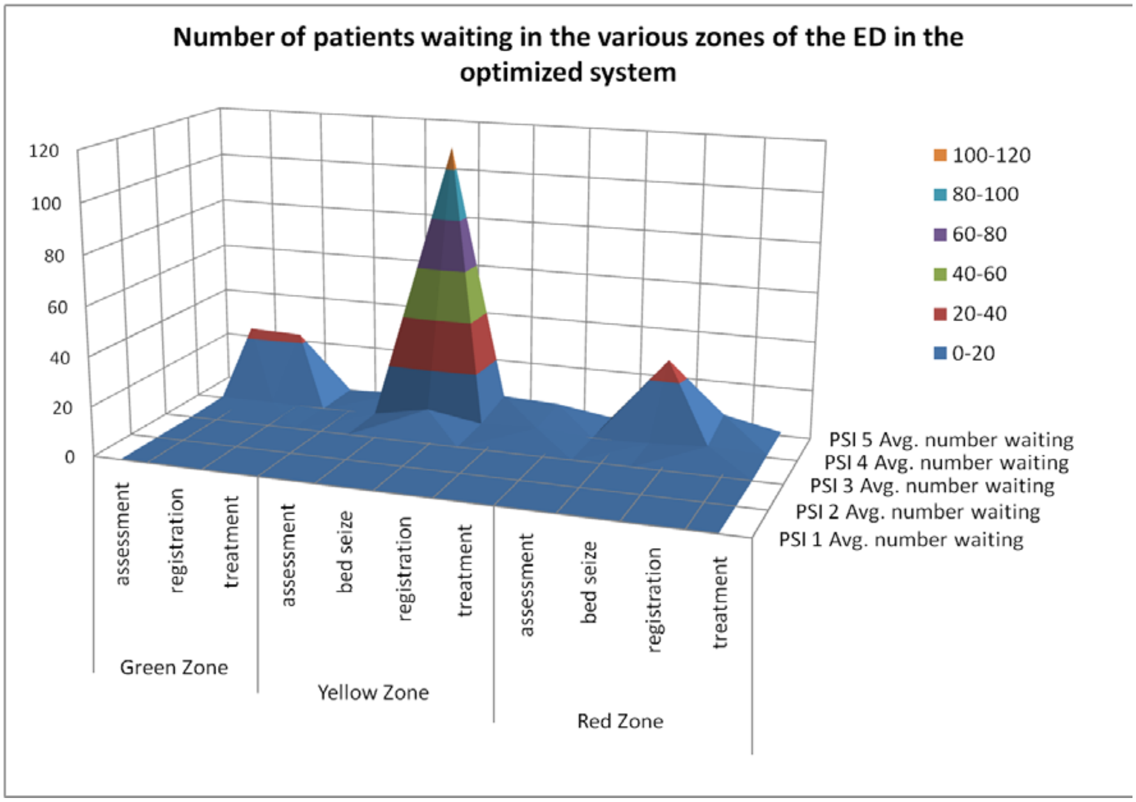


Figure 28: Number of Patients Waiting in the Various Zones of the ED in the Optimized System

Conclusions

A simulation model that replicates the dynamics in the ED during a pandemic influenza outbreak was created. The main goal for this model was to assess the system capacity and capabilities to respond to this type of disaster. It was found that the most critical zone was not the green zone which had the highest demand, or the red zone that treated the most ill patients, but it was the yellow zone that showed larger resource utilization for the nurses and queue length and waiting times. After the system was optimized, a new allocation was determined by assigning a percentage of total available nurses to each zone in the ED. The results were favorable; moreover, number of patients waiting in queue, and waiting times were reduced about 90% in the yellow zone. Also, the resource utilization for the nurses in the various zones was more balance throughout the system. This study corroborates the argument of how important nurses are in the healthcare delivery, and by concentrating on this resource, the quality and efficiency of the system improves. This study is intended to help policy makers in the process of making decisions on how to allocate resources, and improve efficiency of the system.

Future Research

Research on the area of allocation of resources can be expanded to other critical areas of the hospital such as physicians, vaccines, antiviral medications, beds, and ventilators. These resources are also very critical for the operation of the hospital during pick patient demand scenarios.

Hospital managers make very complex decisions. But in cases of mass casualty events where there does not exit enough experience, the process of decision-making turns come complex; thus, it is essential to use computer support systems to evaluate policies, and the potential impact on the hospital performance. These policies include: when to discharge a patient? How often treatment should be delivered?

The scope can also be expanded to other institutions that are affected by the emergence of pandemic influenza virus such as transportation systems, schools and airports so strategies can be planned ahead by simulating theses systems.

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APPENDICES

Appendix A: World Health Organization Pandemic Phases

WHO Phases	
INTER-PANDEMIC PERIOD	
1	No new influenza virus subtypes have been detected in humans. An influenza virus subtype that has caused human infection may be present in animals. If present in animals, the risk of human disease is considered to be low.
2	No new influenza virus subtypes have been detected in humans. However, a circulating animal influenza virus subtype poses a substantial risk of human disease.
PANDEMIC ALERT PERIOD	
3	Human infection(s) with a new subtype, but no human-to-human spread, or at most rare instances of spread to a close contact.
4	Small cluster(s) with limited human-to-human transmission but spread is highly localized, suggesting that the virus is not well adapted to humans.
5	Larger cluster(s) but human-to-human spread still localized, suggesting that the virus is becoming increasingly better adapted to humans, but may not yet be fully transmissible (substantial pandemic risk).
PANDEMIC PERIOD	
6	Pandemic phase: increased and sustained transmission in general population.

Figure 29: WHO Pandemic Phases

Appendix B: Percentage of Visits for Influenza-like Illness Reported by Sentinel Providers, National Summary 2007-08 and Previous 2 Seasons

Table 14: Percentage of Visits for Influenza-like Illness

CDC Week (YYYY WW)	%ILI from Sentinel Providers	%ARI from DOD/ VA	Sentinel Provider Baseline	DoD/ VA Base line	CDC Week (YYYY WW)	%ILI from Sentinel Providers	%ARI from DOD/ VA	Sentinel Provider Baseline	DoD/ VA Baseli ne
2005-40	1.2	2.16	2.2	3.2	**2007-04**	2.777	2.73	2.2	3.2
2005-41	1.218	2.13	2.2	3.2	**2007-05**	3.031	3.12	2.2	3.2
2005-42	1.298	2.18	2.2	3.2	**2007-06**	3.533	3.33	2.2	3.2
2005-43	1.345	2.3	2.2	3.2	**2007-07**	3.55	3.32	2.2	3.2
2005-44	1.592	2.37	2.2	3.2	**2007-08**	3.28	3.38	2.2	3.2
2005-45	1.47	2.52	2.2	3.2	**2007-09**	2.891	3	2.2	3.2
2005-46	1.608	2.43	2.2	3.2	**2007-10**	2.628	2.91	2.2	3.2
2005-47	1.84	2.83	2.2	3.2	**2007-11**	2.517	2.65	2.2	3.2
2005-48	1.76	2.81	2.2	3.2	**2007-12**	2.098	2.52	2.2	3.2
2005-49	1.942	2.94	2.2	3.2	**2007-13**	1.85	2.24	2.2	3.2
2005-50	2.357	3.17	2.2	3.2	**2007-14**	1.393	2.16	2.2	3.2
2005-51	2.962	3.59	2.2	3.2	**2007-15**	1.455	2.22	2.2	3.2
2005-52	3.262	4.36	2.2	3.2	**2007-16**	1.14	2.14	2.2	3.2
2006-01	2.607	3.59	2.2	3.2	**2007-17**	1.057	2.01	2.2	3.2
2006-02	2.248	2.82	2.2	3.2	**2007-18**	0.986	1.88	2.2	3.2
2006-03	2.357	2.89	2.2	3.2	**2007-19**	1.041	1.84	2.2	3.2
2006-04	2.407	2.84	2.2	3.2	**2007-20**	0.931	1.8	2.2	3.2
2006-05	2.52	3.03	2.2	3.2	**2007-21**	0.951	1.73	2.2	3.2
2006-06	2.656	3.19	2.2	3.2	**2007-22**	0.972	1.82	2.2	3.2
2006-07	3.125	3.26	2.2	3.2	**2007-23**	0.724	1.58	2.2	3.2
2006-08	3.103	3.47	2.2	3.2	**2007-24**	0.824	1.5	2.2	3.2
2006-09	3.165	3.15	2.2	3.2	**2007-25**	0.778	1.47	2.2	3.2
2006-10	3.096	3.08	2.2	3.2	**2007-26**	0.809	1.46	2.2	3.2
2006-11	2.654	2.86	2.2	3.2	**2007-27**	0.662	1.69	2.2	3.2
2006-12	2.42	2.82	2.2	3.2	**2007-28**	0.616	1.46	2.2	3.2
2006-13	2.364	2.76	2.2	3.2	**2007-29**	0.609	1.33	2.2	3.2
2006-14	1.868	2.5	2.2	3.2	**2007-30**	0.63	1.19	2.2	3.2
2006-15	1.46	2.27	2.2	3.2	**2007-31**	0.576	1.13	2.2	3.2
2006-16	1.317	2.2	2.2	3.2	**2007-32**	0.657	1.46	2.2	3.2
2006-17	1.151	2	2.2	3.2	**2007-33**	0.674	1.48	2.2	3.2
2006-18	1.074	2	2.2	3.2	**2007-34**	0.835	1.42	2.2	3.2
2006-19	1.048	1.97	2.2	3.2	**2007-35**	0.638	1.61	2.2	3.2
2006-20	1.025	1.96	2.2	3.2	**2007-36**	0.959	1.95	2.2	3.2
2006-21	0.913	1.86	2.2	3.2	**2007-37**	1.032	1.9	2.2	3.2
2006-22	0.958	1.89	2.2	3.2	**2007-38**	1.043	1.95	2.2	3.2
2006-23	0.869	1.67	2.2	3.2	**2007-39**	1.143	1.96	2.2	3.2
2006-24	0.79	1.61	2.2	3.2	**2007-40**	1.003	1.92	2.2	3.2
2006-25	0.776	1.6	2.2	3.2	**2007-41**	1.224	2.01	2.2	3.2
2006-26	0.725	1.53	2.2	3.2	**2007-42**	1.286	1.83	2.2	3.2

Appendix B: (continued)

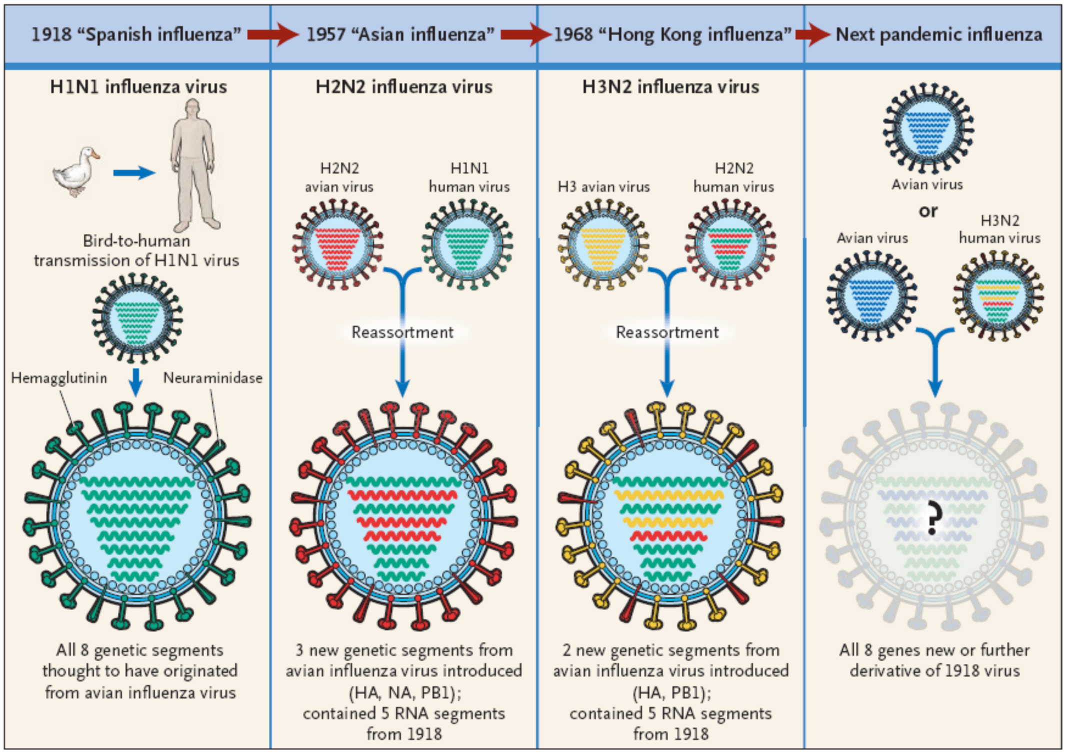
2006-30	**0.635**	**1.44**	**2.2**	**3.2**	**2007-46**	**1.633**	**2.24**	**2.2**	**3.2**
2006-31	0.609	1.42	2.2	3.2	**2007-47**	1.829	2.42	2.2	3.2
2006-32	0.687	1.46	2.2	3.2	**2007-48**	1.628	2.42	2.2	3.2
2006-33	0.616	1.59	2.2	3.2	**2007-49**	1.645	2.44	2.2	3.2
2006-34	0.599	1.73	2.2	3.2	**2007-50**	1.714	2.49	2.2	3.2
2006-35	0.621	1.8	2.2	3.2	**2007-51**	1.95	2.63	2.2	3.2
2006-36	0.801	2.08	2.2	3.2	**2007-52**	2.546	3.7	2.2	3.2
2006-37	0.773	1.99	2.2	3.2	**2008-01**	2.447	3.39	2.2	3.2
2006-38	0.806	2.14	2.2	3.2	**2008-02**	2.307	2.56	2.2	3.2
2006-39	0.787	2.1	2.2	3.2	**2008-03**	2.654	2.52	2.2	3.2
2006-40	1.146	2.08	2.2	3.2	**2008-04**	3.971	3.03	2.2	3.2
2006-41	1.148	2.02	2.2	3.2	**2008-05**	5.031	3.28	2.2	3.2
2006-42	1.225	2.05	2.2	3.2	**2008-06**	5.743	3.52	2.2	3.2
2006-43	1.208	2.07	2.2	3.2	**2008-07**	5.964	3.54	2.2	3.2
2006-44	1.312	2.13	2.2	3.2	**2008-08**	5.623	3.72	2.2	3.2
2006-45	1.453	2.37	2.2	3.2	**2008-09**	4.499	3.3	2.2	3.2
2006-46	1.523	2.26	2.2	3.2	**2008-10**	3.828	3.05	2.2	3.2
2006-47	1.884	2.59	2.2	3.2	**2008-11**	3.219	2.74	2.2	3.2
2006-48	1.795	2.6	2.2	3.2	**2008-12**	2.538	2.57	2.2	3.2
2006-49	1.959	2.69	2.2	3.2	**2008-13**	2.073	2.49	2.2	3.2
2006-50	2.378	2.84	2.2	3.2	**2008-14**	1.673	2.23	2.2	3.2
2006-51	2.836	2.96	2.2	3.2	**2008-15**	1.313	2.08	2.2	3.2
2006-52	2.982	3.84	2.2	3.2	**2008-16**	1.135	2.06	2.2	3.2
2007-01	2.372	3.3	2.2	3.2	**2008-17**	0.981	1.94	2.2	3.2
2007-02	2.081	2.65	2.2	3.2	**2008-18**	0.87	1.91	2.2	3.2
2007-03	2.275	2.68	2.2	3.2	**2008-19**	0.824	1.8	2.2	3.2
					2008-20	0.802	1.78	2.2	3.2

Appendix C: Neural Networks code

```
%##############################################################
%############### Neural Networks Forecasting ###################
%######### Application: Patient Demand due to seasonal influenza ###
%##############################################################
% The data needs to be separated into two subsets: testing data and validation data
% The testing data would be used to train the network and the validation data would
%be used to test network
% Data for y: years, w: weeks, d: demand is loaded...
g=(unidrnd(2,13,1));
k=0;
for i=1:13
for c=1:4
k=k+1;
vec(k)=i;
vec2(k)=g(i);
end
end
data=[ y w d vec' vec2'];

for i=1:1 %FOR EACH VALIDATION SET
valid=data(find(data(:,5)==i),1:3);
clear tdata
z=0;
for j=1:2%TRAINING DATA SET
if i ~=j
z=z+1;
if z==1
tdata=data(find(data(:,5)==j),1:3);
else
tdata=[tdata;data(find(data(:,5)==j),1:3)];
end
end
end
%*****************Neural Networks building*************************
p=tdata(:,2)';
t=tdata(:,3)';
val.P=valid(:,2)';
val.T=valid(:,3)';
net=newff(minmax(p),[3,1],{'tansig','purelin'},'trainlm');
net.trainParam.show = 25;
net.trainParam.epochs = 400;
net = init(net);
[net,tr]=train(net,p,t);
%END NN############################################
```

Appendix D: Mechanisms of Pandemic Virus Origination



The Two Mechanisms whereby Pandemic Influenza Originates.

In 1918, an H1N1 virus closely related to avian viruses adapted to replicate efficiently in humans. In 1957 and in 1968, reassortment events led to new viruses that resulted in pandemic influenza. The 1957 influenza virus (Asian influenza, an H2N2 virus) acquired three genetic segments from an avian species (a hemagglutinin, a neuraminidase, and a polymerase gene, PB1), and the 1968 influenza virus (Hong Kong influenza, an H3N2 virus) acquired two genetic segments from an avian species (hemagglutinin and PB1). Future pandemic strains could arise through either mechanism.

Figure 30: Mechanisms of Pandemic Origination

Appendix E: Statistical Test of MAD

- Comparison for MAD metric performance between **Seasonal Decomposition and the Fourier series:**

H_0: $\mu_1 = \mu_2$
H_A: $\mu_1 \neq \mu_2$

	N	Mean	Std Dev.	95% CI
Seasonal Decomposition	127	2.877	3.97	
Fourier Series	137	3.664	5.63	

t-test	0.095752
sp	4.906095
v	249.2501

T-Test of mean difference = 0 (vs not = 0): T-Value = 0.0957 P-Value = 0.18821
Based on this, there is no evidence to reject H_0: $\mu_1 = \mu_2$.
Where: μ_1 and μ_2 represent the Mean Absolute Deviation (MAD) for Seasonal Decomposition and regression analysis methods (Fourier series).
.

- Comparison for MAD metric performance between **Seasonal Decomposition and Neural Networks:**

H_0: $\mu_1 = \mu_2$
H_A: $\mu_1 \neq \mu_2$

	N	Mean	Std Dev.	95% CI
Seasonal Decomposition	127	2.877	3.971	
Neural Network	137	3.560	5.027	

t-test	0.077332
sp	4.550612
v	262.0108

T-Test of mean difference = 0 (vs not = 0): T-Value = 0.077 P-Value = 0.2202
Based on this, there is no evidence to reject H_0: $\mu_1 = \mu_2$.
Where: μ_1 and μ_2 represent the Mean Absolute Deviation (MAD) for Seasonal Decomposition and Neural Networks.

Appendix E: (continued)

- Comparison for MAD metric performance between **Neural Networks and regression analysis:**

H_0: $\mu_1 = \mu_2$

H_A: $\mu_1 \neq \mu_2$

	N	Mean	Std Dev.	95% CI
Neural Networks	137	3.56	5.027	±0.8494
Fourier Series	137	3.66	5.635	±0.9520

t-test	0.012628
Sp	5.339966
v	268.5372

95% CI for mean difference: (-0.477, 0.686)

T-Test of mean difference = 0 (vs not = 0): T-Value = 0.012 P-Value = 0.87

Based on this, there is no evidence to reject H_0: $\mu_1 = \mu_2$.

Where μ_1 and μ_2 represent the MAD yielded by Neural Network and regression analysis method respectively.

Appendix F: Assumptions for Pandemic Influenza Impact

The following tables document estimates of potential severe pandemic impacts to the State of Florida, with estimates based on planning assumptions derived from the HHS Pandemic Influenza Plan (November 2005):

Table 1: Pandemic Influenza Impact, Florida 2006

	%	Florida
Attack Rate	35%	6.41 million
Seeking Treatment	75% of cases	4.8 million
Hospitalization Rate	10%	640,000
Case Fatality Rate	2%	128,000

Table 2: Impact on Healthcare System
with no antiviral medication

Characteristics	In Each of 1st Wave and 2nd Wave	Florida
Cases	3.2 million	6.4 million
Hospitalized (10% of cases)	320,000	640,000
Surge Beds (130%)	65,000	135,000
ICU Total	48,000	96,000
ICU Ventilators	24,000	48,000
Surge Ventilators	5,000	10,000
Case Fatality Rate (2%)	64,000	128,000

Table 3. Impact on Healthcare System
with antiviral medication for 20%-25% of population*

Characteristics	In Each of 1st Wave and 2nd Wave	Florida
Hospitalized	80,000 – 160,000	160,000 - 320,000
Surge Beds	20,000 – 32,500	40,000 – 65,000
Surge Ventilators	1,500 – 2,500	3,000 – 5,000
Case Fatality Rate	16,000 - 32,000	32,000 - 64,000

*Assumes 50%-75% reduction in number of hospitalizations/fatalities

These impact estimates are based on a standard statistical model that does not consider differences in healthcare systems, practice patterns or healthcare-seeking behavior in Florida. Other statistical models that estimate impacts are available. Nonetheless, these tables provide an overview of the potential magnitude and impact of the next influenza pandemic in Florida. Estimates using Flu Aid, specialized software developed by the Centers for Disease Control and Prevention (CDC), can be viewed at http://www.pandemicflu.gov/plan/tools.html.

Figure 31: Assumptions for the Pandemic Influenza Impact

Appendix G: Number of beds per hospital in Tampa

Table 15: Number of beds per Hospital in Tampa

Hospital	**Number of beds**	**Capacity**
Tampa General Hospital	877	36.03%
University Community Hospital	431	17.71%
James A. Haley Veterans' Hospital	**327**	**13.43%**
St Joseph's Hospital	309	12.70%
Town & Country Hospital	201	8.26%
Memorial Hospital Of Tampa	180	7.40%
University Community Hospital At Carrollwood	109	4.48%
Total Number of Beds - Hillsborough County - Tampa	*2434*	

Appendix H: Weekly demand of patients for five scenarios

Table 16: Demand of Patients by Week

week	PSI1	PSI2	PSI3	PSI4	PSI5
KPPC	**1**	**6.8**	**13.6**	**27.2**	**54.3**
40	12.4	84.4	168.7	337.4	673.6
41	13.1	89.0	178.0	356.1	710.8
42	14.0	95.0	189.9	379.8	758.3
43	15.0	102.3	204.6	409.2	816.9
44	16.3	111.1	222.2	444.4	887.1
45	17.8	121.3	242.6	485.2	968.6
46	19.5	132.8	265.6	531.3	1060.6
47	21.4	145.4	290.9	581.7	1161.3
48	23.4	158.9	317.7	635.5	1268.6
49	25.4	172.8	345.5	691.1	1379.6
50	27.5	186.7	373.4	746.9	1491.1
51	29.5	200.3	400.6	801.1	1599.3
52	31.3	213.0	425.9	851.8	1700.5
1	33.0	224.3	448.6	897.2	1791.1
2	34.4	233.9	467.7	935.5	1867.6
3	35.5	241.3	482.6	965.1	1926.7
4	36.2	246.2	492.4	984.8	1965.9
5	36.5	248.4	496.8	993.6	1983.5
6	36.4	247.7	495.5	990.9	1978.2
7	35.9	244.2	488.4	976.7	1949.8
8	35.0	237.8	475.6	951.3	1899.0
9	33.7	228.8	457.7	915.3	1827.3
10	32.0	217.5	435.0	870.1	1736.9
11	30.0	204.2	408.5	816.9	1630.9
12	27.9	189.4	378.8	757.7	1512.6
13	25.5	173.6	347.1	694.3	1386.0
14	23.1	157.2	314.4	628.7	1255.1
15	20.7	140.8	281.6	563.1	1124.2
16	18.4	124.9	249.7	499.5	997.1
17	16.2	109.9	219.7	439.5	877.4
18	14.1	96.2	192.4	384.8	768.1
19	12.4	84.1	168.3	336.6	671.9
20	10.9	73.9	147.9	295.7	590.4
21	9.7	65.7	131.4	262.8	524.6
22	8.7	59.5	118.9	237.9	474.8
23	8.1	55.2	110.4	220.7	440.6
24	7.8	52.7	105.4	210.8	420.9
25	7.6	51.8	103.7	207.4	414.0

Appendix I: Time estimates for the processes held in the ED.

- Processing times (minutes) using a triangular distribution (Patvivatsiri 2006)

Table 17: Processing Times

Activity	Red Area	Yellow Area	Green Area
Bedside Registration	(15,20,25)	(15,20,25)	(15,20,25)
Baseline assessment	(7,12,15)	(7,12,15)	(7,12,15)
MD evaluation (delay)	(15,25,40)	(8,15,30)	(5,15,25)
Nursing Treatment	(30,50,120)	(30,50,90)	(15,30,60)

Appendix J: Snapshot of simulation animation

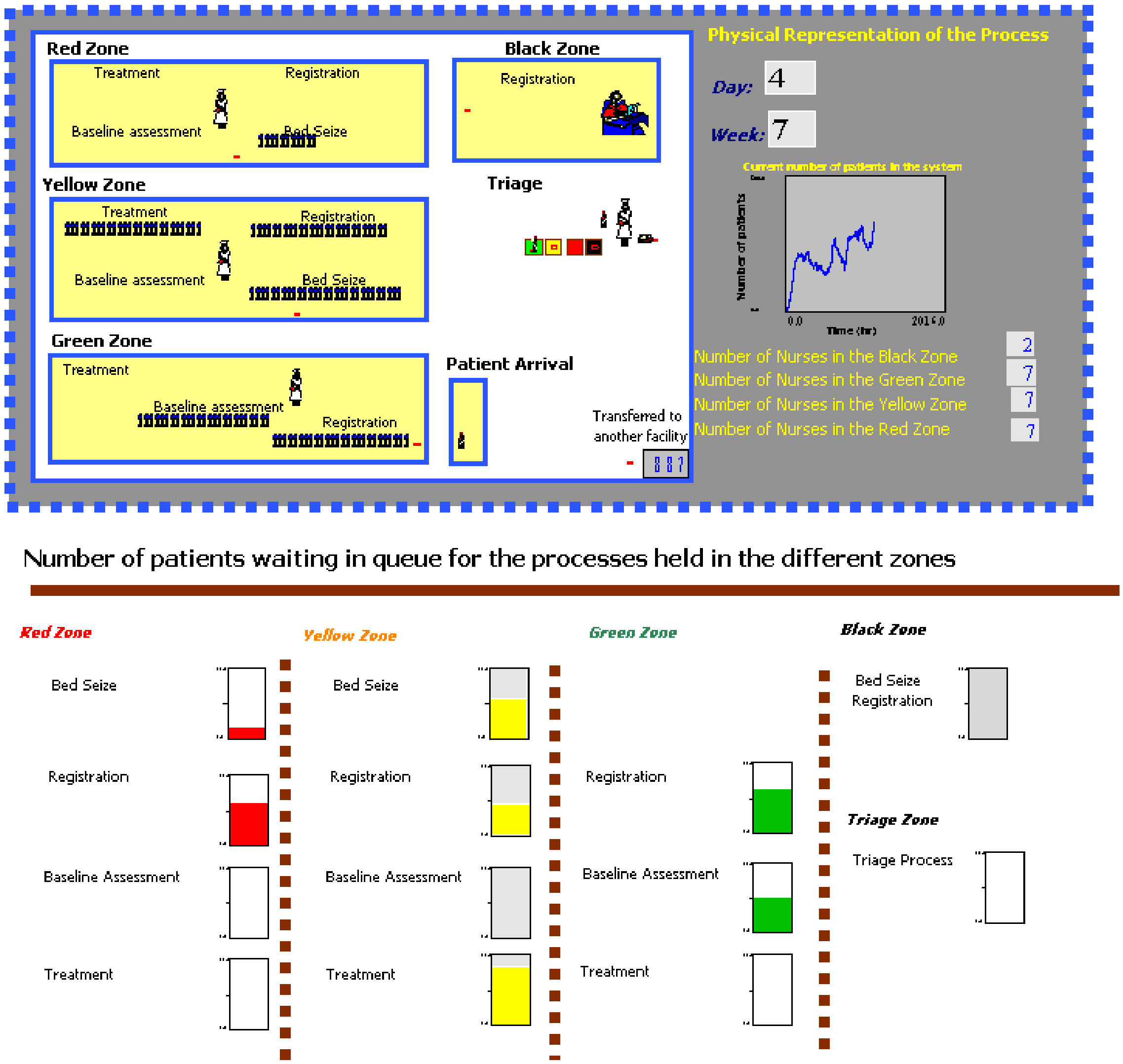


Figure 32: Snapshot of Simulation Animation

Appendix K: SIMAN simulation summary report

ARENA Simulation Results
Summary for Replication 5 of 5
Project: Unnamed Project Run execution date : 6/29/2009
Analyst: Florentino Rico Model revision date: 6/29/2009
Replication ended at time : 2016.0 Hours
Base Time Units: Hours

TALLY VARIABLES

Identifier	Average	Half Width	Minimum	Maximum	Observations
Time in Red Zone	223.78	(Insuf)	195.99	256.03	126
Cycle time for Black People	18.761	(Insuf)	12.536	24.243	137
Cycle time for Red Patients	223.83	(Insuf)	196.04	256.06	126
Time in Green Zone	1.9810	.04576	.76149	3.7033	1883
Time in Yellow Zone	148.31	.21076	144.29	153.90	696
Cycle time for Green Patients	2.0290	.04585	.80718	3.7527	1883
Cycle time for Yellow Patients	148.35	.21075	144.34	153.95	696
Entity 1.VATime	.04791	3.1376E-04	.02401	.07445	2842
Entity 1.NVATime	.00000	.00000	.00000	.00000	2842
Entity 1.WaitTime	12.227	2.4081	.00000	108.25	2842
Entity 1.TranTime	.00000	.00000	.00000	.00000	2842
Entity 1.OtherTime	36.229	4.9355	.76149	256.03	2842
Entity 1.TotalTime	48.505	5.8177	.80718	256.06	2842
Entity 2.VATime	--	--	--	--	0
Entity 2.NVATime	--	--	--	--	0
Entity 2.WaitTime	--	--	--	--	0
Entity 2.TranTime	--	--	--	--	0
Entity 2.OtherTime	--	--	--	--	0
Entity 2.TotalTime	--	--	--	--	0
Seizing nurse and bed in Black zone.Queue.	.00000	(Insuf)	.00000	.00000	138
R_assessment.Queue.WaitingTime	.00000	(Insuf)	.00000	.00000	137
Y_assessment.Queue.WaitingTime	4.9622	.91262	.00000	48.620	734
Y_Bed_Seize.Queue.WaitingTime	.00000	.00000	.00000	.00000	736
G_assessment.Queue.WaitingTime	7.1185E-04	.00147	.00000	.26842	1883
Triage Process.Queue.WaitingTime	.00000	.00000	.00000	.00000	2894
R_Treatment_Seize.Queue.WaitingTime	4.8617E-06	1.0022E-05	.00000	.03501	7201
Patients transferring to zones.Queue.Waiti	.00000	.00000	.00000	.00000	2894
R_Bed_Seize.Queue.WaitingTime	.00000	(Insuf)	.00000	.00000	137
Y_registration.Queue.WaitingTime	27.260	6.1539	.00000	87.930	736
R_registration.Queue.WaitingTime	.00000	(Insuf)	.00000	.00000	137
B_nurse_serize.Queue.WaitingTime	.00000	(Insuf)	.00000	.00000	138
G_Treatment_Seize.Queue.WaitingTime	.00000	.00000	.00000	.00000	1883
Y_Treatment_Seize.Queue.WaitingTime	1.1406	.19503	.00000	5.0907	10767
G_registration.Queue.WaitingTime	4.6187E-04	6.3822E-04	.00000	.20801	1883

Appendix K: (Continued)

DISCRETE-CHANGE VARIABLES

Identifier	Average	Half Width	Minimum	Maximum	Final Value
Number of Patients in Black Zone	1.2725	(Insuf)	.00000	6.0000	1.0000
Number of Patients in Yellow Zone	384.39	(Corr)	.00000	736.00	736.00
Number of Patients in Green Zone	969.09	(Corr)	.00000	1883.0	1883.0
Number of Patients in Red Zone	69.138	(Insuf)	.00000	137.00	137.00
Entity 1.WIP	70.798	(Corr)	.00000	97.000	52.000
Entity 2.WIP	1.0000	(Insuf)	.00000	1.0000	1.0000
Black zone_bed.NumberBusy	1.2725	(Insuf)	.00000	6.0000	1.0000
Black zone_bed.NumberScheduled	6000.0	(Insuf)	6000.0	6000.0	6000.0
Black zone_bed.Utilization	2.1209E-04	(Insuf)	.00000	.00100	1.6667E-04
Yellow zone_nurse.NumberBusy	15.474	(Corr)	.00000	21.000	15.000
Yellow zone_nurse.NumberScheduled	16.000	(Insuf)	15.000	21.000	15.000
Yellow zone_nurse.Utilization	.97487	(Corr)	.00000	1.0000	1.0000
Red zone_nurse.NumberBusy	4.0392	(Corr)	.00000	15.000	2.0000
Red zone_nurse.NumberScheduled	17.000	(Insuf)	15.000	21.000	21.000
Red zone_nurse.Utilization	.24663	(Corr)	.00000	1.0000	.09524
Black zone_nurse.NumberBusy	.02272	(Insuf)	.00000	2.0000	.00000
Black zone_nurse.NumberScheduled	40.000	(Insuf)	40.000	40.000	40.000
Black zone_nurse.Utilization	5.6812E-04	(Insuf)	.00000	.05000	.00000
Red zone_bed.NumberBusy	14.539	(Insuf)	.00000	28.000	11.000
Red zone_bed.NumberScheduled	40.000	(Insuf)	40.000	40.000	40.000
Red zone_bed.Utilization	.36348	(Insuf)	.00000	.70000	.27500
Yellow zone_bed.NumberBusy	53.067	(Corr)	.00000	72.000	40.000
Yellow zone_bed.NumberScheduled	111.00	(Insuf)	111.00	111.00	111.00
Yellow zone_bed.Utilization	.47809	(Corr)	.00000	.64865	.36036
Green zone_nurse.NumberBusy	2.0071	(Corr)	.00000	17.000	.00000
Green zone_nurse.NumberScheduled	16.000	(Insuf)	15.000	21.000	21.000
Green zone_nurse.Utilization	.12709	(Corr)	.00000	1.0000	.00000
triage_nurse.NumberBusy	.06875	(Corr)	.00000	3.0000	.00000
triage_nurse.NumberScheduled	7.0000	(Insuf)	7.0000	7.0000	7.0000
triage_nurse.Utilization	.00982	(Corr)	.00000	.42857	.00000
Seizing nurse and bed in Black zone.Queue.	.00000	(Insuf)	.00000	.00000	.00000
R_assessment.Queue.NumberInQueue	.00000	(Insuf)	.00000	.00000	.00000
Y_assessment.Queue.NumberInQueue	1.8076	.39363	.00000	30.000	2.0000
Y_Bed_Seize.Queue.NumberInQueue	.00000	(Insuf)	.00000	.00000	.00000
G_assessment.Queue.NumberInQueue	6.6489E-04	(Insuf)	.00000	3.0000	.00000
Triage Process.Queue.NumberInQueue	.00000	(Insuf)	.00000	.00000	.00000
R_Treatment_Seize.Queue.NumberInQueue	1.7366E-05	(Insuf)	.00000	1.0000	.00000
Patients transferring to zones.Queue.Numbe	.00000	(Insuf)	.00000	.00000	.00000
R_Bed_Seize.Queue.NumberInQueue	.00000	(Insuf)	.00000	.00000	.00000
Y_registration.Queue.NumberInQueue	9.9524	2.0751	.00000	32.000	.00000
R_registration.Queue.NumberInQueue	.00000	(Insuf)	.00000	.00000	.00000
B_nurse_serize.Queue.NumberInQueue	.00000	(Insuf)	.00000	.00000	.00000
G_Treatment_Seize.Queue.NumberInQueue	.00000	(Insuf)	.00000	.00000	.00000
Y_Treatment_Seize.Queue.NumberInQueue	6.0921	1.0385	.00000	29.000	2.0000

Appendix K: (Continued)

G_registration.Queue.NumberInQueue	4.3140E-04 (Insuf)	.00000	3.0000	.00000

COUNTERS

Identifier	Count	Limit
Numbe system in	2894	Infinite
transferred patients	0	Infinite
yellow_patient_out	696	Infinite
green_patient_in	1883	Infinite
red_patient_out	126	Infinite
green_patient_out	1883	Infinite
yellow_patient_in	736	Infinite
patients_admitted	2894	Infinite
red_patient_in	137	Infinite

OUTPUTS

Identifier	Value
Entity 1.NumberIn	2894.0
Entity 1.NumberOut	2842.0
Entity 2.NumberIn	1.0000
Entity 2.NumberOut	.00000
Black zone_bed.NumberSeized	138.00
Black zone_bed.ScheduledUtilization	2.1209E-04
Yellow zone_nurse.NumberSeized	35243.
Yellow zone_nurse.ScheduledUtilization	.96714
Red zone_nurse.NumberSeized	7749.0
Red zone_nurse.ScheduledUtilization	.23760
Black zone_nurse.NumberSeized	138.00
Black zone_nurse.ScheduledUtilization	5.6812E-04
Red zone_bed.NumberSeized	137.00
Red zone_bed.ScheduledUtilization	.36348
Yellow zone_bed.NumberSeized	736.00
Yellow zone_bed.ScheduledUtilization	.47809
Green zone_nurse.NumberSeized	13181.
Green zone_nurse.ScheduledUtilization	.12544
triage_nurse.NumberSeized	2894.0
triage_nurse.ScheduledUtilization	.00982
System.NumberOut	2842.0

Appendix K: (Continued)

ARENA Simulation Results
ITS Department
Output Summary for 5 Replications

Project: Unnamed Project — Run execution date : 6/29/2009
Analyst: Florentino Rico — Model revision date: 6/29/2009

OUTPUTS

Identifier	Average	Half-width	Minimum	Maximum	# Replications
Entity 1.NumberIn	2901.0	54.220	2842.0	2965.0	5
Entity 1.NumberOut	2839.4	46.156	2779.0	2881.0	5
Entity 2.NumberIn	1.0000	.00000	1.0000	1.0000	5
Entity 2.NumberOut	.00000	.00000	.00000	.00000	5
Black zone_bed.NumberSeized	140.60	11.959	130.00	153.00	5
Black zone_bed.ScheduledUtilization	2.1575E-04	1.4112E-05	2.0382E-04	2.3037E-04	5
Yellow zone_nurse.NumberSeized	34774.	553.19	34326.	35243.	5
Yellow zone_nurse.ScheduledUtilization	.95910	.01278	.94450	.96977	5
Red zone_nurse.NumberSeized	7911.8	650.48	7434.0	8569.0	5
Red zone_nurse.ScheduledUtilization	.24307	.01921	.22933	.26244	5
Black zone_nurse.NumberSeized	140.60	11.959	130.00	153.00	5
Black zone_nurse.ScheduledUtilization	5.7867E-04	5.0374E-05	5.3223E-04	6.3146E-04	5
Red zone_bed.NumberSeized	139.00	10.679	130.00	148.00	5
Red zone_bed.ScheduledUtilization	.37148	.03039	.34949	.40249	5
Yellow zone_bed.NumberSeized	735.40	35.955	691.00	772.00	5
Yellow zone_bed.ScheduledUtilization	.47563	.02235	.44642	.49605	5
Green zone_nurse.NumberSeized	13193.	143.82	13097.	13391.	5
Green zone_nurse.ScheduledUtilization	.12552	.00128	.12467	.12730	5
triage_nurse.NumberSeized	2901.0	54.220	2842.0	2965.0	5
triage_nurse.ScheduledUtilization	.00992	2.4261E-04	.00965	.01016	5
System.NumberOut	2839.4	46.156	2779.0	2881.0	5

Simulation run time: 0.87 minutes.
Simulation run complete.

Appendix L: Queue length and waiting times for the current system

Table 18: Queue length and Waiting Times Results

		Green Zone			Yellow Zone				Red Zone			
		assessment	registration	treatment	assessment	bed seize	registration	treatment	assessment	bed seize	registration	treatment
PSI 1	Avg. waiting time (hrs)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Avg. number waiting	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
PSI 2	Avg. waiting time (hrs)	0.0	0.0	0.0	0.6	0.0	1.6	0.2	0.0	0.0	0.0	0.0
	Avg. number waiting	0.0	0.0	0.0	0.1	0.0	0.3	0.7	0.0	0.0	0.0	0.0
PSI 3	Avg. waiting time (hrs)	0.0	0.0	0.0	4.8	0.0	27.3	1.2	0.0	0.0	0.0	0.0
	Avg. number waiting	0.0	0.0	0.0	1.8	0.0	10.0	6.2	0.0	0.0	0.0	0.0
PSI 4	Avg. waiting time (hrs)	0.0	0.0	0.0	1.0	0.6	49.8	3.1	0.0	0.0	0.0	0.0
	Avg. number waiting	0.0	0.0	0.0	4.0	0.4	28.7	16.6	0.0	0.0	0.0	0.0
PSI 5	Avg. waiting time (hrs)	0.7	0.7	0.0	7.4	35.3	42.4	4.9	0.0	26.6	0.0	0.0
	Avg. number waiting	2.7	2.6	0.0	6.7	33.2	39.7	25.8	0.0	5.0	0.0	0.0