ACCOUNTING FOR INDIVIDUAL CHOICE IN PUBLIC HEALTH EMERGENCY RESPONSE PLANNING

by

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Abstract

During public health emergencies, organizations in charge require an immediate and efficient method of distributing supplies over a large scale area. Due to the uncertainty of where individuals will choose to receive supplies, these distribution strategies have to account for the unknown demand at each facility. Current techniques rely on population ratios or requests by health care providers. This can lead to an increased disparity in individuals' access to the medical supplies.

This research proposes a mathematical programming model, along with a solution methodology to inform distribution system planning for public health emergency response. The problem is motivated by distribution planning for pandemic influenza vaccines or countermeasures. The model uses an individual choice constraint to determine what facility the individual will choose to receive their supplies. This model also determines where to allocate supplies in order to meet the demand of each facility. The model was solved using a decomposition method. This method allows large problems to be solved quickly without losing equity in the solution. In the absence of publicly-available data on actual distribution plans from previous pandemic response efforts, the method is applied to another representative data set. A computational study of the equity and number of people served depict how the model performed compared to the actual data. The results show that implementing an individual choice constraint will improve the effectiveness of a public health emergency response campaign without losing equity.

The thesis provides several contributions to prior research. The first contribution is an optimization model that implements individual choice in a constraint. This determines where individuals will choose to receive their supplies so improved decisions can be made

about where to allocate the resources. Another contribution provided is a solution methodology to solve large problems using a decomposition method. This provides a faster response to the public health emergency by splitting the problem into smaller subproblems. This research also provides a computational study using a large data set and the impact of using a model that accounts for individual choice in a distribution campaign.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

This thesis introduces a new model and solution methodology to inform distribution system planning for public health emergency response. The work is motivated by the need to quickly and efficiently distribute supplies in events such as an influenza pandemic or other disease outbreak. The goals public health authorities want to achieve include maximizing the number of people who receive the supplies, while minimizing distance and waiting time. The response also needs to have an equitable solution such that everyone has an equal chance at receiving supplies. The current methods use simple population ratios or rely on health care providers requesting supplies to allocate the supplies. These methods do not account for individuals' choices on where they want to receive supplies. Incorporating individual choice into a mathematical program is a fundamental advancement of this thesis.

The research done in this thesis explores how accounting for the decision of where individuals choose to receive supplies impacts the distribution of the supplies. Examples of such items include vaccines, medical countermeasures, or other items needed during the response. The work is motivated by the 2009 H1N1 outbreak. The 2009 H1N1 outbreak was the second recorded pandemic involving the H1N1 strain, the first being the Spanish flu of 1918 [26]. Since the virus originated in pigs, the term swine flu was given to this new strain of H1N1; however, there was no link to show that contact with pigs caused the virus [5].

The outbreak was first identified in Veracruz, Mexico, in March 2009 [27]. This caused the schools, libraries, museums, and other public gathering places to be closed in an attempt to mitigate the spread of the virus. This attempt failed to stop the spread of the virus and the virus eventually made its way to the United States. By June 2009, the World Health Organization officially declared the outbreak a pandemic [9]. According to the United States Department of Health, a pandemic is “global disease outbreak and is determined by how the disease spreads, not how many deaths it causes. [28]

The virus was able to spread rapidly due to it being a new strain of the H1N1 virus, which meant humans had little to no immunity to the virus. Since it was a new strain, a new vaccine needed to be created. By October 2009 [6], a vaccine had been created and tested to be used in humans and the vaccination campaign began. Originally, there were massive shortages across the United States. This caused public health officials to urge citizens in the priority groups (pregnant woman, children, and elderly) to receive the vaccine [5].

Towards the end of December the vaccination campaign was open to all citizens. By January 2010, approximately 82.4 million vaccines had been administered [29]. Finally, in May 2010 flu activity levels were back to typical summer levels [6]. In all, approximately 18,000 [33] people had died worldwide.

1.1 Research Motivation

Since public health emergencies require an immediate and efficient response, it is necessary to create tools that can provide these immediate and efficient solutions. Due to the uncertainty of where individuals will choose to receive supplies, the distribution of the resources needs to take into account the decisions of these individuals. By accounting for these individual decisions, a public health planner will be able to distribute the supplies in an efficient manner.

There is a lack of research that takes into account the decisions individuals make in an optimization model. The majority of the research assumes individuals can be assigned to a given facility. However, this is not feasible in real-world applications because individuals can make decisions on where they want to receive their supplies. The research done in this thesis looks to showcase how accounting for these decisions will affect a response campaign.

1.2 Research Contributions

Current research on public health emergency response has thus far been focusing on setting up vaccination centers and distributing supplies to areas most in need. Since there is a lack of research that takes into account the decision of the consumers in a public health setting, the research conducted in this thesis takes into account individual choice on deciding where to receive their needed supplies. This contribution provides public health officials with the information on where their citizens will go to receive their supplies. This knowledge will allow the public health officials to properly allocate the supplies to these locations, thus allowing more people access to these products.

The second contribution to the prior research is a solution methodology to solve large problems. Since the response to the public health emergency needs to be immediate, one must be able to find a solution in a reasonable amount of time. The problem is that public health emergencies tend to be large in scale. This makes optimizing a model difficult due to the amount of data involved and will slow the response to the emergency. The problem instance investigated in this thesis ran for three weeks, in that time, no feasible solution was found. To repair this problem, this thesis describes a decomposition method to be used to solve large scale problems effectively. This decomposition method breaks the original problem into smaller subproblems in order to obtain a solution.

Finally, the research provides a computational study using data from a large scale distribution effort. Since data on actual distribution plans from previous pandemic response efforts are not publicly available, the method is applied to another representative data set. Distribution plans found by the model are compared to the results of the actual distribution of the product in the data set. The computational study investigates how the sequence in which subproblems are solved can affect the distribution of supplies. It also compares two sequences of subproblems to the actual distribution.

1.3 Outline

The remainder of the thesis is organized in the following way. Chapter 2 explores previous literature on public health preparedness, individual choice, waiting time, and equity. The chapter also explains the importance of each topic and how it relates to the research done in this thesis.

Chapter 3 explains the motivation behind the research and introduces a general model to optimize the distribution of supplies. The model includes the individual choice constraint. This constraint examines all the possible facilities each individual within a census tract could visit. The individual would then only be able to visit a facility if it is more beneficial to visit that facility as opposed to any other.

In Chapter 4, there is an explanation of how the general model was adapted for the data set and how the model decomposition method was used to solve the problem. The chapter provides step-by-step instructions on the decomposition method so that it can be adapted to be used for any large problem. Chapter 4 also discusses the results of the different decomposition methods and compares them to the actual distribution.

Finally, Chapter 5 summarizes the results gathered from Chapter 4. This chapter also provides the recommendations of this research and offers future research to be done.

Chapter 2

Literature Review

This research is motivated by logistics challenges that arise during public health emergencies, such as an influenza pandemic. According to Lee [18], one of those challenges is that public health emergencies require an immediate and efficient method of distributing antibiotic/antiviral medications, vaccines, or other needed supplies over a large scale area. Since individuals make autonomous choices about if and where they will go to receive supplies, these challenges are further complicated by uncertainty about their choices. Due to the uncertainty of where people will go, infrastructure amongst various forms of government and businesses involved in the response needs to be “flexible, scalable, sustainable, and elastic” [18]. This chapter summarizes several streams of literature that are relevant to this topic, including papers that apply operations research to public health preparedness, models that capture individual choice on deciding between facilities, methods for modeling waiting time in service systems, and procedures to measure equity of a system.

2.1 Applying Operations Research to Public Health Preparedness

Ever since the terrorist attacks of September 11, 2001, and the 2001 anthrax attacks, the United States federal government has put billions of dollars into improving the preparation for and response to public health emergencies [23]. According to Nelson, a public health emergency is any situation "whose scale, timing, or unpredictability threatens to overwhelm routine capabilities" [23]. The goal of an effective preparedness strategy is to mitigate the ill effects of these emergencies, which include pandemics, death, economic disruptions, and disruption in government activities. Such events can cost billions of dollars [14]. For the United States to have an effective strategy to prepare for and respond to these public health emergencies, the public health system in each state must be able to respond quickly and effectively. Each state's preparedness strategy will involve a "coordinated and continuous process of planning and implementation that relies on measuring performance and taking corrective action" [23]. The decisions that must be made include where to locate facilities to provide care to the people, how many resources to allocate at each facility, and how quickly the population must be served.

From this definition of preparedness and the decisions that need to be planned, it is apparent that operations research would be an effective tool to use to create these strategies. Operations research has the capability to create a coordinated strategy and be continuously improved. It also heavily relies on performance measures and can be adjusted to meet the constraints of the problem. Using the performance measures and constraints, operations research can find the optimal solution to the problem. This solution would be the most efficient and cost effective solution to the problem.

According to the CDC, "An influenza pandemic can occur when a non-human influenza virus gains the ability for efficient and sustained human-to-human transmission and then spreads globally" [7]. These pandemics are able to spread easily through the human population because there is little to no immunity to these viruses in humans [7]. This has led to the use of operations research to improve clinical planning and dispensing of the vaccine to curb the outbreak.

In previous research, a combination of simulation software and queueing models was used to create an efficient design to distribute supplies such as vaccines [1]. Most effort was put into the design of the POD (point of dispensing) layouts and choosing their locations [18]. These PODs are simply places where mass dispensing of supplies is done [11]. The researchers used simulation models to see how the changes made to the layout would affect the amount of time spent in the system. Using this data, they identified a better layout to the PODs and the researchers also created a program that allows them to enter in variables such as size of population, hours open, and the staffing level. The program then takes these inputs and, using queueing theory, determines the number of workers needed to operate the POD.

Operations research models have additionally been developed to advise public health policy and preparedness strategies related to bioterror attacks using anthrax [10] or smallpox [16], bioterror attacks on the food supply chain [30], and pandemic influenza [12, 13]. Researchers have stressed the importance of using these models in public health situations and how best to construct and report these models.

2.2 Individual Choice

As stated earlier, one of the most difficult aspects of using operations research to determine where to distribute emergency supplies is not knowing where people will go. Most traditional optimization models assume demands can be assigned to resources, for example job scheduling [31] and facility location models [19]. In the job scheduling model used by Rachaniotis [25], people were assigned to a specific medical team. Assigning people to specific distribution sites results in a simpler optimization model; however, the time and monetary resources needed to enforce assignment rules during a pandemic prevents this approach.

Few models in the literature specifically account for individual choice in disaster preparedness and response logistic problems. According to Knight [17], the main factors people use to choose amongst facilities are reputation, distance, and congestion. Using routing games, these authors were able to determine what facility an individual chose or if they would balk. However, since reputation and distance were held constant, the only thing that affected the choice was the congestion at each facility. This shows that congestion at a facility is an important factor in individuals' choices and demonstrates the impact of these choices.

In the article by Yi [34], the research modeled the logistics of delivering supplies or transporting wounded during a disaster. Instead of using an assignment solution, the model allowed the drivers to choose whether they would deliver the supplies to the necessary zone or if they would leave the supplies at a checkpoint in order to take wounded back to the hospital. If the supplies were left at a checkpoint then another truck needed to finish the delivery. This allowed them to create a more realistic model and create a solution that would help with the overall disaster relief. This research showed that implementing an individual choice constraint can improve the system; however, this research focused on the truck drivers' point of view, not that of public health officials.

In the models developed by Heier Stamm [15], the impact of individual choice on the efficiency of public health systems was measured. This research compared the system efficiency that resulted from individuals' choices to that of hypothetical assignments by a centralized planner. However, distribution policies were assumed to be fixed, instead of being decision variable in the model.

2.3 Waiting Time

Another difficulty of creating an accurate depiction of individuals' choices is determining the waiting time at the facilities and associated balking behavior. The waiting time is often used to model the congestion at the facility. Waiting time is often most accurately modeled as a nonlinear function of the number of people at a facility. Prior research has used various methods to accurately model waiting time without using a nonlinear formulation. These ways of depicting waiting time include modeling waiting time as a constraint and modeling waiting time in the objective function.

Baron et al. [3] put the waiting time as a constraint in the model for a single-server case and multiple server case. This constraint prevented the the probability of waiting in a queue for more than a certain time limit from exceeding a set level. In their single-server case, they proposed an M/G/1 approach to solving for the moment generating function (MGF) for the waiting time. The MGF was then inverted to find the probability distribution of the waiting times, which was then used to solve for the service rate. The problem with this is that the calculation would have to be solved numerically, thus creating an approximation on the bounds of the waiting time probability distribution. This provided them with accurate estimates of the capacity at each facility. In the multiple-server case [3], Baron first had to find the minimum number of servers that could be possible at the facilities. Once the minimum number of servers was found, the authors used this number to find bounds for the waiting time probability.

Marianov and Serra [20] also modeled waiting time as a constraint. However, their approach used a linear approximation for a single server case. The authors also created a linear equivalent of the waiting time probability distribution for multiple servers. Since both these models contain linear equivalents for solving waiting times, the authors were able to use commercial integer programming packages to solve these models. Heuristics were able to find solutions very close to and sometimes better than the integer programming software. This was due to the run-time/branching being limited. The heuristics performed quite well in terms of CPU time and solution quality.

Aboolian et al. [2] used waiting time in the objective function. This allows there to be no upper limit on the waiting time but tries to find a solution that minimizes the waiting time. This approach was used by other researchers; however, the problem of the nonlinear aspect of calculating the waiting time exists. Aboolian et al. [2] created a highly nonlinear integer program, due to the waiting time in the objective function. In order to bypass this problem the authors created a metahueristic to find a solution. The authors were also able to find an exact solution but the authors needed to ignore the server assignment cost. Since there was no longer a server assignment cost the problem became a typical uncapacitated facility location problem. This exact formulation performed well with small to medium sized data sets and when the waiting time cost was small.

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Overall, prior research showed that modeling waiting time requires heuristics or approximations. The model used in this thesis used an approximation for waiting time and was used as a measure of the equity of the solution.

2.4 Equity

Equity with respect to public health can be defined as "as equal access to available care for equal need, equal utilization for equal need, and equal quality of care for all" [32]. The need to establish an equitable solution is a major difference between public health models and typical operations research models. In typical operations research models, the model looks for the most efficient solution. An efficient solution is one that minimizes or maximizes the cost function over the entire population [24]. In a public health scenario, this would cause certain portions of the population to receive vastly lower quality of service. However, there are multiple methods to measure equity and no agreement on which method is the best [22]. According to the research done by Marsh and Schilling [21], several methods of measuring equity were analyzed. These methods include the mean absolute deviation, which has been used in facility location problems [4, 19] to develop an equitable solution. This measure was used for analyzing the equity of the solution for the H1N1 problem discussed in this thesis.

2.5 Summary

Overall, the prior research provided the background information needed to create an effective model to distribute supplies. The research showed that modeling for individual choices can be done and can provide a more realistic model. It also showed the importance to account for congestion and waiting time; however, without specific data on the facility size, the waiting time can not be accurately approximated. This meant that the waiting time would be used to analyze the equity of the solution. Finally, it showed the importance of accounting for equity and how it can be measured.

Chapter 3

Methods

This chapter introduces a mathematical programming model that determines where to distribute supplies during a public health emergency response, such as a pandemic. It begins first with motivation behind the model and the reasons for selecting the criteria used. Next, the optimization model is shown along with the explanation of the decision variables, parameters, and constraints. Finally, this chapter discusses how the model is used to evaluate the distribution of the supplies.

3.1 Motivation

This thesis considers the problem faced by a state public health agency in determining how best to allocate scarce supplies in a public health emergency response. The approach is general and can be adopted to fit any mass dispensing strategy; however, this thesis was motivated by the H1N1 pandemic so the discussion is from that perspective. The model used provides state policymakers insight on which facilities to distribute the supplies to and the quantity that each facility receives. There are several factors that need to be considered to create a realistic model. These factors include individual choice, waiting time, distance, total number of people served, and equity of the solution.

Individual choice is an important factor to consider for policymakers. By knowing where individuals would travel to receive supplies, policymakers can best allocate the supplies to those facilities. The factors that influence the individuals' choices include the distance to the facility, the number of people currently located there, and the supply at that facility. If there were a facility slightly further away but with less people, then a person may choose to travel the extra distance to receive their supplies at a faster rate. The same applies with a facility that has more supply. If the individual knows a facility has more supply, then they would travel to that facility because it provides them a better chance of being served.

Waiting time can influence individual choice. If people are under a time constraint, due to work or family, then they would want to receive their supplies as quickly as possible. This means an individual would choose a facility that allows them to quickly receive their supplies. This can be affected by the number of workers at the facility, the amount of supply, and the congestion of the facility. The reason policymakers should care about waiting time is to quickly stop the spread of the pandemic. Long waiting times can also lead to people balking and not receiving the supplies. Therefore it is important to ensure that the supplies are distributed as quickly as possible. These waiting times can also be used to analyze the equity of distribution of supplies by creating a solution where the waiting time is similar across facilities or communities.

In a pandemic, it is important that as many people receive the vaccine or other medical countermeasures as possible. This reduces the spread of the disease and allows a faster recovery from the pandemic. There are some people who are more susceptible to these diseases or may contribute most to their spread. Depending on the virus, these groups include pregnant woman, elderly, young children, and people with chronic health conditions. In the case of vaccination campaigns, it is extremely important that as many of these people as possible receive the vaccine. By prioritizing people in target groups, policymakers are able to lower the amount of casualties that pandemics can cause. Since people in these target groups are most at risk, targeting them limits the disease spread, morbidity, and mortality.

Finally, a good strategy is one that is equitable. This can be measured by ensuring that the average distance traveled amongst individuals who are served is approximately the same. This means that the population that is served travels about the same distance to receive their supplies. Another measure of equity is the fraction of people that receive the supplies from each census tract, which should be similar across census tracts. By ensuring this, there is no perceived favoritism amongst the population. Policymakers can also analyze the average waiting time throughout the system. This allows policymakers to visualize which facilities may need more workers to ensure that the service process runs smoothly.

3.2 Model

This section introduces a model to optimize the allocation of scarce supplies while accounting for individual choice and equity factors. This model maximizes the number of people served while minimizing the distance they travel. The primary decision variables in the model include the supply at a facility and the percentage of people from each census tract that go a given facility. The notation is summarized below:

<u>Decision Variables:</u>

s_k : Total supply at facility k

W_k : Total waiting time at facility k

y_{jk} : Percentage of people from census tract j receiving service at facility k

$$x_{jk} : \begin{cases} 1 & \text{If anyone from census tract } j \text{ is served at facility } k \\ 0 & \text{If else.} \end{cases}$$

Parameters:

N : Set of census tracts, $n = |N|$

L : Set of facilities, $l = |L|$

P_j : Population of census tract j

d_{jk} : Distance between census tract j and facility k

S : Total supply

α: Minimum percentage served

β: Benefit value

γ: Time value

M : Sufficiently large number

$$\text{Maximize} \quad \sum_{j=1}^{n} \sum_{k=1}^{l} P_j y_{jk}(\beta - d_{jk}) \tag{3.1}$$

$$\sum_{k=1}^{l} y_{jk} \leq 1 \qquad \forall j \in N \tag{3.2}$$

$$\sum_{j=1}^{n} P_j y_{jk} - s_k \leq 0 \qquad \forall k \in L \tag{3.3}$$

$$d_{jk} + \sum_{j=1}^{n} P_j y_{jk} - s_k \leq d_{ji} + \sum_{j=1}^{n} P_j y_{jl} - s_l + M(1 - x_{jk}) \qquad \forall j \in N \quad \forall k \in L \quad \forall l \in L \neq k \tag{3.4}$$

$$W_k = \sum_{j=1}^{n} \gamma P_j y_{jk} \qquad \forall j \in N \tag{3.5}$$

$$\sum_{k=1}^{l} y_{jk} \geq \alpha \qquad \forall j \in N \tag{3.6}$$

$$\sum_{k=1}^{l} s_k \leq S \tag{3.7}$$

$$y_{jk} \leq x_{jk} \qquad \forall j \in N \quad \forall k \in L \tag{3.8}$$

The continuous variable y_{jk} represents the percentage of the population from census tract j served at facility k. A continuous variable is selected to allow the model to capture the choices of small numbers of people while achieving improved computational tractibility as compared to an integer variable that corresponds to individual people. The binary variable x_{jk} equals 1 if someone from census tract j is served at facility k; otherwise the variable is equal 0. Integer variable s_k denotes how much supply is located at facility k. Finally, waiting time at facility k is represented by the continuous variable W_k.

After the variables are created, the parameters are added. The first parameter is the set of census tracts in the system and is denoted by N. The parameter L is the set of facilities available to select. The number of people living within census tract j is denoted by P_j.

The distance between each census tract and each facility is represented by d_{jk}, where it is assumed that the population is located at the centroid of the census tract. The total supply available to distribute is denoted by S. To ensure a certain percentage of individuals in each census tract is served, the model sets the minimum percentage to α. The amount of time it takes for each individual to be served is represented by γ. This γ value allows the model to approximate the waiting time. Finally, the benefit the state realizes for providing supplies to an individual is denoted by β.

The objective function 3.1 tries to maximize the number of people that get supplies, while minimizing the distance traveled by those served. Due to the distance being multiplied by the number of people, β was multiplied by the number of people served. This value must be sufficiently large to ensure that receiving the supply is beneficial regardless of distance. Constraint 3.2 prevents the sum of y_{jk} over all facilities k from exceeding 1. Similarly, constraint 3.3 prevents more people at a facility than there is supply. Constraint 3.4 captures the individual preference between facilities based on distance, available supply, and how many people are currently there. This constraint is the major difference of this model as compared to most other assignment type problems. It allows individuals to choose where to receive their supplies rather than being assigned to a facility. If any portion of the population from census tract j is served at facility k, then the distance, available supply, and number of people currently at this facility must be less than that of any other facility. If no person from census tract j is served at facility k, then x_{jk} equals zero and the M parameter ensures that the constraint is not binding. As discussed earlier in Chapter 2, these are the factors individuals base their decisions on. The only factor discussed in chapter 2 that was not used was the reputation of the facility because this information was unavailable. Constraint 3.5 defines the waiting time at each facility. This waiting time is approximated using the γ parameter and shows how long it would take for the next individual that shows up to receive supplies. Since information about staffing of the facilities was unavailable, the research assumes that there is a single server at each facility. Due to this assumption, the waiting time in this model should be seen as the number of labor hours required in order to provide supplies to all individuals who visit that facility. Constraint 3.6 requires that a fraction of at least α of each census tract population be served. This ensures a degree of equity and can also be used to ensure that enough supplies are available to high priority groups in each census tract. Constraint 3.7 prevents the cumulative supply at all facilities from exceeding the total supply available. Constraint 3.8 connects the y_{jk} variable and the x_{jk} variable so that x_{jk} must equal to one if any portion of the census tract j is served at facility k.

3.3 Insights from Model

As stated in Section 2.2, few operations research models use the individual choice constraint. However, the model used in this research included an individual choice constraint. Since public health officials cannot realistically assign people to certain facilities, it was important to create a model that models how people would decide where to receive the supplies. This creates a more realistic view for the policymakers to best distribute the supplies by providing information on where certain portions of people from each census tract would travel to.

The model introduced in this thesis also requires at least a certain certain portion of each census tract to receive the supplies. This also helps ensure a degree of equity in the system by not favoring census tracts with the largest populations. If there was no minimum amount, census tracts with larger distance to travel would be ignored in favor for census tracts with large population and short travel distances.

3.4 Summary

Overall, this chapter goes into more detail about the motivation behind the model and how the factors were chosen. The chapter then explains the general model that was created, including justification of parameters and constraints were created. Finally, it discusses the insights that can be gained from the model.

Chapter 4

Computational Study

Chapter 3 introduced a general model to help policy makers optimize public health emergency supply distribution. It also discussed the importance of individual choice, waiting time, distance, and total number of people served in designing a realistic model. The chapter also explored how equity could be analyzed. This chapter applies the model using actual data from the distribution of a scarce product to create a strategy for distributing the supplies. This alternative data set is used in the absence of publicly-available distribution data for previous pandemic response efforts to demonstrate the model capabilities and potential for practical insights. The strategy indicated by the model results is then compared to the actual distribution data to determine whether the model could have provided a more effective distribution of supplies and infer its potential to guide future policies.

4.1 Data and Parameter Choices

The model requires three main types of data: populations and their associated locations, product shipment quantities and locations, and distance from populations to facilities that received supplies. The initial data used for the model contained the 2010 census data for the Kansas side of the Kansas City Metropolitan area, see Figure 4.1. The populations considered in this study are the 231 census tracts that belong to the Kansas City Metropolitan on the Kansas side, which have a combined total population of 846,346 according to the 2010 United States Census. It was assumed that the population was centered at the census tract's centroid. The supply data contained the longitude and latitude coordinates of each facility that received a shipment of product during the study period. The data also included the product quantity each facility had received. The road network distance from each census tract to each facility within ten miles was computed using Network Analyst in ArcGIS. For census tracts where there were no facilities within ten miles, the allowable distance was increased to twenty miles, which meant some of the facilities would be located on the Missouri side. However, it ensured that every census tract had a facility it could travel to. A total of 160 facilities and 230,700 product units are used in this study, where each person is considered served upon the receipt of one product. Thus across the study area, there were approximately 3.67 people per product available.

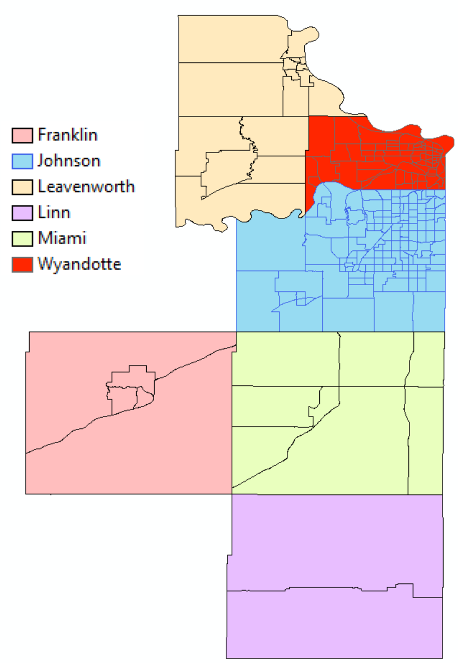

Figure 4.1: *Map of Census Tracts by County*

Chapter 3 introduced the general parameters to be used in the model. The parameter α signified the minimum allowable percentage of people receiving the supply from each census tract. Originally, α was set to a value of 27%. This was due to there being 3.67 people per product, which was 27% of the population. Using this parameter value, the solver was unable to find a feasible solution after a computation time of 10 hours. The constraint on serving a minimum fraction of each census tract's population conflicts with the individual choice constraint, since individuals must be willing to travel to facilities. As a result, the value for α was iteratively lowered until a viable solution was able to be found within a computation time of 4 hours. The largest value of α for which a solution could be found within the time limit was 2%. This value was used in the remainder of the computational study.

For the parameter β, which symbolized the benefit of receiving the supply, the value of 600,000 was used to ensure that the total distance traveled by a census tract would not be larger than the benefit of receiving the supply. This value was calculated by multiplying the maximum population by the maximum distance it can travel, and then multiplying that number by 3.5 and rounding up to the nearest hundred thousand. The product of the maximum census tract population and maximum corresponding distance yields the worst-case total distance traveled by residents of a census tract. Multiplying this by 3.5 ensures that β will be sufficiently large enough to ensure that receiving a product is beneficial regardless of distance.

The parameter γ, which symbolized the waiting time, was valued at 0.8333 hours per patient. This value comes from the CDC guidelines that state that the vaccination process for an individual should not take more than fifty minutes from beginning to end [1]. As stated in Section 3.2, the waiting time in the model represents the number of labor hours required in order to serve all individuals who visit that facility.

4.2 Solution Methodology

In the full model, there were 28,278 decision variables and 1,036,008 constraints. Due to the scale of the problem, a direct solution procedure was not found after the model ran for over a week. Even if the model was able to find a viable solution after a week, the amount of time needed to discover this solution is not a feasible option in a public health emergency situation. The solution needs to be obtained in about a day in order to provide the quick planning decisions required and allow time for analysis of the solution. Therefore a different approach was needed. This section introduces a problem decomposition approach used to obtain a viable solution.

The initial decomposition step is to determine how many subproblems the problem would be split into. Algorithm 1 discusses the steps to determine the size and number of subproblems needed. This algorithm initial sets the number of subproblems to a value of one. If a solution cannot be found, the number of subproblems is increased by one. The rest of the algorithm then splits the data in half and allocates the data to each subproblem. If both the subproblems contain data from a single census tract, then all the data on that census tract is allocated to the subproblem were the data first appears. This process is then repeated until a solution can be found.

When the decomposition method was used for this research, each subproblem contained approximately 3,000 possible combinations of census tracts to facilities. This meant that the problem would be split into six subproblems such that all census tracts not located in Johnson or Wyandotte County would be in the first subproblem, all of Wyandotte County was located in the second subproblem, and all of Johnson County was split into the remaining four subproblems.

The decomposition method also requires a new set of parameters, C_k. For a given subproblem, the value of C_k represents the total number of people from the previous sub-

Algorithm 1 Determining number of subproblems and size

```
Set inital number of subproblems to 1
Set TotalData to number of feasible combinations of census tracts to facilities
while There exists a subproblem that cannot be solved do
  Number of Subproblems = Number of Subproblems + 1

  for all Subproblems do
    DataSize = TotalData / Number of Subproblems
    Set k=0 and x=1
    for Subproblem_j = 0,1,..., Number of Subproblems do
      for k <DataSize do
        Insert k into Subproblem_j
        Set k = DataSize and DataSize=DataSize *x
        Set x = x + 1
      end for
    end for
    if Census tract i is in multiple subproblems then
      Move all of census tract i into subproblem is first appears
    end if
  end for
end while
```

problems that are located at facility k. This parameter set was needed to let the current subproblem being solved know how many people from the previous subproblems were located at each facility. To capture this parameter in the model, the following changes to the constraints can be seen in equation 4.1 and equation 4.2.

$$\sum_{j=1}^{n} P_j y_{jk} + C_k - s_k \leq 0 \qquad \forall k \in L \tag{4.1}$$

$$d_{jk} + \sum_{j=1}^{n} P_j y_{jk} + C_k - s_k \leq d_{ji} + \sum_{j=1}^{n} P_j y_{jl} + C_l - s_l + M(1 - x_{jk}) \tag{4.2}$$
$$\forall j \in N \quad \forall k \in L \quad \forall l \in L \neq k$$

Since there are several subproblems, a new parameter S_p was introduced to signify the total supply available to be allocated in subproblem p. The value of parameter S_p is illustrated in equation 4.3.

$$S_p = \frac{P_p}{TotalPop} S + S_{p-1} \qquad \forall p \in P \tag{4.3}$$

This value ensured that the supply for each subproblem, S_p, is equal to that subproblem's portion of the total population, P_p/Total Pop, multiplied by the total supply, S, available to all subproblems. This value is then added to the supply of the previous problem, S_{p-1}, to account for the people currently located at those facilities. The population composition and supply of the six subproblems can be seen in Table 4.1 and Table 4.2.

Table 4.1: *Population Composition of Six Subproblems (Percent of Total Population)*

Subproblem 1	Subproblem 2	Subproblem 3	Subproblem 4	Subproblem 5	Subproblem 6
0.1709	0.1861	0.1071	0.1566	0.1807	0.1986

Table 4.2: *Supply of Six Subproblems (Number of Products)*

Subproblem 1	Subproblem 2	Subproblem 3	Subproblem 4	Subproblem 5	Subproblem 6
39432	42934	24699	36132	41692	45811

The process for solving subproblems and updating C_k values is summarized Algorithm 2 for detailed steps.

The sequence in which subproblems are solved influences the final solution obtained. Two sequences were compared: geographic and greedy. The geographic sequence was determined by ordering the subproblems in such a way that the outer rural areas were solved first and the larger urban areas were last. This allowed the census tracts in rural areas, which had fewer

Algorithm 2 Subproblem Solution Method

Set $C_k = 0$ for all k
while An Unsolved Subproblem Remains **do**
  Solve Subproblem
  Update, for all k, $C_k = C_k +$ Number of people who went to k
end while

options in facilities, to be solved first. The order of the greedy sequence was determined by running all subproblems as the initial problem and choosing the subproblem that achieved the highest ratio of objective value to population of the subproblem. The chosen candidate was removed from the candidate list and the process was repeated until all subproblems were assigned an order.

The model was implemented in CPLEX Studio IDE version 12.5, using the tuple data structure to reduce memory by analyzing only the feasible combinations of census tracts and facilities. Each subproblem was solved on a Windows operating system with an Intel Core2 Duo processor at 3 gigahertz and four gigabytes of RAM.

4.3 Results

The following section discusses the results from the decomposition approach using the two sequences, in which supply at each facility is a decision variable, and those from a model in which supplies are fixed at the values from the actual distribution data. It then compares the methods on equity, service rates, and supply allocation.

4.3.1 Geographic Sequence

The solution for the geographic sequence resulted in 230,690 people receiving the supply. The total distance traveled was 189,786.855 miles, or an average of 0.82 miles per person. The solution allocated the supplies amongst the facilities such that about 99% of the available

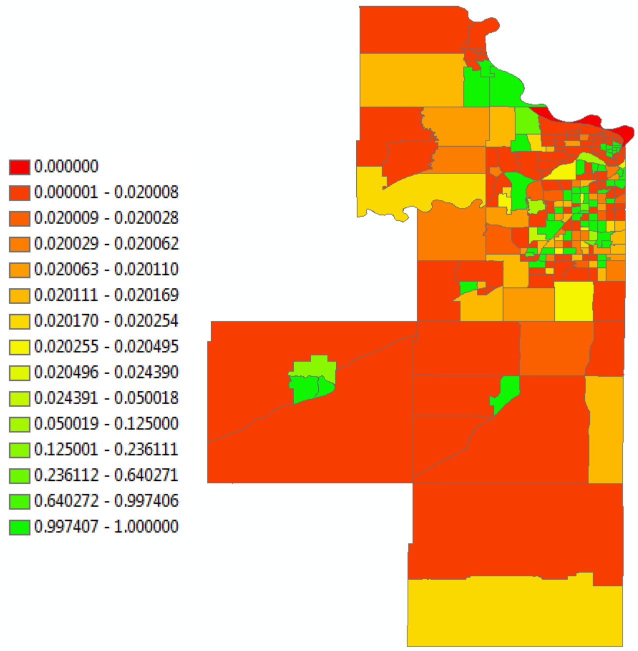

Figure 4.2: *Percentage of Population Served*

supply was used. Figure 4.2 shows the percentage of people from each census tract who were served. The three census tracts that received no supply had populations of zero. As the figure illustrates, most census tracts have about 2% of their population served. A closer look at the results shows that the minimum percentage of all census tracts was 2%, and that only this minimum value was achieved for 89 out of 231 census tracts. The run-time for the geographic sequence was 8 hours 40 minutes and 31 seconds

The weighted distance measure shows the ratio between the total distance traveled by individuals from a census tract and the number of people served at that census tract. The weighted distance for the geographic sequence can be seen in Figure 4.3. The majority of the urban census tracts have a weighted distance under two miles, while the rural areas have to travel up to fifteen miles to receive the supply. The weighted distance has a range of 0 miles to 15.144 miles.

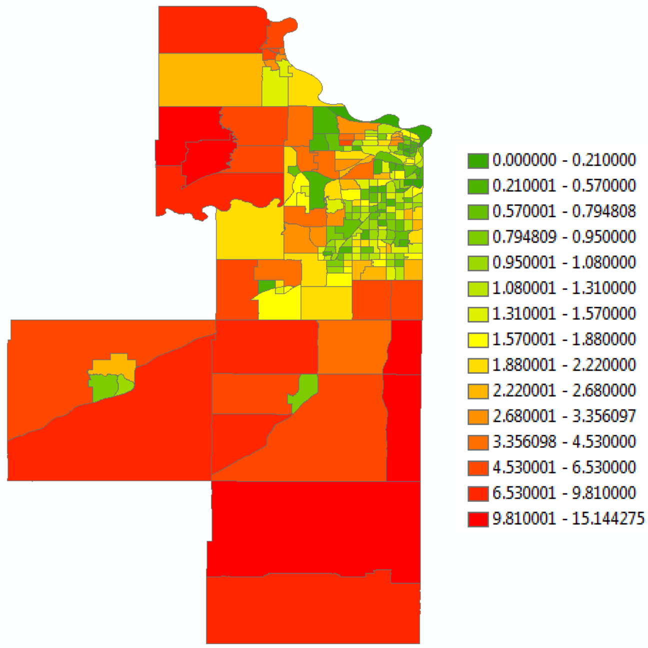

Figure 4.3: *Weighted Distance in Miles (Geographic Sequence)*

The weighted waiting time for each census tract was determined by using equation 4.4. Recall that facility k takes W_k to finish serving everyone that goes there. Weighted waiting time thus shows how busy the facilities that the census tracts visit are for the given method. Thus, it is important to have smaller numbers so that the people who receive the supply receive it as quickly as possible. Figure 4.4 shows that most census tracts receive their supply from a facility with a waiting time of about 300 hours or less. There are a few census tracts that receive their supply from facilities with higher waiting times, most of which are located in the urban areas. This is due to the way the supplies were distributed. Figure 4.5 shows how the supplies were distributed amongst the facilities. In the more urban areas, there are more facilities with large quantities of supply. This leads to more people going to this facility thus increasing the waiting time. However, this distribution of supplies is what allowed the weighted distance to be lower.

$$WeightedW_j = \frac{\sum_{k=1}^{l} P_j y_{jk} W_k}{\sum_{k=1}^{l} Pjy_{jk}} \quad \forall j \in N \tag{4.4}$$

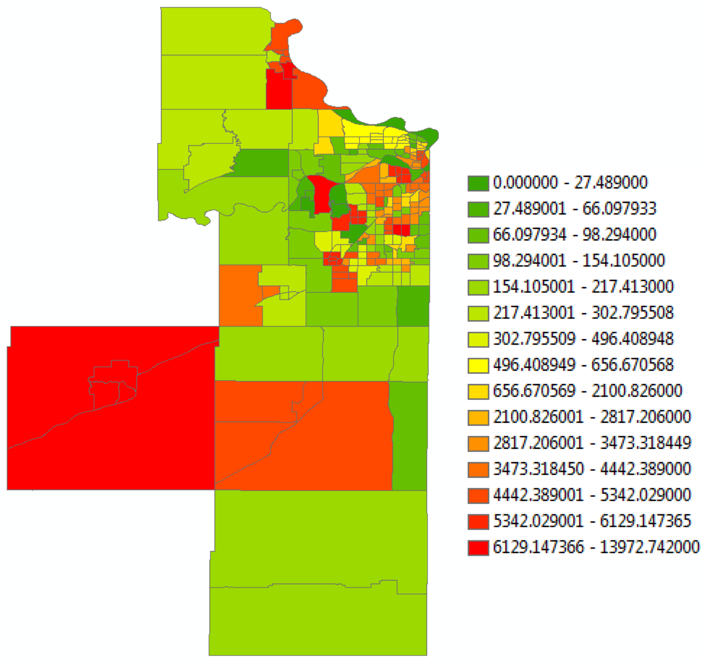

Figure 4.4: *Weighted Waiting Time in Hours (Geographic Sequence)*

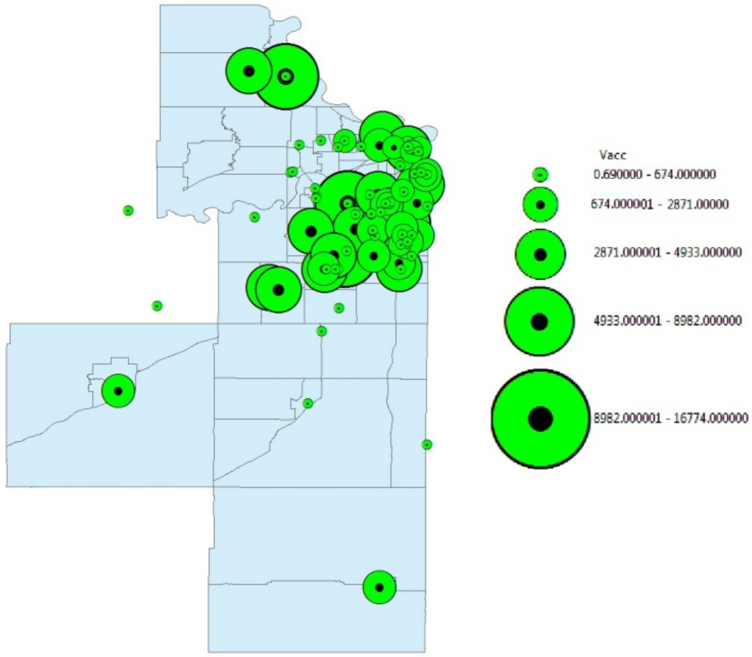

Figure 4.5: *Supply Allocation by Facility (Geographic Sequence)*

To analyze the equity of the solution, the mean absolute deviation (MAD) was calculated for weighted waiting time and distance, respectively. This was done by taking the absolute value of the difference between the weighted distance (waiting time) for the census tract and the overall average distance (waiting time) for all census tracts. For the geographic sequence, the weighted distance MAD is 1.44 miles and 2,196.375 hours for the waiting time. However, Figure 4.6 depicts that the weighted distance traveled is lower than the average feasible travel distance in all census tracts.

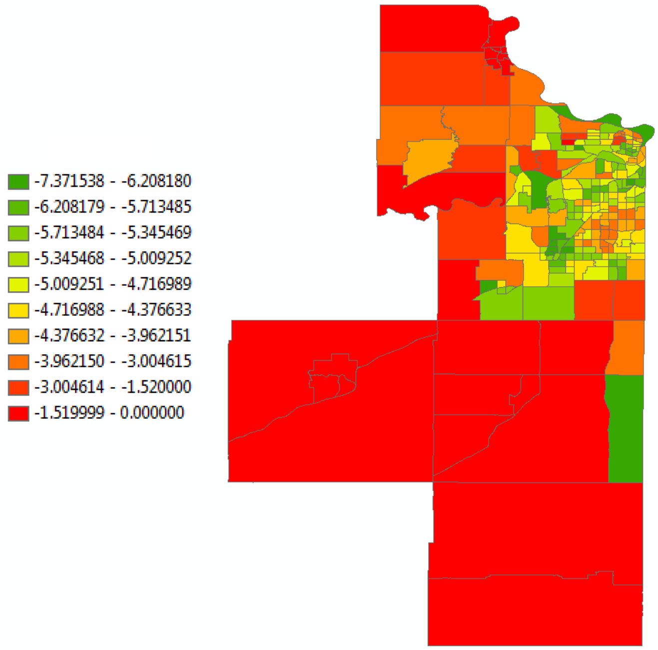

Figure 4.6: *Comparing Weighted Distance to Average Distance (Geographic Sequence)*

4.3.2 Greedy Sequence

The greedy sequence had a run-time of 9 hours and 32 minutes and resulted in 230,692 people receiving the supply. The three census tracts with a population of zero received no supply. The total distance traveled by the people who received the supply was 194,852 miles or about 0.84 miles per person. Figure 4.7 below shows the percentage of people served in each census tract. The census tracts with the higher proportion of their populations receiving the supply tend to be in the more urban areas.

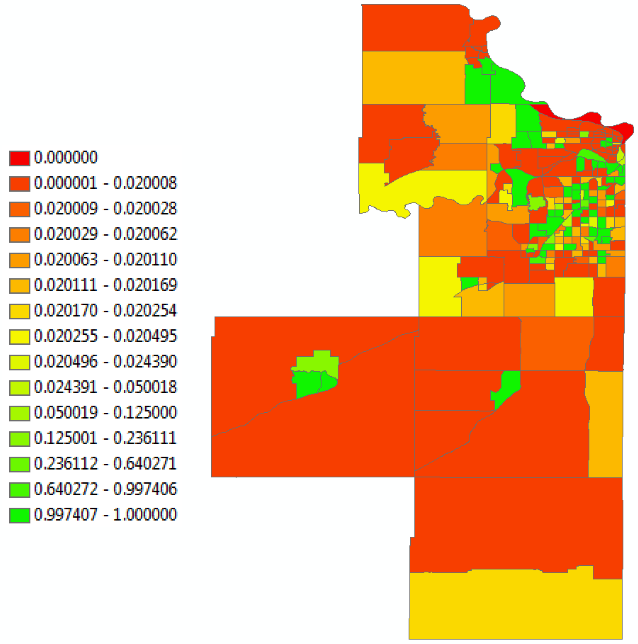

Figure 4.7: *Percentage of Population Served (Greedy Sequence)*

The results of the weighted distance and weighted waiting time can be seen in Figure 4.8 and Figure 4.9 respectively. The urban areas tended to have a lower weighted distance but had a higher weighted waiting time. This makes sense because these urban areas had a higher proportion of their population receive the supply, which means there are more people located at the facilities near them which leads to a higher waiting time. This is further explained in Figure 4.10. Since a large portion of the supply is located in the urban areas, the distance needed for them to travel is lower. However, this large supply means more people visit these facilities to receive their supplies thus causing the high wait times.

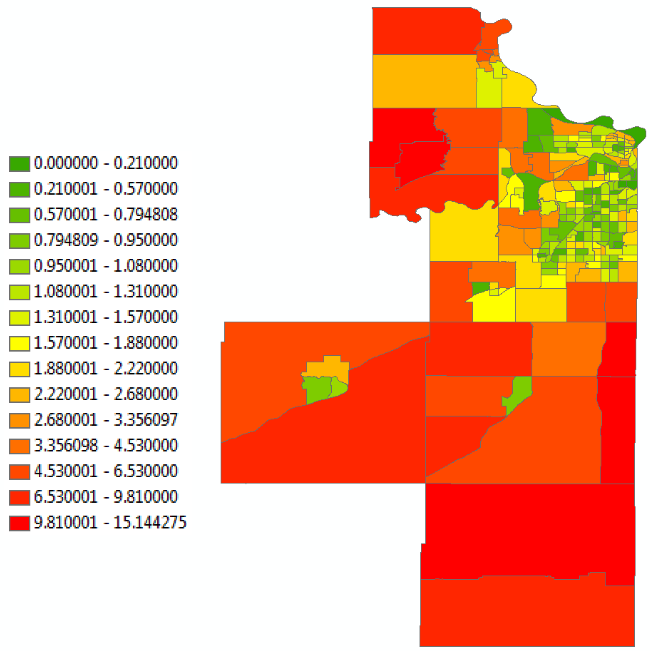

Figure 4.8: *Weighted Distance in Miles (Greedy Sequence)*

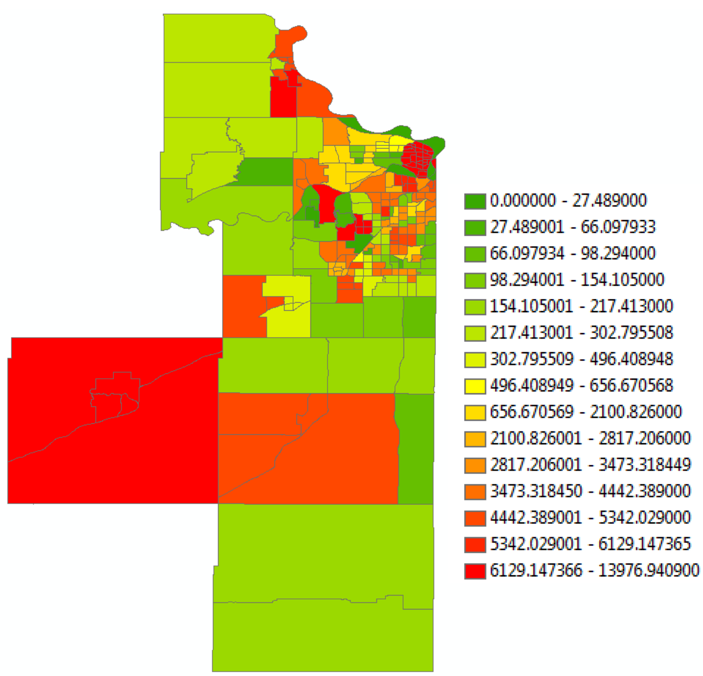

Figure 4.9: *Weighted Waiting Time in Hours (Greedy Sequence)*

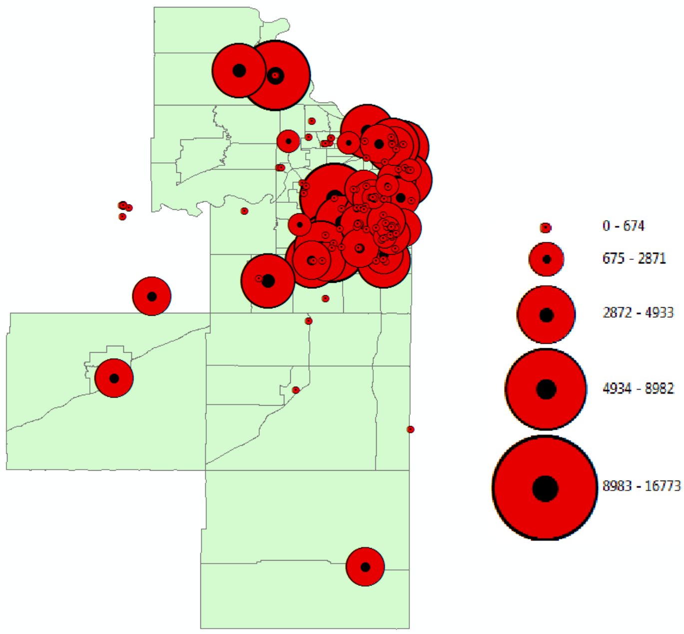

Figure 4.10: *Supply Allocation by Facility (Greedy Sequence)*

For the greedy sequence, the weighted distance MAD is 1.38 miles and 2,448.492 hours for the waiting time. Figure 4.11 illustrates again that the weighted distance traveled is lower than the average feasible travel distance in all census tracts.

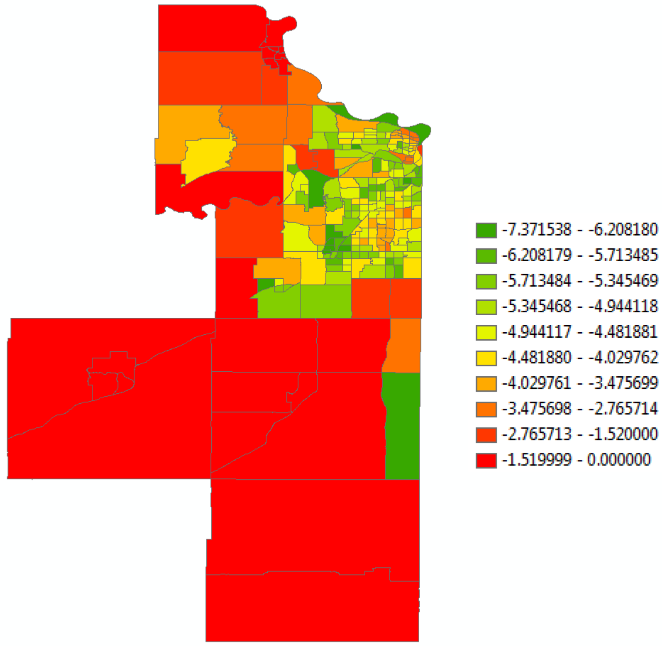

Figure 4.11: *Comparing Weighted Distance to Average Distance (Greedy Sequence)*

4.3.3 Actual Allocation

To measure the impact of accounting for individual choice when determining how to allocate resources, the model was solved with a supply at each facility exogenous and fixed at the values given in the actual data. All other constraints, including the individual choice constraint, remained the same. No solution could be found in a computation time of 10 hours in which at least 2% of each census tract was served, so this constraint was removed. In the resulting solution only 205,567 people were served. Due to the individual choice constraint, there was not a suitable facility for more of the people to travel to. Figure 4.12 shows the the percentage of each census tract that was served. As the figure illustrates, there are several census tracts for which most of the population is served; however, many census tracts receive little to no supply. This method had a total run-time of 11 hours 38 minutes and 19 seconds.

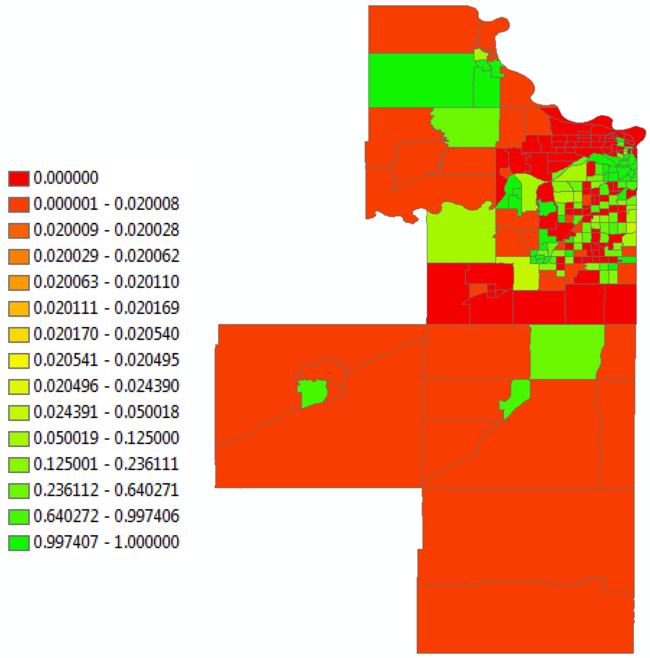

Figure 4.12: *Percentage of Population Served (Actual Allocation)*

The weighted distance for the actual distribution can be seen in Figure 4.13. With this distribution, observe that the census tracts on the county borders tend to have a lower weighted distance. This is due to there being several facilities along these borders receiving over 1100 units of supply. However, the census tracts in the rural areas have extremely large weighted distances. Since the facilities closest to these rural census tracts have a lower supply quantity, people from the rural census tracts must travel further in order to receive the supply.

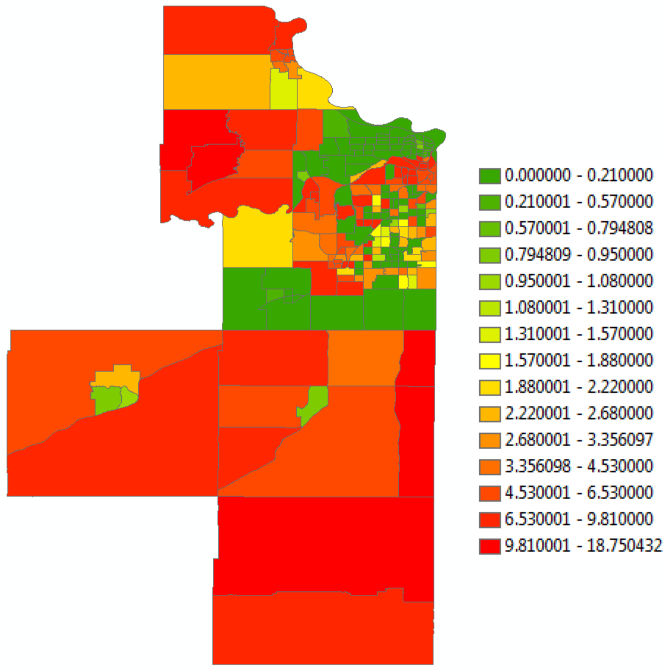

Figure 4.13: *Weighted Distance in Miles (Actual Allocation)*

The weighted waiting time for the actual method, Figure 4.14, shows a fairly even spread across all the census tracts because no one area seems to benefit the most. Both rural and urban areas contain census tracts with very low and very high weighted waiting times. Figure 4.15 illustrates the cause of the higher wait times: the areas with a higher wait time are near facilities with large quantities of supply, which means more people would visit these facilities thus increasing the waiting time.

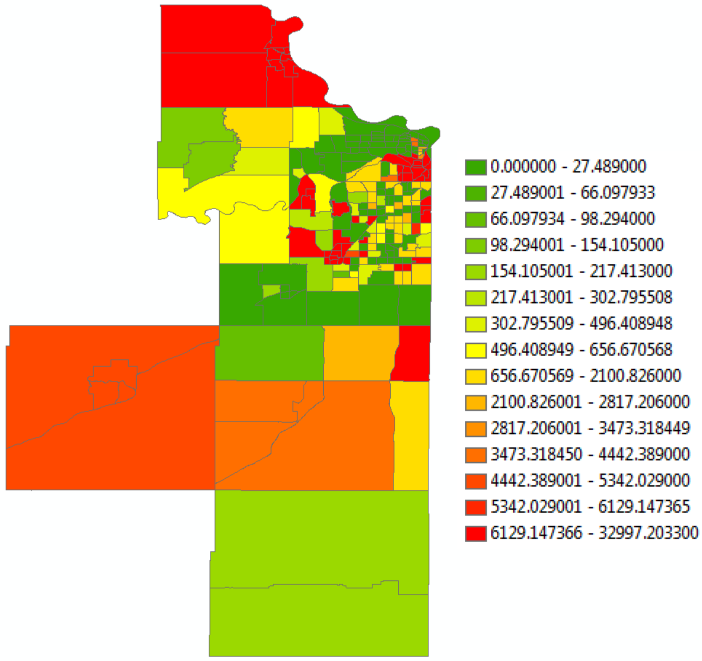

Figure 4.14: *Weighted Waiting Time in Hours (Actual Allocation)*

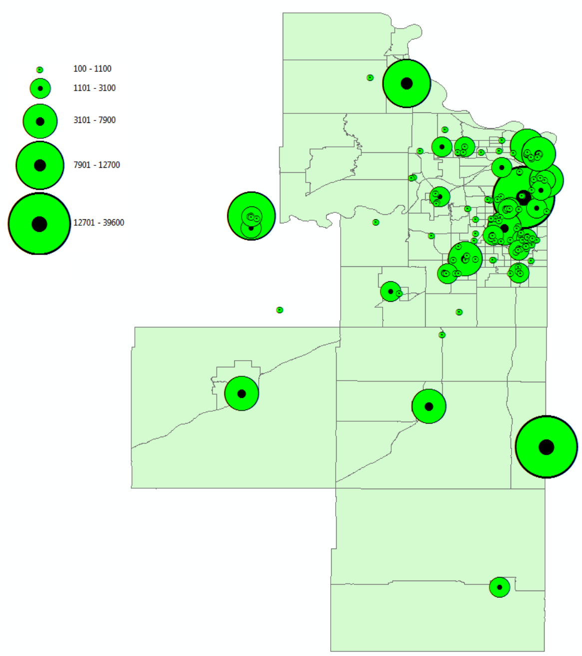

Figure 4.15: *Supply Allocation by Facility (Actual Allocation)*

For the actual distribution, the weighted distance MAD is 2.851 miles and the weighted waiting time MAD is 7336.573 hours. When comparing the actual weighted distance traveled to the average distance to feasible facilities, Figure 4.16, the census tracts on the county borders have a lower weighted distance. However, there are a few census tracts who travel further than the average distance to feasible solutions. This is again due to the distribution of the supply.

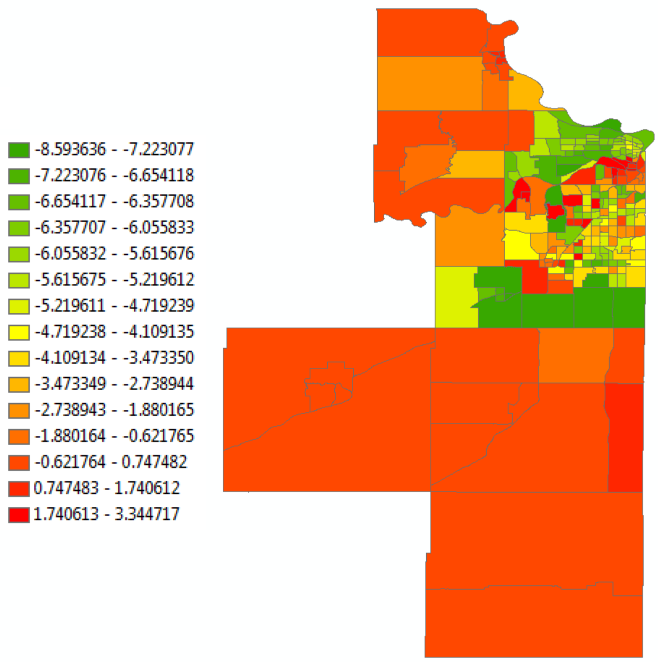

Figure 4.16: *Comparing Weighted Distance to Average Distance (Actual Allocation)*

4.3.4 Comparison

Finally, when comparing the models together, it is evident that the actual distribution could be greatly improved, see Table 4.3 for comparisons. The greedy and geographic sequences generated an improved solution in terms of people served and equity. During a public health emergency, these factors are extremely important in mitigating the damage caused by the emergency. When comparing the two sequence methods, it is difficult to see which is the best choice. The greedy sequence has the better weighted distance MAD; however, the geographic sequence has the better weighted waiting time MAD. Also, when comparing the the weighted distance for each census tract, the geographic sequence appears to be very similar to the greedy sequence. Figure 4.17 shows the differences in the weighted distance between the geographic and greedy sequences. All of the census tracts where there was no change were removed to clearly see the differences. It is seen that among the census tracts that change, most change in favor of the geographic sequence. However, the ones that change in favor of the greedy sequence have a higher displacement than the ones that change in favor of the geographic sequence. This means that the differences where the greedy sequence is better change more drastically. When comparing the weighted waiting times, Figure 4.18, it is seen that the geographic sequence has the edge. The majority of the census tracts that favor the greedy sequence are improved minimally. Overall, it can be seen that the order in which the subproblems are solved does affect the waiting times experienced at the facilities. However, it has very minimal effect on the weighted distance traveled by the census tracts.

Table 4.3: *Comparison of the Models*

Measure	Geographic	Greedy	Actual
People Served	230,690	230,692	205,567
Average Distance Traveled(miles)	0.82	0.84	4.12
Weighted Distance MAD(miles)	1.44	1.38	2.851
Weighted Wait Time MAD (hours)	2196.375	2448.492	7336.573

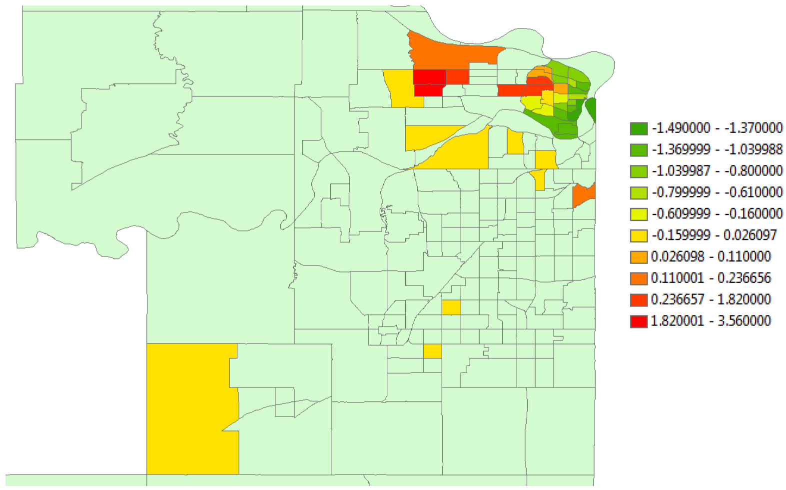

Figure 4.17: *Weighted Distance Comparison of Geographic and Greedy Sequence(Miles)*

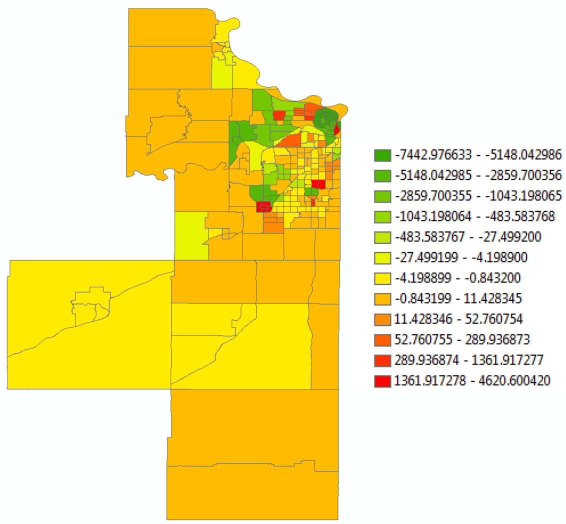

Figure 4.18: *Weighted Waiting Time Comparison of Geographic and Greedy Sequence(Hours)*

Creating a model that takes into account an individual choice constraint can increase the potential number of people that can receive the supply, decrease distance, and improve equity. The model used in this thesis found that 12% more people receive the supply compared to the actual allocation. When accounting for an individual choice constraint, the average distance traveled by the census tracts was three miles shorter, while the MAD of the weighted distance was 50% smaller. Finally, the solution has far less deviation in the distances and wait times, which means it is a more equitable solution.

4.4 Policy Implications

From a public health planner's point of view, implementing a mathematical model that utilizes an individual choice constraint has the potential to increase the number of people that are able to receive the supplies in question, such as vaccines or other medical countermeasures. This model can be used on a typical desktop computer by using the problem decomposition method discussed in 4.2. Since the difference in the weighted waiting time was in favor of the geographic method and the difference in the distance was minimal, the geographic method should be used to establish a public health emergency response campaign. Also, due to the need for a quick and efficient solution, it would not be feasible to work through all the various sequences of subproblems that are required when using the greedy method. The geographic sequence was shown to provide 25,000 more people easy access to the supply. This equated to approximately 12% increase in number of people served over the actual distribution.

This study has some limitations. First, it assumes that individuals know where supplies are and that they use this information to make decisions. For influenza vaccines, such information is available on the Vaccine Locator [8]. Second, the specific findings of the case study rest on the form of the individual choice constraint. The solution process is generalizable to other forms, and more study on individual choices is identified as a specific area for future research. While actual vaccine campaign data are not readily available, the computational study demonstrates the potential insights to be gained.

Chapter 5

Recommendations

During the H1N1 outbreak, there were approximately 61 million cases in the United States from April 2009 to April 2010 with 12,470 deaths. The severity of this outbreak was due to the lack of a vaccine existing to mitigate the spread of the disease. This increased the necessity for a quick and effective vaccination campaign. However, the current strategies used for public health emergency response efforts of this nature fail to implement an individual choice constraint to model where people would go to receive supplies. This research demonstrates the differences an individual choice constraint can make on a public health emergency response effort such as a vaccination campaign. The research compares the hypothetical number of people served using the distribution scheme from the model to the number of people served given the actual distribution plan from a representative data set.

Due to the real potential for supply shortages in public health emergency response, it is important to ensure everyone has an equitable chance at receiving the supplies. Using the linear programming model, this thesis was able to show implementing a distribution scheme that takes into account an individual's choice can improve the number of people who receive supplies. The model also compared the percentage served, distance traveled and waiting time each census tract would experience under the various distribution schemes. Since it was a public health problem, the distribution scheme needed the solution to be equitable. Thus, mean absolute deviations of the distance traveled and waiting time were used to examine the equity of the solution along with comparing the actual distance traveled to the average distance to all feasible facilities.

The thesis also provides a method for solving the model on any computer with CPLEX Studio IDE version 12.5 to solve the model. These decomposition methods provide an option to solve these large-scale problems while still providing an equitable solution. It also provides a way to implement memory intensive constraints such as the individual choice constraint. In all, this thesis contributes several improvements that can improve the efficiency and effectiveness of the response to a large scale public health emergency.

The research done has shown the need for future research in several areas. The first is the need to understand more about the factors people consider when choosing where to receive supplies. This work will allow the individual choice constraint to better represent actual human decisions, which will lead to improved response campaigns. Another area for future research is comparing the decomposition methods to a provably optimal solution. This would provide insight into how close the decomposition methods were to the truly optimal solution. Finally, improved quality of data would allow a true comparison to the number of people vaccinated under the actual vaccination campaign to a theoretical vaccination campaign. It would also allow a more accurate depiction of the waiting time. In order to create a more realistic depiction of the waiting time, it is recommended that standardized record-keeping is developed such that it does not interfere with the response effort.

In conclusion, the following recommendations are supported by this research:

1. Use an optimization model that implements an individual choice constraint, similar to the one mentioned in Chapter 3.2, in order to best distribute medical supplies.

2. Use geographic decomposition method to solve a large scale problem rather than a

greedy method.

3. Discover how individuals make choices on where to receive medical supplies, to establish the most realistic constraint.

4. Promote standardized record-keeping that does not interfere with the response efforts.

5. Create new models that use individual choice and equity constraints to establish public health emergency response strategies.

Bibliography

[1] Aaby, K., Herrmann, J. W., Jordan, C. S., Treadwell, M., and Wood, K. (2006). Montgomery countys public health service uses operations research to plan emergency mass dispensing and vaccination clinics. *Interfaces*, 36(6):569–579.

[2] Aboolian, R., Berman, O., and Drezner, Z. (2008). Location and allocation of service units on a congested network. *IIE Transactions*, 40(4):422–433.

[3] Baron, O., Berman, O., and Krass, D. (2008). Facility location with stochastic demand and constraints on waiting time. *Manufacturing and Service Operations Management*, 10(3):484–505.

[4] Berman, O. and Kaplan, E. H. (1990). Equity maximizing facility location schemes. *Transportation Science*, 24(2):137–144.

[5] Centers for Disease Control and Prevention (2010a). 2009 H1N1 flu (swine flu) and you. http://www.cdc.gov/H1N1flu/qa.htmc.

[6] Centers for Disease Control and Prevention (2010b). The 2009 H1N1 pandemic: Summary highlights, April 2009 - April 2010. http://www.cdc.gov/h1n1flu/cdcresponse.htm.

[7] Centers for Disease Control and Prevention (2013a). CDC resources for pandemic flu. http://www.cdc.gov/flu/pandemic-resources/index.htm.

[8] Centers for Disease Control and Prevention (2013b). Key facts about seasonal flu vaccine. http://www.cdc.gov/flu/protect/keyfacts.htm.

[9] Chan, M. (2009). World now at the start of 2009 influenza pandemic. http://www.who.int/mediacentre/news/statements/2009/.

[10] Craft, D. L., Wein, L. M., and Wilkins, A. H. (2005). Analyzing bioterror response logistics: The case of anthrax. *Management Science*, 51(5):679–694.

[11] District of Columbia Department of Health (2012). Closed point-of-dispensing intitiative. http://www.state.gov/documents/organization/203930.pdf.

[12] Ekici, A. (2009). Modelling influenza pandemic, intervention strategies, and food distribution. In *Proceedings of the 2009 Society for Health Systems Conference*. Society for Health Systems Conference.

[13] Ekici, A., Keskinocak, P., and Swann, J. L. (2008). Pandemic influenza response. In *Proceedings of the 40th Conference on Winter Simulation*, WSC '08, pages 1592–1600. Winter Simulation Conference.

[14] Garfield, R. (2005). State preparedness for bioterrorism and public health emergencies. In *Bipartisan Congressional Health Policy Conference*, number 829. The Commonwealth Fund.

[15] Heier Stamm, J. L. (2010). *Design and analysis of humanitarian and public health logistics systems*. PhD thesis, Georgia Institute of Technology.

[16] Kaplan, E. H. and Wein, L. M. (2005). Decision making for bioterror preparedness: Examples from smallpox vaccination policy. In Brandeau, M., Sainfort, F., and Pierskalla, W., editors, *Operations Research and Health Care*, volume 70 of *International Series in Operations Research and Management Science*, pages 519–536. Springer US.

[17] Knight, V. A. and Harper, P. R. (2013). Selfish routing in public services. *European Journal of Operational Research*, 230(1):122 – 132.

[18] Lee, E. K., Pietz, F., and Benecke, B. (2010). Public health, emergency response, and medical preparedness ii: Medical countermeasures dispensing and large-scale disaster relief efforts. In *Wiley Encyclopedia of Operations Research and Management Science*. John Wiley and Sons, Inc.

[19] Lejeune, M. A. and Prasad, S. Y. (2013). Effectiveness-equity models for facility location problems on tree networks. *Networks an International Journal*, 62(4):243–254.

[20] Marianov, V. and Serra, D. (1996). Probabilistic maximal covering location-allocation models with constrained waiting time or queue length for congested systems. Economics Working Papers 177, Department of Economics and Business, Universitat Pompeu Fabra.

[21] Marsh, M. T. and Schilling, D. A. (1994). Equity measurement in facility location analysis: A review and framework. *European Journal of Operational Research*, 74(1):1–17.

[22] Moore, B. (2012). Impact of decentralized decision making on access to cholera treatment in Haiti. Master's thesis, Kansas State University.

[23] Nelson, C., Lurie, N., Wasserman, J., and Zakowski, S. (2007). Conceptualizing and defining public health emergency preparedness. *American Journal of Public Health*, 97(S1):9–11.

[24] Ogryczak, W. (2009). Inequality measures and equitable locations. *Annals of Operations Research*, 167(1):61–86.

[25] Rachaniotis, N. P., Dasaklis, T. K., and Pappis, C. P. (2012). A deterministic resource scheduling model in epidemic control: A case study. *European Journal of Operational Research*, 216(1):225 – 231.

[26] Taubenberger, J. and Morens, D. (2006). 1918 influenza: the mother of all pandemics. *Emerging Infectious Diseases*, 12(1):15 – 22.

[27] Tuckman, J. and Booth, R. (2009). Four-year-old could hold key in search of swine flu outbreak. *The Guardian*.

[28] United States Department of Health and Human Services (2013). About pandemics. http://www.flu.gov/pandemic/about/.

[29] Vellozzi, C., Broder, K. R., Haber, P., Guh, A., Nguyen, M., Cano, M., Lewis, P., McNeil, M. M., Bryant, M., Singleton, J., Martin, D., and DeStefano, F. (2010). Adverse events following influenza a (H1N1) 2009 monovalent vaccines reported to the vaccine adverse event reporting system, United States, October 1, 2009 - January 31, 2010. *Vaccine*, 28(45):7248 – 7255.

[30] Wein, L. M. and Liu, Y. (2005). Analyzing a bioterror attack on the food supply: The case of botulinum toxin in milk. *Proceedings of the National Academy of Sciences of the United States of America*, 102(28):9984–9989.

[31] Wex, F., Schryen, G., and Neumann, D. (2013). Decision modeling for assignments of collaborative rescue units during emergency response. In *Proceedings of the Annual Hawaii International Conference on System Sciences*, pages 166–175.

[32] Whitehead, M. (1991). The concepts and principles of equity and health. *Health Promotion International*, 6(3):217–228.

[33] World Health Organization (2010). Pandemic (h1n1) 2009 - update 101. http://www.who.int/csr/don/2010$_0$5$_2$1/en/.

[34] Yi, W. and Kumar, A. (2007). Ant colony optimization for disaster relief operations. *Transportation Research Part E: Logistics and Transportation Review*, 43(6):660 – 672.