UTILIZING AGENT BASED SIMULATION AND GAME THEORY TECHNIQUES TO OPTIMIZE AN INDIVIDUAL'S SURVIVAL DECISIONS DURING AN EPIDEMIC

by

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ABSTRACT

History has shown that epidemics can occur at random and without warning — devastating the populations which they impact. As a preventative measure, modern medicine has helped to reduce the number of diseases that can instigate such an event, nevertheless natural and man-made disease mutations place us continuously at risk of such an outbreak.

As a second line of defense, extensive research has been conducted to better understand spread patterns and the efficacy of various containment and mitigation strategies. However, these simulation models have primarily focused on minimizing the impact to groups of people either from an economic or societal perspective and little study has been focused on determining the utility maximizing strategy for an individual.

Therefore, this work explores the decisions of individuals to determine emergent behaviors and characteristics which lead to increased probability of survival during an epidemic. This is done by leveraging linear program optimization techniques and the concept of Agent Based Simulation, to more accurately capture the complexity inherent in most real-world systems via the interactions of individual entities.

This research builds on 5 years of study focused on rural epidemic simulation, resulting in the development of a 4,000-line computer code simulation package. This adaptable simulation can accurately model the interactions of individuals to discern the impact of any general disease type, and can be implemented on the population of any contiguous counties within Kansas. Furthermore, a computational study performed on the 17 counties of northwestern Kansas provides game theoretical based insights as to what decisions increase the likelihood of survival. For example, statistically significant findings suggest that an individual is four times more likely to become infected if they rush stores for supplies after a government issued warning instead of remaining at home.

This work serves as a meaningful step in understanding emergent phenomena during an epidemic which, subsequently, provides novel insight to an individual's utility maximizing strategy. Understanding the main findings of this research could save your life.

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DEDICATION

This work is dedicated to my mom and dad, for their support and motivation, and to my friends, for their diversions and entertainment.

1 – INTRODUCTION

As a popular genre of the American entertainment industry, apocalyptic based movies and books depicting outbreaks of disease leading to the extinction of almost all human life are common. To support the storyline there is always an individual or small group which manages to not only survive the infection but also to evade those of whom the chaos and death has dissolved away all morality. In the movie *I AM LEGEND*, as the only survivor in the New York City metro area actor Will Smith had faced survival odds of roughly 1:20,000,000; although fictitious, a real-world analogy is that of the bubonic plague in Europe, where in some cities and villages survivors represented as little 20 percent of the original populations (Alchon, 2003).

The ability of few to survive while the vast majority perishes begs the questions: How? Why? Are the survivors genetically immune? Are they simply stronger and healthier? Maybe they received better treatment after becoming sick and managed to recover? Or did the decisions that they make allow them to live? This work explores the decisions of individuals to determine emergent behaviors and characteristics which lead to an increased probability of survival during a pandemic.

1.1 – EPIDEMICS

Disease is believed to have plagued all forms of life for almost as long as life has existed; evidence in support of this is provided in the fossil record of a bird dated at over 90 million years old (Zimmerman & Zimmerman, 2003). An unknown number of infectious diseases exist and have been studied in various capacities for centuries. Variations exist in the disease pathogen — virus, bacterium, fungus, prion, or parasite — as well as in the available treatments, morbidity and mortality rates, and transmissibility — airborne, direct contact, indirect contact, or via a carrier agent. The immeasurable combinations of these and other factors has made understanding and developing protection against disease a tedious and ongoing process, with most progress having been made in the last century of human history.

While disease is a constant aspect of life, massive outbreaks of particular strands occur intermittently, impacting huge numbers of individuals and loom as a realistic basis to a true apocalypse. These pervasions of disease throughout a species become an epidemic and the diffusion of an epidemic over a large geographic area, typically a continent, becomes a pandemic. This work focuses on disease transmission and the individual preventative measures that can be taken during an epidemic, and formally defines such as an outbreak of a disease that spreads more quickly, extensively, and devastatingly among a group of people than would normally be expected.

Much effort in understanding the spread of epidemics has been undertaken and largely focuses on the mitigation strategies available to government agencies (Carlyle, 2009), (Bisset, Feng, Marathe, & Yardi, 2009), (Ferguson, et al., 2006), & (Scoglia, et al., 2010). Balancing the financial impact and moral qualms of preventative strategies ranging from school closings to quarantines against the likelihood of contagion and death is a common focus. These studies began with aggregate mathematical models ignoring spatial distributions (Hyman & Stanley, 1988) & (Lloyd, 2001) and have evolved to computer simulations (Tsai, et al., 2010) & (Premashthira, Salman, Hill, Reich, & Wagner, 2011) that accurately model such an event. However, consideration of disease transmission from an alternate perspective — that of the individual and how their decisions both bring about exposure and facilitate disease spread — is a novel concept that this work helps to further. Understanding the basic unit of an epidemic, the individual, is a key step to prevention.

While not a preventative measure, consider this treatment based analogy of the then state-of-the-art medical treatment applied to George Washington when he was suffering from a sore throat and respiratory illness. This analogy exemplifies the importance of correct decisions to the individual. Unknowingly doctors administered what was a toxic mercury based tonic via mouth and direct injection. This was followed by the ingestion of a poisonous white salt, application of caustic poultices, the inhalation of vinegar vapors, and the draining of almost half of his blood. This combination of treatments resulted in perspiration, vomiting, skin and throat blistering, burned lungs, and eventually death. What was likely brought on by pneumonia or a similar infection was exacerbated by decisions based on an incorrect understanding of the disease (Zimmerman & Zimmerman, 2003). This parallels current lack of understanding in regards to epidemics; for example, after an outbreak, should the decision of an individual be to isolate themselves or flee? How will this decision compiled with those of others impact society?

Consider this example of the best reaction for an individual which resulted in the worst case scenario for society: the siege of Kaffa by Tartars in 1347. After disease decimated the besieging army of Tartars, in a final act of rage before withdrawing, they catapulted infected bodies into the city. Fearing infection, the residents fled to Italy unknowingly bringing the sickness along. Although Italian officials recognized the onset of plague and attempted to isolate the refugee carrying ships, infection spread. Within a year the pandemic, now understood to be a combination of bubonic and pneumonic plague, had spread to as far north as England and as far east as Germany. When it finally ended the European population of some 40 million had been reduced to less than 15 million (Bugl, 2001).

Now consider this example from the alternate perspective: society's best reaction at the expense of the individual. After the plague became widespread on the mainland, Italian officials would isolate entire households having even a single inhabitant with symptoms of illness. In these situations the healthy were left to become infected, and even in cases where these individuals never succumbed to sickness the fear of contagion was such that the healthy were left trapped within their homes to die from lack of food and water (Bugl, 2001).

It is apparent that not always does the best case scenario for society translate into the best outcome for an individual, nor does the cumulative best reaction of individuals necessarily lead to the best case scenario for society. Indeed both anticipating the collective decisions of individuals and understanding the implications of a government-led response are fundamental for an appropriate mitigation strategy. For example, if the government quarantines an area with the expectation that local medical staff will administer the requisite treatments, will the manpower to provide such care remain available or will the medical staff prioritize personal health and family over that of society?

From the perspective of an individual, understanding how certain traits influence decisions and alters the likelihood of infection and survival is fundamental to optimizing personal utility during an epidemic. For example, consider how the forethought — or paranoia — of an individual to stockpile supplies against a perceived apocalypse could enable isolation of the individual decreasing the likelihood of encounters and subsequently, infection. This work explores these and other questions regarding epidemics through the use of simulation.

1.2 – Simulation

Frequently, problems arise which are too complex to define mathematically, unethical to examine via experimentation, or cost prohibitive to study by either technique. To better understand the elements of such a scenario, simulation is frequently utilized. As the lead time for creating an accurate and specific simulation is significant, it is necessary to create a general, hypothetical situation beforehand and apply the knowledge gained if an epidemic or similar outbreak were to occur. As such, these generalized scenarios are built upon numerous, research-backed assumptions.

Computer simulations follow a prescribed sequence of equations bundled into various subroutines. Generally, these subroutines serve as a hypothetical representation of a subset of the issue in question; the output of each is collated to represent a single iteration of the simulation. The development of the equations is partially stochastic, to depict the inherent randomness of the actual system, and partially based on various assumptions and parameters. Through research, the assumptions and parameters applied can be more formally defined adding to the robustness of the simulation. After multiple iterations of the simulation, statistical significance is achieved and the simulation output is applicable in real-world situations.

1.2.1 – Simulation Applications

Computer simulation is applicable to the vast number and variety of domains in which insight of complex systems is desired. Such use occurs in the study of natural systems including the domains of physics, chemistry, and biology; and human systems: economics, social science, engineering, and psychology. This breadth of applicability implies common, everyday use as is indeed the case; specifically, practical applications include flight simulators, weather forecasting, logistics systems, traffic engineering, computer games, and industrial process design, among many others (Drake, 2003).

1.2.2 – Agent Based Simulation

Many recent advances in simulation research have incorporated a technique known as Agent Based Simulation (ABS). ABS is an increasingly utilized technique which enables researchers to more accurately capture the complexity inherent in most real-world systems by studying the interactions of individual entities. These interactions result in patterns or emergent phenomena: the ability to discern such is the main benefit of ABS.

For example, consider that a traffic jam which results from the interactions between individuals vehicles may grow in the opposite direction of the movement of the vehicles causing it. The counterintuitive nature of emergent phenomenon makes such occurrences difficult to predict and understand. Since ABS takes the bottom-up approach it enables researchers to avoid forming assumptions based on what they expect the outcome to be and instead leverage known rules on which the individual entities base decisions. The concept of emergence is discussed further in the following chapter, and additional detail is available in Holland (1998).

Epidemic simulation is not the only field in which ABS is applied. Applications vary from small and straightforward, typically seeking to determine the most relevant features of a system based on idealized and easily interchangeable assumptions, to the large and specific, typically intended for the support of broad, real-world policy questions constructed from actual data. Example applications range from air traffic control optimization (Folcik, et al., 2011) to urban crime analysis (Malleson, 2009) and even modeling molecular self-assembly within the chemistry domain (Troisi, Wong, & Ratner, 2005).

1.3 – Research Motivation

The National Bio- and Agro-Defense Facility (NBAF) is a state-of-the-art biocontainment facility currently under construction on the Kansas State University campus in Manhattan, Kansas — the location where this research was conducted. This facility is to replace the Plum Island Animal Disease Center (PIADC) as the national research center for the study of foreign animal, emerging, and zoonotic diseases that threaten animal agriculture and public health (Department of Homeland Security, 2012).

This facility will study a variety of agents including the most dangerous and exotic diseases which each pose a high risk of aerosol transmitted laboratory infections, are severe to fatal in humans for which vaccines or other treatments are not available, and other hemorrhagic diseases necessitating the highest containment level: biosafety level 4. Specifically, diseases which this facility will study include the Hendra Virus, African Swine Fever, Foot and Mouth Disease, and Contagious Bovine Pleuropneumonia, among others (Department of Homeland Security, 2012).

There are concerns about NBAF's ability to never allow a containment leak largely due to multiple such occurrences at the isolated PIADC during its existence (Department of Homeland Security, 2012). As NBAF will study dangerous and highly-infectious zoonotic agents — diseases which can be transmitted from animals to humans — this research explores the decisions which will assist local residents in surviving a containment breach if one were to occur.

Furthermore, this research takes an alternative approach to typical epidemic modeling. Traditional approaches must make assumptions as to what behaviors will be successful, from which the patterns exhibited by society can be studied and society's best response to an outbreak identified. Whereas this work leverages ABS to first look to the individual and from their interactions identify the emergent patterns. This approach allows for the various behaviors and traits that individuals can exhibit to be analyzed and linked with successful outcomes. Additionally, through game theoretic methodologies, the equilibria resulting from the cumulative decisions of society can be determined, which allows for alternate, superior individual actions to be identified.

As the researcher, his friends, and family live in close proximity to NBAF, the motivation for this work is of a personal nature. For this reason, optimizing the decisions of the individual in an epidemic scenario by leveraging the most advanced form of all applicable technologies is the focus of this work.

1.4 – Research Contributions

This work is the result of five years of associated research concerning the optimization of epidemic mitigation strategies in rural areas. As such, the simulation package developed for this paper addresses deficiencies noted in earlier models and includes a number of novel implementations.

One such improvement is the application of ABS which executes a linear program for each agent at certain decision points to optimize their choice under individualized constraints. Not only does this technique leverage complex strategies to find the best available decisions, but it looks from the individual's perspective as opposed to that of society. This serves as an alternative to the popular approach of optimizing a government's mitigation strategy; with the findings helping to fill the resultant knowledge void.

Another improvement is the incorporation of decisions points throughout the model to closely approximate the available decision set in the real-world. The decision structure is constructed such that the primary decision influences secondary decisions which in turn constrain the available tertiary decisions. An additional set of global decisions are also available and dependent on the specific characteristics of the individual. This work also incorporates census based population and geographic data, to approximate the actual densities and spatial separation of the counties in Kansas included in this study. These elements, coupled with the use of adjustable disease characteristics and programmable disease transmission methods, allow for the accurate replication of a disease in a real-world setting.

In terms of modeling techniques, there are various additional contributions provided by this work, with more detail included within the subsequent discussion. The advanced simulation package created from the combined utilization of these novel techniques allows for the accurate determination of general equilibria strategies that are applicable to real-world scenarios; with this knowledge an individual can optimize their decision during an epidemic. For example, key findings suggest that an individual is four times more likely to become infected if they rush stores for supplies after a government issued warning instead of remaining at home. Furthermore, during a looting scenario, regardless of whether an individual loots expensive items or supplies necessary for survival, their likelihood of infection increases over ten-fold as compared to the decision to remain at home.

1.5 – Discussion Outline

The following chapters provide additional detail regarding the topics introduced, the simulation on which this work is based, and the insights garnered from analysis of the output data.

Chapter 2 supplements the reader's knowledge on relevant topics and highlights particular items of note. Discussion is provided on the mathematical modeling of epidemics, the simulating of epidemics, considerations regarding ABS, and relevant topics concerning decision and game theory.

Chapter 3 describes the simulation structure, including considerations regarding the contact network and decision optimization methodology, and details all major computations and applications of theory. Within this section the analysis of the simulation results is presented and summary output provided.

Chapter 4 introduces the computational results of this research in detail. Specifically, the data that indicates the specific characteristics and decisions which increase the propensity of survival are appraised. The implications of various equilibria situations based on game theoretical inferences of emergent societal trends is also supplied.

Chapter 5 reviews the qualitative and quantifiable results of this research while providing closing thoughts concerning this work. Recommendations for the application of techniques utilized herein to related studies are offered, with closing comments summarizing proposed extensions to this research.

2 – Background Information

This research builds upon the foundation provided by decades of work in the areas of epidemic modeling and simulation, ABS, decision theory, and game theory. This chapter provides an overview of these topics to insure the requisite understanding and highlight particular ideas that were leveraged in this research.

The first section of this chapter introduces the topic of mathematically modeling the spread of infectious diseases, with background information on graph theory provided. The second section describes the particulars of epidemic simulation and discusses considerations typically made when doing such. The third section discusses the concept of ABS, highlighting the benefits of utilizing such a technique as well as providing example applications. This chapter concludes with brief discussions on both decision and game theory.

2.1 – Mathematically Modeling Epidemics

The theoretical and technical foundation to simulating is the incorporation of various mathematical models. This section provides the necessary background on such topics as applied in this work, beginning with an overview of graph theory as applied to epidemic modeling and including discussion on contact networks. Additional detail on this topic can be found in the work of (Bisset, Feng, Marathe, & Yardi, 2009).

2.1.1 – Epidemic Modeling with Graph Theory

Graph theory is a computational technique applied to a variety of problems ranging from determining the pronunciation of a language based on rhyming corpus (Sonderegger, 2010), to optimizing the effectiveness of a health care system (Da Gama Torres, Poley Martins Ferreira, & Pacca Loureiro Luna, 2006). Simulating the spread of an epidemic through a population is another common application of graph theory. When doing such, a contact network $G = (V, E)$ is developed, where the population of n individuals is represented by the vertex set $V = \{v_1, v_2, \dots, v_n\}$ and the edge set $E = \{e_1, e_2, \dots, e_m\}$ represents the m interactions between individuals. An edge is defined as a set of two vertices $e_i = \{v_j, v_k\}$, with the likelihood of the disease spreading between individuals i and j is represented by weighting the edge $\{i, j\}$ with the probability p_{ij} (Carlyle, 2009).

When considering indirect infection from one individual to another, such as if a contagious person was to contaminate an area that a susceptible person subsequently visits, directed graphs are commonly utilized. A directed graph follows the definition of a contact network provided above, replacing the edges with arcs. Formally, the directed contact network $G = (V, A)$ consists of a set of n vertices where $V = \{v_1, v_2, \dots, v_n\}$ and a set of m arcs, $A = \{a_1, a_2, \dots, a_m\}$, where an arc is the ordered set of two vertices (v_i, v_j). This formulation enables the existence of an arc from the first visitor to an area, individual i, to the second, individual j, where the probability of passing the infection is represented by the arc weight p_{ij} and can be different than the weight p_{ji}.

A special form of a graph which frequently arises in the application of graph theory to epidemic modeling is a clique or complete graph. This is a graph in which every vertex is adjacent to each other vertex. A clique, K_n, is a graph of n vertices with edges $E = \{\{v_i, v_j\} : i, j \in \{1, \dots, n\},\ i \neq j\}$. Cliques consist of $\binom{n}{2} = \frac{n(n-1)}{2}$ edges. An example application of a clique in epidemic modeling is provided in the subsequent discussion.

2.1.2 – Considerations for an Accurate Contact Network

Modeling the spread of a disease throughout a population requires the consideration of a multitude of factors. These include spatial and temporal separation as well as differences in how the disease impacts individuals and at what stage each individual is in the disease progression. Developing an accurate simulation therefore is based on including these factors in the creation of appropriate contact networks.

2.1.2.1 – Spatial and Temporal Separation

To address how the dimensions of space and time can separate individuals and impact disease spread, models are first constrained within an *(x,y)* coordinate system. This coordinate system is populated with the individuals in question where each is assigned a location. Parameters constrain the movements of individuals, and for a given time segment the initial and final coordinates of each individual are stored as points $P = (x_1, y_1)$ and $Q = (x_2, y_2)$, respectively. Time is represented by iterating this coordinate system and the movement of individual i is stored as the line segment $\overline{PQ}_i$ connecting the individual's starting and ending locations. Encounters between individuals can then be determined by the intersection, or approximation, of these line segments during each time period, where the set of encounters, A', is such that $A' \subseteq A \;\forall\; a_i = (v_i, v_j) : \;\overline{PQ}_i \perp \overline{PQ}_j$.

Since the encounters an individual experiences can change every time segment, the contact network must be a continuously updated, directed clique with the disease's transmission calculated at the end of each iteration. This is modeled by updating the original contact network with edge weights $p_{ij} = 0 \;\forall\; a_i \notin A'$. Disease transmission can then be simulated as is discussed in the following section.

2.1.2.2 – Simultaneous, Sequential Disease State Models

SSDSM is a technique which enables researchers to account for where an individual falls within the different stages of a disease's progression, the different classes of individuals, and to what extent an individual exhibits symptoms. Examples of the stages of a disease include *HEALTHY, EXPOSED, CARRIER, DORMANT, RECOVERED/DEAD* and follow a prescribed, sequential pattern according to the particular disease and individual. Simultaneously, the exhibition of symptoms by individuals is tracked allowing for variation in the degree to which symptoms can be seen. Throughout this process the classifications of susceptibility as well as infectious or non-infectious are stored (Newman, 2002).

A *Healthy, Exposed, Recovered* (HER) Model is a basic example of sequential disease state modeling. Individuals are initialized in the *healthy* stage and can only progress to the next by becoming infected. This occurs if an individual i is classified as *SUSCEPTIBLE* and encounters an individual j classified as *INFECTIOUS*, after which a random number is generated that is greater than the edge weight p_{ij}. The individual i then remains in the *EXPOSED* stage of the model for a prescribed period of time before progressing to the next. Simultaneously, the symptomatic classification of the individual can progress from asymptomatic to a particular degree of symptomatic, according to the disease and individual. The final state of the model, *RECOVERED*, typically represents an individual that can no longer become infected and is either *RECOVERED AND IMMUNE* or *DEAD*.

2.2 – SIMULATING EPIDEMICS

To understand the implications of a scenario in which the problem is too complex to define mathematically or unethical to conduct via experimentation, simulation is frequently utilized. Understanding and optimizing the survival decisions of an individual during an epidemic is a situation meeting both these criterions.

Coburn, Wagner, & Blower (2009) examine simulation studies conducted on H1N1 and other influenza strains to gain insights as to the impact and effectiveness of mitigation measures if such an epidemic were to occur. Researchers compare the R_0 of past epidemics to that of H1N1 and, based on simulated findings, determine the feasibility of various containment strategies. Researchers conclude by identifying the need for new simulation models which incorporate additional biological complexity. For example, understanding the disease transmission dynamics in bird, pig, and human populations as they occur simultaneously is necessary to effectively identify appropriate interventions and pandemic preparedness planning.

Longini, et al. (2007) model the effects of a bioterrorist release of smallpox in a structured urban population through the use of a stochastic simulation. Modeling their 50,000 node connectivity graph after survey data collected on Portland, Oregon, the researchers were able to closely approximate the average clustering coefficient — the degree to which the populations are clustered into close mixing groups — and the mean shortest path between these clusters. Researchers also collected disease parameter estimates and other information from a panel of smallpox experts. This utilization of real-world and expert-backed data has resulted in general findings that can be applied if such an event were to occur.

Easton, Carlyle, Anderson, & James (2011) use simulation to explore the impact of an epidemic to a small, rural Kansas town. Citing much prior work in understanding how an infectious disease may spread in an urban center, the researchers perceived a lack of knowledge in how the different behaviors of rural individuals may impact disease spread: such as the tendency to more frequently travel longer distances by car. A generic simulation package was created in which the impacts of various possible government-led mitigation strategies were explored.

While the application of simulation to epidemic modeling is popular, it is only one of many application domains. For example, Wong-Ekkabut, et al. (2008), apply simulation to explore the translocation of fullerene clusters through a lipid membrane and to understand the impact of high fullerene concentrations on membrane properties. Due to the difficulty of isolating the impacts of nano-sized fullerene molecules, simulation was selected as the most appropriate investigative tool. Lee & Lam (2008) employ computer simulation to a physical system to determine the effectiveness of alternate methodologies in heat transfer while drilling a geothermal heat pump. As the physical properties of the system components were known or easily and accurately approximated, computer simulation was a more cost effective method as compared to performing a statistically significant set of physical experiments.

2.3 – Agent Based Simulation

A refinement to traditional simulation techniques, ABS is an emergent methodology that enables researchers to more accurately capture the complexity inherent in most real-world systems. The application of ABS to epidemic simulation is one such area. This section provides an overview of this technique, with additional information available in Bonabeau (2001) and additional examples of applications available in the research of Macal & North (2006).

2.3.1 – Fundamentals of Agent Based Simulation

ABS divides the system under study into a collection of agents, which fundamentally, are entities capable of making independent decisions. While more precise definitions of agents vary, the following are characteristics which are typically employed and that have been assumed for this work:

- Agents are discrete units; each with a set of individual characteristics that can vary between entities. Agents belonging to the same classification can have a set of shared characteristics.

- Agents are autonomous, decision-making entities that are capable of functioning independently from their environment and others.
- Agents are located within a structured environment in which they interact with other agents and their surroundings. They are capable of perceiving information specific to that which they interact and responding accordingly.
- Along with their characteristics, agents are governed by a simple set of rules which constrain their decisions and actions.
- Agents are flexible: able to adapt their behavior based on feedback from their environment as they seek to achieve an objective. In some cases, agents are able to modify their governing rules based on their actions and associated feedback (Macal & North, 2006).

2.3.2 – Background of Agent Based Simulation

ABS is a computationally intensive procedure; as such the concept which was formed in the late 1940's did not reach popularity until the 1990's. This interdisciplinary tool has theoretical basis rooted in the same fields it serves, borrowing elements from complex systems, systems science, computer science, management science, game theory, emergence, computational sociology, evolutionary programming, and traditional modeling and simulation. As its conceptual foundation is the idea that systems are built from bottom-up, ABS is most closely related to the field of Complex Adaptive Systems (Macal & North, 2006).

2.3.2.1 – Complex Adaptive Systems

Complex Adaptive Systems (CAS) are a special case of complex systems, which explores the biological systems properties of adaptation and emergence. Study in CAS is focused on determining the appearance of complex behaviors in nature which are brought about by the coalescence of actions from the simple, autonomous agents that make up the system.

The idea of adaption consists of an agent's ability to learn based on its interactions and alter subsequent behavior accordingly. This is evident in the biological sense when you consider how an organism fits itself to the environment over the short-term, and how a species evolves to best exploit its environment over the long-term.

Emergence is the concept of much coming from little. Consider a board game, such as chess, which is governed by a set of simple rules. The fewer than two-dozen basic rules give rise to a vast level of complexity. This complexity should not be confused with randomness; rather it reflects the available patterns that can arise as constrained by the governing rules. Based on this and specific to the system in question, emergence can take the form of a single preeminent pattern, multiple discernible patterns, or so many patterns as to appear random (Holland, 1998).

As pioneer in the field of CAS, John Holland has worked extensively in defining the various properties of such a system, and as CAS is the foundation to ABS, these properties and mechanisms are the basic structural principles of such simulations (Holland, 1995):

- Aggregation: The generalization of related entities into a single classification; for example, each vehicle in a parking lot is an independent unit, yet collectively all vehicles can be grouped into the identifying set, vehicles, and share the same basic properties.
- Nonlinearity: The concept that the whole is not equivalent to the sum of the parts, as is the case in linear equations; this invalidates the option of simple extrapolation. Conversely, these nonlinear systems account for the interactions of dissimilar variables whereby the sum of the parts is greater than the whole.
- Flows: The transfer and transformation of resources, including information, between the agents of the system. Considerations of this principle include the multiplier effect, what impact introducing an additional agent has on the system, and the recycling effect, what impact enabling the reuse of resources has on the system.
- Diversity: As agents interact and alter their governing rules based on their individual learnings, the evolution of these agents can lead to increasing distinction within a single classification of entities.
- Tagging: The mechanism associated with distinguishing the various elements from their aggregate groupings.
- Internal Models: A consistent environment from which the interacting agents can rationally perceive how their actions led to the corresponding outcome.

– Building Blocks: The idea that the decomposition of a complex system results in simple parts that can be combined and utilized in various ways; an example is that of facial features — eyes, nose, mouth, etc. — which could be separated, mixed up, and recombined in the manner of building blocks (Ferraioli, 2006).

2.3.3 – Boids

A simple yet effective example of ABS is the Boids simulation, where a Boid is an ABS entity representing a single member of a flock of birds. Created by Craig Reynolds, this early application of ABS simulates the flocking patterns of birds, and nicely demonstrates how the interactions of autonomous agents governed by a simple set of rules exhibits emergence. Each simulated bird navigates according to its perception of the local, dynamic environment as constrained by the following movement rules:

1. Cohesion: attempt to stay close to nearby boids;
2. Alignment: attempt to match the velocity of nearby boids; and
3. Separation: attempt to avoid collisions with nearby boids (Reynolds, 1987).

After several iterations, the movements of this leaderless flock become reflective of a coordinated migration system. These simple, decisions rules inferred from the local environment and individualized decision making leads to two observations on ABS: (1) sustainable patterns can emerge from systems regulated by basic, deterministic rules inferred from local information, and (2) emergent patterns can be highly sensitive to the initial environment (Macal & North, 2006).

2.3.4 – Applications of Agent Based Simulation

As understanding of ABS has improved, the application of this modeling technique has grown in terms of both number of works and application domains. Furthermore, many researchers have argued that it is the only technology available that can accurately account for the complexity that arises from the individual interactions and behaviors that are inherent aspects of these systems. Recent research in the areas of human social systems, physical systems, and biological systems has utilized ABS. When ABS is applied to the study of epidemics, concepts are borrowed from applications in each of these domains.

The following are cases which argue that ABS is the superior modeling technique for the corresponding domain and specific question addressed. This discussion provides insight to the spectrum of ABS applications and prefaces an overview of ABS as applied to epidemic modeling.

2.3.4.1 – Human Social Systems

Charania, Olds, & DePasquale (2006) utilize ABS as a tool to examine the viability and predict various possible scenarios for a future market in sub-orbital space tourism. Agents are defined as the stakeholder entities of the industry, consisting of consumers, producers, and the government. Each agent provides or demands a specific set of products and services according to their preferences, interacts with other agents and their environment based on a constraining set of behaviors, and seek to maximize their profit or utility accordingly.

2.3.4.2 – Physical Systems

Van Dam, Lukszo, Ferreira, & Sirikijpanichkul (2007) apply ABS to the negotiation process involved in determining the location of intermodal freight hubs, specifically road-rail interchanges. It was determined that ABS is superior to the alternative, multi-objective decision analysis, since it more accurately captures the preferences of individual actors. In this work agents are comprised of hub operators, terminal operators, infrastructure providers, hub users, and communities, each with a decision factor that guides their actions.

2.3.4.3 – Biological Systems

Folcik, et al. (2011) address the biological system application of ABS in their work to analyze the dynamic communication network of the immune response. In this model, agents represent leukocytes and tissue cells structured within an environment of organ tissues, lymphoid tissues, and blood. The infection of these virtual tissues by cytokines, chemokines, and pathogens occurs according to the program specifications, setting off a signal which the agents respond to according to logic rules. With the intent of designing effective therapeutic interventions, network topologies and the histories of successful and failed agent interactions are analyzed.

2.3.4.4 – Epidemic Modeling

Ferguson, et al. (2006) combine concepts from human, physical, and biological systems modeling in their application of ABS to pandemic influenza mitigation. Researchers use high-resolution population density and travel pattern data of and between the United States and Great Britain to construct their simulation environment structure. Accurately modeling this physical system allows them to explicitly model disease transmission. Researchers then consider the interactions of individuals within the household, the general community, and in schools/workplaces; household quarantines, border restrictions, and school closings are available decisions that impact transmission within each of these settings. The understanding of this human system aspect allows researchers to identify the effectiveness of each mitigation policy. R_0 — the number of individuals a single, infected agent is likely to contaminate — is also considered and sensitivity analysis conducted over the likely range of values. This incorporation addresses the biological systems aspect and further bolsters the efficacy of this simulation.

2.4 – Decision & Game Theory

In ABS, entities repeatedly choose between multiple alternatives as they seek to optimize an objective. These decisions are based upon the agent's stored knowledge and governing rules. Since decision and game theory are concerned with selecting the best action from a set of alternatives, these topics are frequently applied within an ABS.

2.4.1 – Decision Theory

When the outcome and subsequent payoff is dependent on the inherent randomness of nature, decision theory should be applied. The basis of decision theory is the assumption that nature does not care whether the individual is happy or not. A basic decision theory model is a payoff matrix with rows representing the various alternatives that can be chosen and columns as the possible resultant states of nature. Each state of nature has a corresponding probability that represents the likelihood of its occurrence, where the probabilities sum to one. Payoffs are typically denoted in terms of utility as defined by a utility function. A more detailed introduction to decision theory can be found in Peterson (2009).

There are multiple strategies on which an individual can base its decision; common techniques include Expected Value, Maximin, Maximum Likelihood, and Regret Analysis. Expected Value is the most common tactic by which individuals select the alternative where the sum of each payoff multiplied by its probability of occurring is maximized.

Maximin is pessimistic approach where the individual expects nature to position them in the worst possible state after their alternative is selected. This decision examines each alternative and selects the strategy that guarantees the highest minimum payoff. Maximum Likelihood focuses on the probabilities associated with each state of nature. For the most likely resultant state, individuals select the alternative that provides the highest payoff.

Regret Analysis takes an alternative approach by first transforming the payoff matrix to a regret matrix. Each value in a regret matrix represents the amount of forgone payoff for that state of nature if instead the optimal alternative would have been chosen. The strategies of Expected Value, Maximin, and Maximum Likelihood, among others that are applicable to a payoff matrix can also be applied to a regret matrix.

2.4.2 – GAME THEORY

As an expansion to decision theory, where the focus is concerned with understanding decisions against nature, game theory is the study of optimizing decisions versus an intelligent opponent. Formally, game theory is the study of mathematical models of conflict and cooperation between intelligent, rational decision makers. Key assumptions are that players have perfect information, are rational, and are able to compute with perfect accuracy. The goal of game theory is to understand the general principles explaining how and why individuals or organizations interact as they make decisions seeking to maximize personal utility. McCain (2010) provides additional insight to the field of game theory.

2.4.3 – NASH EQUILIBRIUM

The primary theoretical tool to analyze a game is Nash equilibrium (Madani, 2010). Nash equilibrium is a state in which, given a set of decisions representing the decision of every player, any single player cannot change their decision and improve their payoff. Thus, Nash equilibrium occurs when each player is playing the best response given every other players decisions are fixed.

Nash equilibrium is to be applied to finite, non-cooperative games by two or more players and can be a mixed strategy whereby individuals choose an alternative based upon a probability distribution. For example, if the equilibrium state for society is to isolate themselves at home during the initial stages of an epidemic, an individual can use this knowledge to understand that the risk of an encounter if they were to leave in search of supplies is lower before other households begin to exhaust their stockpiles.

2.4.4 – Pareto Optimality

A second general principle commonly explored in game theory is Pareto optimality. Along with Pareto optimality, consideration is given to Pareto improvements and Pareto dominated decision sets. A Pareto improvement occurs when, given a set of decisions for a group of players, there exists another set of decisions where all players are at least as well off and at least one player has improved their payoff; in this case the initial decision set is considered Pareto dominated. When no additional Pareto improvements can be made to a decision set, that decision set is considered a Pareto optimal solution. This solution, in contrast to Nash equilibrium, does not necessarily reflect equality between players but is simply a point of efficiency.

For example, in a hostile encounter between two parties during an epidemic scenario, with both parties having guns, hand to hand fighting would be a Pareto dominated decision set. As hand to hand combat greatly increases the probability of obtaining the disease, a Pareto improvement could be made transitioning the groups to the decision set of using their guns and staying at a distance. This solution would then be considered Pareto optimal, as no superior strategies exist.

2.4.5 – Applications of Decision & Game Theory

From their original application in understanding the behaviors of firms, markets, and consumers in economics, decision and game theory have since been applied to the study of human and animal behaviors in a multitude of scenarios. Some domains of application include political science (Landa & Meirowitz, 2009), computational economics (Tesfatsion, 2008), resource economics, and biology, as briefly overviewed to provide a frame of reference in the following section.

2.4.5.1 – Traditional Applications

In the field of economics, research typically models a game as an abstraction of a particular economic situation; phenomena of study include auctions, duopolies, oligopolies, voting systems, agent based computational economics, behavioral economics, and information economics. Madani (2010) applies game theoretical techniques to the study of water resource conflicts. Alternative techniques such as optimization methods are founded on assumptions that are not always accurate; in contrast, the game theory approach allows for the prioritization of an individual's objectives over that of society which allows for the identification of such instigating behaviors

Evolution is a common study of game theory in the biology domain, to the point where the study of evolutionary game theory has developed into its own field. Models of such games typically use a standardized level of evolutionary fitness as the payoff, resulting in such a level of explanatory success that Maynard Smith, an early researcher in this field, stated "[p]aradoxically, it has turned out that game theory is more readily applied to biology than to the field of economic behavior for which it was originally designed." (McKenzie, 2009)

Melbinger, Cremer, & Frey (2010) apply evolutionary game theory to study growing populations by analyzing the growth dynamics and internal evolution of the population in contrast to the common approach of focusing on the relative fitness benefits from different mutations. This combination of traditional evolutionary game theory with common models of population dynamics allows the researchers to consider the dilemma of cooperation within these populations and provide an alternative process to explain population growth than previous models.

2.4.5.2 – Epidemic Modeling

As the application of game theoretical techniques continues to expand into new domains, it has become apparent that epidemic modeling is one such application area.

Reluga (2010) explores the impact of social distancing practiced in response to an epidemic, in terms of game theoretical methodologies. Social distancing practices can reduce the severity of an epidemic and are a result of the collective decisions of individuals. Since the effectiveness of social distancing depends on the extent to which individuals practice the strategy and since individuals must weigh the drawbacks of isolating themselves against the less tangible benefits of avoiding infection, its usefulness as a control measure can be limited. Through game theory, researchers identify equilibria strategies from which they determine how individuals can best use social distancing.

Schimit & Monteiro (2011) study the implications, from a game theoretic angle, of personal vaccination decisions on public health. Researchers create a contact network structured as a probabilistic cellular automaton on which they analyze the propagation of a contagious infection when combated by various vaccination strategies. The model is designed as a game in which the players consist of the cost and perceived-risk minimizing government and the susceptible newborns whose decision to vaccinate is prohibited until neighboring individuals become infected or when the government promotes an immunization program.

2.5 – Chapter Summary

New and innovative techniques are continually applied to progress research in epidemic planning preparedness and mitigation strategies. Combining the foundations provided from the mathematical modeling of infectious diseases and epidemic simulation with the strategies of ABS and game theory is a natural next step in this frontier. The combination of these elements allows for the variety of factors inherent in disease spread; the subtleties presented from the intertwined environmental structure of human, physical, and biological systems; and the interactions of individuals resulting in the emergence of equilibria states, to be more accurately addressed. This concatenation allows for the best available representation of a real-world scenario. The following chapter presents the simulation design considerations undertaken to integrate these features and serves as the basis to this work.

3 – AGENT BASED EPIDEMIC SIMULATION

This work builds upon the knowledge gained from five years of research concerned with the optimization of government-led, epidemic mitigation strategies in rural areas. Prior research has highlighted two key areas in need of more comprehensive examination, which this work addresses: (1) to more accurately emulate a real-world scenario; and (2) to understand how an individual can exploit knowledge of the equilibria resulting from the cumulative decisions of others. As such, the objectives maintained throughout the development of this simulation package consist of the following:

- to expand on the functionality of earlier models by incorporating the most advanced epidemic modeling techniques;
- to explore alternate approaches that decrease the number and magnitude of modeling assumptions necessary; and
- to understand how the decisions and interactions of individuals can influence global equilibria.

The remainder of this chapter contains discussion pertinent to each of these three objectives. Specifically, the first section describes the incorporation of ABS to epidemic modeling and linear programming for decision optimization. Discussion on simulation core considerations is provided, background on decision attributes is supplied, and applications in the areas of goal setting, movements, and encounters serve as illustrative cases to relate the discussion and conclude the section. The second section details the considerations and strategies governing disease propagation. This consists of an overview of the disease properties assumed for this work and discussion on the disease transmission methodology of the simulation package.

3.1 – AGENT BASED SIMULATION: INTELLIGENT DECISION MAKING

When modeling a scenario, to accurately understand emergent patterns from the collective interactions of a group of individuals it is necessary to employ ABS. This allows for the relaxation of various assumptions necessary in traditional models.

For example, instead of creating a probability that two individuals come into contact with each other based on some distance parameter as compared to a random number, ABS allows for the daily decisions of each individual to be made based upon their current circumstances and memory of past events. From this, a step by step travel path for each individual is constructed and the determination of an encounter is based on the intersection of those travel segments at a particular time. The next section provides additional examples of ABS while overviewing the core structure specific to this simulation package.

3.1.1 – Simulation Core Structure

The structure of this simulation is based on the concepts of ABS discussed in Chapter 2. This section provides detail on prominent ABS considerations incorporated into this simulation package, beginning with an overview of the consistent environment which facilitates the flow of resources between agents. This is followed by discussion on the basic unit to which the system was decomposed into: the agent. In this simulation, agents are discrete, autonomous units that are located within an environment and characterized by individual traits, some of which are updatable according to the agent's past experiences. An agent is defined as the family or sub-family unit in question, according to prior decisions of the family, and is composed of the individuals making up the group. An example of a sub-family unit would be the group that left the home location in search of supplies. This section ends with discussion on fundamental considerations involved in creating a simulation. Specifically, discussion on the management of both running time and memory is provided as is related to advancing simulated time.

3.1.1.1 – Environment

This work incorporates census based population and geographic data, to approximate the actual densities and spatial separation of the counties and cities included in the scope. From this data, a realistic environmental structure following an *(x,y)* coordinate system is created to govern the agent's interactions. When considering directional travel from a point, 0 to 360 degrees is defined clockwise corresponding to a particular heading where 0 degrees represents north, 90 degrees east, and so forth.

The environmental structure is created by randomly distributing the home locations for each family making up the city's population within a grid of equivalent size to that city's true land area. If the individual lives in a rural area, then their home location is assigned randomly within the boundaries of the county. Each city is then assign individualized characteristics which can fluctuate over time, disease progression, and the decisions of its residents; these attributes are factored into the decisions of residents.

For example, the current level of *EMERGENCY SERVICES* provided in a city is an aggregation of police, fire, paramedic, hospital, as well as other, similar services. This variable is dependent on the number of emergency response workers available, and can influence an individual's decision to stay at their home or flee the city for fear of such events as rioting and lack of medical care if they were to become sick. Other city-level statistics, such as the number of individuals in each health state, are tracked and utilized. More detail on city-level decision parameters is provided in the section 3.1.2.1.

The simulation environment also contains locations within the coordinate system known as *STOCKPILES*. These are locations that are significant to agents as they may contain stockpiles of supplies and have a level of defensibility associated with them, allowing them to serve as a safe home location. A *STOCKPILES'* level of defensibility is known as its *FORTIFICATION.* Dependent upon its type and past raids, a *STOCKPILE* may contain *FOOD*, *WATER*, *GENERAL SUPPLIES*, *MEDICAL SUPPLIES*, *WEAPONS*, *AMMUNITION*, *VEHICLES*, and/or *FUEL*. A specialized type of *STOCKPILE* is a hospital, and if the *EMERGENCY SERVICES* of its home city are still in operation an agent can receive medical help at that location. As these locations attract agents, multi-agent encounters can occur at stockpiles while only one-on-one encounters are possible elsewhere.

There are three classifications of *STOCKPILES*: a vacant person's home, typically having low levels of supplies and relatively high *FORTIFICATION*; an occupied person's home, with its supplies dependent on the occupying family and its *FORTIFICATION* added to the family's strength during an encounter with an attacking family; and a store, which depending on its type has varying levels of *FORTIFICATION* and supply levels. Examples of stores represented by stockpiles include grocery stores, gun shops, hardware stores, car dealerships, gas stations, pharmacies, and hospitals.

When the simulation is initialized, each agent is assigned a home *STOCKPILE*. An agent can choose to leave their home location by carrying out the *DAY STRATEGY*: *FLEE*. Agents choose to do this in response to high prevalence of infection or rioting in their city. It should be noted that during the *DAY STRATEGY* of *STAY HOME* agents can choose to expend *GENERAL SUPPLIES* in an effort to increase their home *STOCKPILE'S FORTIFICATION.* The decision to do this is based on recent encounters at their home and their level of *GENERAL SUPPLIES*.

3.1.1.2 – AGENT POPULATION

The main component of this simulation package is the agent population. Every individual making up the population of the counties in the modeling area has specific characteristics. Since it can be assumed that in an epidemic scenario the noteworthy actions of an individual are shared with that individual's family, memory spanning two weeks into the past is stored for each family unit. Based on 2010 census figures of average household size, this enables a population 2.5-times what would otherwise be constrained by memory limitations to be simulated (United States Census Bureau, 2011).

As such, over 56,000 individuals are simulated as agents, with the decision making processes of each facilitated by over 75 individualized variables in addition to the dozens of global variables shared by multiple agents. Besides location, the main differentiating characteristics between families when the simulation is initiated are their level of morality; risk tolerance; ability to remain calm; propensity to hoard goods in anticipation of some such disaster; their level of *FOOD, WATER, GENERAL SUPPLIES, MEDICAL SUPPLIES, WEAPONS, AMMUNITION, VEHICLES,* and *FUEL*; and differences resulting from the aggregation of family member traits such as strength, eating/drinking rate, and overall health.

After multiple iterations of the simulation, the major differentiating factor between families are the memories gained from the decisions that each family has made. For example, some of the histories stored include current supply level, knowledge of the disease severity, happiness of a particular day's strategy, which direction a search party left in, the success of that search party, and the location of any stockpiles encountered during the trip. More detail on the parameters associated with agents is provided in the section 3.1.2.1.

3.1.1.3 – Time Advance

As this discussion has shown, when utilizing ABS a multitude of decisions points are incorporated throughout the model: this allows for the close approximation to the decision sets available to individuals in the real-world. This simulation package is configured as a two-tier time advance system. This brings about the evaluation of many more decision points during the execution of particular scenarios than would otherwise be possible.

The first tier parallels the advancement of days, during which agents begin by deciding their *DAY STRATEGY.* This is essentially a response to the agent's perception of the situation and governs all subsequent actions for the remainder of the period. At the end of each of these periods output data is recorded; family characteristics, such as the consumption of *FOOD* and *WATER*, are updated; the health status of individuals is updated according to what was consumed and, if infected, how the disease has deteriorated their health; and memories are updated. More detail on how memories are updated is provided in the discussion of the following section.

The second tier represents subdivisions that each day is portioned into; these are referred to as *TIME SEGMENTS*. The number of *TIME SEGMENTS* per day can be adjusted to decrease run time or, conversely, to increase the number of decision points. This work uses a time period of 30 minutes.

The primary use of second tier time advancement is to model the more rapid occurrence of decisions involved during certain *DAY STRATEGIES*. For example, during each of these *TIME SEGMENTS* agents can decide to begin or end their search, and may experience an encounter or find a stockpile. Depending on what happens during the preceding *TIME SEGMENT*, an agent can alter its course of action. More discussion on this topic is provided in section 3.1.2.4.

3.1.1.4 – Dial's Implementation

As a consideration to running time management, the conceptual basis to Dial's implementation is applied to updating agent histories. Conventionally, Dial's implementation is utilized in algorithms seeking the shortest path between an origin and destination node. Dial's decreases solving time in such an algorithm by eliminating the need to find the minimum (Dial, Glover, & Karney, 1979).

In this simulation package, the memories of all agents are updated at the end of each day. Each agent has historical knowledge of 27 different items, which are stored in arrays as values spanning the two week length of an agent's memory. For example, the memory of what *DAY STRATEGY* was performed is stored as a character in the first memory array, $x_{1,i} \in \{n, h, s, p, m\} \; \forall \; i \in \{0, \dots, 13\}$, where each character represents a possible *DAY STRATEGY*. The standard process of updating such an array would be to erase the memory from two weeks ago, stored as $x_{1,13}$; shift all memories back a day, $x_{1,i} = x_{1,i-1} \; \forall \; i : i \neq 0$; and insert the new *DAY STRATEGY* into today's memory slot, $x_{1,0}$. This process must be performed for all agents every day, requiring a non-trivial amount of time.

Dial's provides an alternate process. Instead of maintaining today as day 0 and shifting all memories down a day, a global variable is stored that tracks the current memory day. This allows for today's *DAY STRATEGY* to replace that from two weeks ago directly. This methodology creates additional coding difficulty when calculating averages for a memory array and performing similar tasks, however the decrease to running time outweighs these drawbacks. Variations of this concept are applied throughout this simulation package, such as when all members of a family die. In this instance the deceased family is switched with the last family of the *FAMILIES* array and no longer included in the program's execution.

As has been shown, this simulation package must replicate the decision process of all its constituent agents a massive number of times, each occurrence of which dozens of factors may have to be evaluated. This presents issues with running time and sufficient memory, not to mention the requisite coding. However, the largest obstacle is approximating the optimal decision as the human brain would. The following section discusses the application of integer programming to the optimization of decisions, with examples provided to illustrate significant instances.

3.1.2 – Decision Optimization

There are a large number of decisions available to agents, largely constrained by that agent's past decisions and influenced by a variety of individual and global factors. Each of these different decisions falls into a specific category based on the types of variables and parameters being examined. As such, there is a multitude of different methodologies for determining the agent's choice. Notable decision categories along with an example implementation are provided as follows:

- The evaluation of a small set of family traits: for example, when comparing morality and risk tolerance against a parameter value in the decision to split the family if a family member becomes sick.
- The assessment of parameters resulting from prior decisions: for instance, the calculation of the benefit associated to an additional unit of food is based upon the previous decisions of how many people to include in the search party and how much food is already packed.
- The examination of the agent's memory: as in the decision on what minimum strength a search party should have to avoid losing an attack if one were to occur based on the strength of groups encountered in the past.
- The execution of algorithms to solve integer programs: for example, weighing the benefit of a particular supply against the lost capacity from carrying it.
- Various combinations of these techniques: such as the decision of what good to trade and the subsequent haggling and price setting when conducting a neutral trade with another group of individuals.

Decisions of varying magnitude occur throughout an agent's day, the following discussion provides an example of key instances in the order that an agent would execute the decisions during a day. This discussion is prefaced with a detailed discussion of the major decision parameters. Following that the primary decision of an agent – what strategy to follow for the day – is outlined. The third section discusses an application of integer programming in the agent's selection of gear to take with a search party. The two succeeding sections then introduce necessary information travel decisions and on the novel shape, the recellipse, discussing its formulation and use. This is followed with detail on the evaluation of options during an encounter. Discussion is concluded with an overview of the decision process involved in haggling during a neutral, exchange encounter.

3.1.2.1 – Decision Attributes

There are a multitude of parameters which influence the decisions of agents. These can be categorized into four main groups: (1) constant global parameters; (2) cumulative global parameters, representing the summation of agents portraying a particular trait; (3) constant individual parameters; and (4) updatable individual parameters. Discussion on each is provided in the following.

3.1.2.1.1 – Constant Global Parameters

Constant global parameters are in place to either define the environment and/or represent characteristics of the particular simulation run, such as what disease is being modeled. These values can be altered between runs for sensitivity analyses but do not change after being initialized. Parameters defining the environment consist of the locations for and number of counties, cities, and stockpiles; the populations of counties and cities; and the number of families. When agents die their individual traits are stored but not evaluated. As such separate variables for the living populations are tracked but the initial populations are necessary to access the information of the deceased.

Parameters defining the disease characteristics include the percent of individuals that typically have immunity, methods of disease transmission, the different disease states, and the amount of time spent and levels of infectiousness for each state. The distance over which the virus can be transmitted to another is an additional parameter that can be accepted when modeling airborne transmission. Although all of these parameters can influence the best strategy for an individual, understanding all of the various combinations and resulting strategies is a massive undertaking. Therefore, the scope of this work is to understand the best strategies under the different disease transmission methodologies, holding all other parameters constant.

3.1.2.1.2 – Cumulative Global Parameters

Cumulative global parameters are either used to trigger an event or represent the current status for a city. Those that trigger a status change essentially represent the summation of agents meeting a particular designation. These are stored at the city level and include the number of agents in each disease state, the number of agents that are emergency personnel and working, the number of agents that are emergency personnel and no longer working, and analogous counts for regular workers.

The parameters which represent a city's status consist of the level of *GOVERNMENT ACTION*, whether a city is *POWERED*, and the level of *EMERGENCY SERVICES*. *GOVERNMENT ACTION* consists of government alerts, school closings, work closings, martial law, and quarantines. These events influence the decisions of agents in the impacted city. *MEDIA COVERAGE* works similarly by increasing a family's *INFORMATION LEVEL* but it is the same for all agents regardless of their city.

When, for example, the number of emergency personnel that are no longer going to work drops below a threshold value, then that city is classified as not having any *EMERGENCY SERVICES*. Similarly, the ratio of the regular workforce determines whether the city has *POWER* or not. Equations evaluating the number and percent of individuals that have become sick or are showing symptoms of illness increase both *GOVERNMENT ACTION* and *MEDIA COVERAGE*.

3.1.2.1.3 – Constant Individual Parameters

Constant individual parameters are family traits that influence decisions. These are ubiquitous to this simulation package, influencing the outcome of almost all decisions. As such this work concentrates on understanding how variations in these values impact the likelihood of survival. These values differ between agents but are constant once initialized.

Some of these parameters track family composition and structure. Examples of these include the initial family size, and those that store the traits of individuals: *AGE CLASSIFICATION*, *GENDER, WORKING STATUS, JOB TYPE*, and *BASE STRENGTH*. *AGE CLASSIFICATION* designates whether the individual is a child, adult, or elderly. This classification changes the mean value for the normal distribution used to determine *BASE STRENGTH* and limits whether the individual can be designated as holding a job or not. *JOB TYPE* stores whether the working individual is an emergency response personnel. *BASE STRENGTH* times the updateable individual parameter *HEALTH STATUS* results in a current strength value that is an instrumental factor during encounters.

The most influential of these parameters store values which serve as the basis for the family's thought process. These are *RISK TOLERANCE*, *MORALITY*, *SELF-CONTROL*, and *PROPENSITY TO HOARD* supplies in anticipation of an apocalypse. *PROPENSITY TO HOARD* is a binary variable while both *RISK TOLERANCE, MORALITY,* and *SELF-CONTROL* are stored as zero to one numbers. Throughout the simulation package numerous decision points occur during which an agent weights a value, calculated from its current situation, against one or more of these values.

3.1.2.1.4 – UPDATABLE INDIVIDUAL PARAMETERS

Updatable individual parameters are the largest category of decision parameters. These are an imperative aspect of ABS, as they act as storage of past experiences and decisions. They include histories of decisions and outcomes, parameters to guide travel decisions, individual traits, and family traits. These values are updated according to individualized stipulations, with updates occurring intermittently as instigated by an event.

Histories occupy a significant amount of memory as there are 27 for each agent which are each stored in the form of an array spanning two weeks. Every cell of the array corresponds to a particular day of the agent's past. Examples include the information such as the location of stockpiles visited in the past, the *DAY STRATEGY* chosen, direction of travel, satisfaction of the *DAY STRATEGY* outcome , the strength and number of encounters during excursions and at the home location, what time the search party left, and the family's *INFORMATION LEVEL*. Histories are commonly recalled during the determination of primary decisions such as selecting *DAY STRATEGY*, as they represent the agent's knowledge.

When a family decides to send out a search party, 24 values are set storing location information, recellipse coordinates, information on which supplies to collect, traits of the search group, and other information. Of these, search group traits are the most influential to the outcome of decisions. These include the group's carrying capacity, strength, intensity, current objective, and an array storing identifiers to access the traits of the individuals making up the party. The decisions of agents during an encounter are determined from the evaluation of these values and the outcome of the encounter resolved from the comparison of these values between the involved parties. Location information and recellipse coordinates are utilized in the determination of successive *TRAVEL SEGMENTS*. Information on supplies provides the data necessary for the execution of the integer programming algorithms for raiding stockpiles and exchanging goods.

Individual and family traits track the current characteristics exhibited by the entity in question. For the individual, these include current health state, time periods remaining in that state, and current *HEALTH STATUS*. These are updated as time progresses according to the individual's circumstances and whether they are infected. Family traits consist of the home location, supply levels, and usage rates. Supply levels deplete over time according to the current usage rates which are dependent on the decisions of the family. These parameters are frequently involved in decisions. For example, whether supply levels are such that the risk of leaving the home to search for supplies is warranted.

3.1.2.2 – Day Strategies

Decision points occur throughout an agent's day and are confined by the selection of a particular *DAY STRATEGY*. The selection of *DAY STRATEGY* is governed by the occurrence of certain events, as such the *DAY STRATEGY* can be thought of as the agent's event response. To better illustrate how these types of decisions affect the probability of indirect infection, the initial decision following an event is stored and denoted as the cause of infection if the agent is exposed before the occurrence of another event.

Events include a family member becoming infected, a government mandated 24-hour curfew, city looting/rioting, and rumors or reports of unusually high numbers of sick individuals in either the agents same region, county, or city. After the occurrence of an event, the agent determines its specific *DAY STRATEGY* based on the evaluation of family traits; specifically risk tolerance, morality, self-control, current supply level, and their perception of the severity of the situation. These are each weighted according to the relevance in to particular event and response. For example, in considering whether to loot essential items more emphasis is placed on having a lower supply level than on the agent's ability to remain calm, its self-control.

The responses available to agents are based on the current event type, representing the current situation. Agents are initialized behaving as if everything is *NORMAL*. As rumors or reports of a possible outbreak reach a threshold value, agents will decide to *FLEE* the area or stay and either *RUSH STORES* for supplies, *STAY HOME*, or simply *IGNORE* the warning signs. The outbreak location — same city, same county, or same region in respect to the agent's home — designates different event types. When enough agents *RUSH STORES*, panic ensues and looting/rioting within the particular city begins. In this situation, agents decide whether to *LOOT EXPENSIVE* items, *LOOT SURVIVAL* items, or avoid the mob and *STAY HOME*.

As the severity of the epidemic situation increases, the government begins to implement mitigation strategies. Enacting a 24-hour curfew is one such event. Agents can decide to heed the warning and *STAY HOME*, or ignore it and take advantage of looting opportunities where, again, the agent selects whether to *LOOT EXPENSIVE* items or *LOOT SURVIVAL* items.

When a family member becomes infected all other events are prioritized lower, and the family decides to either *SEEK CARE* for the infected individual, attempt *HOME CARE*, or the infected individual may become resigned to its fate and *ACT WITHOUT WORRY* of infecting others. *ACTING WITHOUT WORRY* reflects an individual with low morality that travels around using its infectiousness to gain desired items.

Secondary decisions, depending upon the particular *DAY STRATEGY*, are also selected. These are stored as parameters and influence the outcome of certain scenarios, such as the outcome to an aggressive encounter. For example, if *LOOT ESSENTIAL ITEMS* is selected as the *DAY STRATEGY*, a secondary decision to be made is which individuals should make up the search party.

Picking the search party considers both past experiences against family traits. Specifically, the memory sets *HOME ENCOUNTERS* and *SEARCH ENCOUNTERS* are examined and, as allowed by the family's *RISK TOLERANCE*, a search group is formed of sufficient strength to escape, discourage, or win an attack, while maintaining sufficient *HOME STRENGTH* so that the home group can do the same. What gear to bring when leaving the house is another secondary decision that applies more advanced techniques as is required by the increased complexity of the situation.

3.1.2.3 – Travel Gear Optimization with Linear Programming

Concepts from the industrial engineering field of linear programming optimization are utilized in the selection of travel gear. This decision is modeled as a form of the knapsack problem and the solution is determined by performing an algorithm where the objective coefficients are iteratively updated.

The traditional example of a knapsack problem is a group going on a backpacking trip. The group desires to bring a variety of goods such as a box of matches, a kettle, a tent, and a deck of cards. The status of each goods is denoted by a binary variable and all are initialized at 0. If a good is selected to be carried along, its designation is changed to a 1. Each item has a capacity and benefit associated with it. In addition, the group has a maximum carrying capacity that constrains what can be brought.

If, for example, the group has a capacity less than that of the tent, then it would be infeasible to decide to bring the tent. Furthermore, since the matches are of similar size to and of more benefit than the deck of cards, the group would decide to bring the matches before the cards. This type of problem is modeled according to the general form:

$$\max \sum_{i=1}^{n} c_i \, x_i$$

$$\text{s.t.} \ \sum_{i=1}^{n} a_i \, x_i \leq b$$

$$x_i \in \{0,1\} \ \ \forall \ \ i \in \{1, \dots, n\}$$

where a_i, $c_i \in \mathbb{R}^+ \ \forall \ \ i \in \{1, \dots, n\}$ and $b \in \mathbb{R}^+$.

To solve this problem the simulation relaxes the constraint of $x_i \in \{0,1\}$ to $x_i \in \ \mathbb{R}^+$. It then performs a subroutine that updates c_i where i was the last good selected, choosing to add single good at a time. The selection of which good to add next is determined according to the ratios of benefit to cost, c_i/a_i, with the good having the highest ratio chosen. This subroutine takes into account the decreased value of adding an additional good of the same type, providing the optimal solution to the linear knapsack problem.

To initialize this algorithm, an agent considers what food and water is necessary to sustain the group for the designated maximum travel time, what number of weapons and ammunition may be necessary for protection, what excess carrying capacity is needed to bring back the desired items, what medical supplies are necessary to avoid infection, and which goods may be useful in a trading situation with another group. This level of benefit for each good type is calculated by evaluating secondary parameters, such as the number of individuals making up the group; earlier experiences, such as the strength of groups encountered in the past; and tertiary parameters set during prior iterations of the algorithm, such as the amount of ammunition necessary to supply the weapons.

3.1.2.4 – Iterative Travel

When an agent selects a *day strategy* that involves leaving the house, a secondary decision is *departure time*. *Departure time* specifies during which *time segment* the agent transitions from the base day strategy of *stay home* to their particular strategy. This begins the process of iterative travel.

Iterative travel is a procedure that allows for the reevaluation of an agent's decision to continue upon their current course and maintain their current objective. Objectives include: hold the same heading and *continue forward*, *change direction*, *raid* a stockpile, hide or *stay* in the same location, and *return home*. Furthermore, during each *time segment* agents may experience an encounter or find a *stockpile*.

If, for example, an agent having the objective *continue forward* finds a stockpile, they measure the chance of a negative encounter against the expected benefits from raiding the *stockpile*. From the outcome of this decision the agent either *approaches* the stockpile or *flees*. During the next *time segment*, if the agent chose *approach* the agent does not continue upon their prior objective and instead seeks to initiate an encounter. Alternately, if the agent chose *flee* the agent decides to give up and set their objective to *return home*, or evaluate its current direction and select between *continue* and *change direction*. If changing direction is chosen as the next objective, the feasibility of the predicted ending location must first be evaluated. This is made possible through the use of a search area: the recellipse.

3.1.2.5 – Rational Search Area: The Recellipse

After an agent selects its *DAY STRATEGY* and before departing, travel parameters are set to constrain the group's search area. This predetermination of a rational search area allows for iterative travel to be performed in a manner analogous to that of a rational individual, as is shown in the following discussion.

Travel parameters are another set of decisions that incorporate multiple decision evaluation methodologies, including the appraisal of an agent's memory and the comparison of family traits against predetermined parameters. Specifically, the travel parameters of *MAX TRAVEL TIME, MAX TRAVEL DISTANCE, INITIAL TRAVEL DIRECTION,* and *TRAVEL SPEED* are set after consideration of factors consisting of whether walking or driving, the location of previously raided stockpiles, directions resulting in high number and intensity of encounters, and the family's risk tolerance, among others.

From these parameters a novel shape is constructed to confine the agent's movements. This shape is a recellipse, the area of which resembles an ellipse with one half inscribed within a rectangle as depicted in Figure 1.

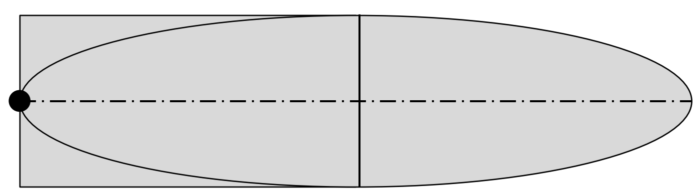

Figure 1: Recellipse

The recellipse is oriented such that the agent's home location is on the perimeter of the recellipse, centered on the short side of the rectangle portion, as denoted by the black dot. The long axis of the recellipse, represented by the midline, is oriented along the *INITIAL TRAVEL DIRECTION* of the agent.

A recellipse centered at the origin of an *(x,y)* coordinate system is shown in Figure 2. The length of the long axis, l, is set to the value of *MAX TRAVEL DISTANCE*. The coordinates of a recellipse are defined as follows:

$$If\ -\frac{l}{2} \le x < 0\ \ then\ \ -\frac{h}{2} \le y \le \frac{h}{2}$$

$$else\ if\ 0 \le x \le \frac{l}{2}\ \ then\ \ \frac{x^2}{l^2} + \frac{y^2}{h^2} \le 1$$

The parameter *MAX TRAVEL TIME* constrains the total area via the variable h. This is done by setting h such that the recellipse perimeter is equal to the maximum distance allowed by the given *MAX TRAVEL TIME* and *TRAVEL SPEED*.

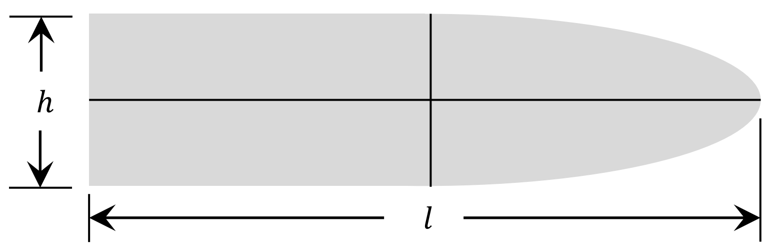

Figure 2: Dimensioned Recellipse

The theory leading to construction of this shape is based on the following main concepts. First, since agents are intelligent and utilize their memory of past experiences they have an intended destination when they set out. Consequently, the long axis of the recellipse represents the vector on which the agent expects to achieve its objective. Since travel carries a higher risk of meeting others and, subsequently, an increased probability of becoming infected or experiencing a negative encounter, agents desire to remain close to home. However, this must be balanced by the need to travel a sufficient distance to find the necessary stockpiles. As a result the far end of the rational search area is arched, cutting off the less likely to be explored far corner points.

Conversely, the corner points near the home location are feasible for exploration due to their proximity to shelter. The area in the opposite direction of the originally sought goal is infeasible since it cannot be expected that a rational individual will retrace all of their steps based on the experiences of a day without simply returning home.

If during an agent's travel, the end point of their next *TRAVEL SEGMENT* falls outside of the recellipse that *TRAVEL SEGMENT* is deemed infeasible. In this situation, a new *TRAVEL SEGMENT* is calculated with their desired direction of travel adjusted 10 degrees in the closest direction to parallel their *INITIAL TRAVEL DIRECTION*. This process is repeated until a *TRAVEL SEGMENT* becomes feasible.

For example, assume that an agent's recellipse is oriented at 90 degrees, as in the previous figures. Further assume that for its next *TRAVEL SEGMENT* the agent desires to travel at 60 degrees and their destination falls outside of the recellipse. Since 60 degrees out of 360 is closer to 90 than it is to 270, the next *TRAVEL SEGMENT* calculated is based on intended travel at 70 degrees. In other words, the agent is traveling away from their home location more so than towards it. As such, they are still searching and to remain rational they will adjust their path to be more in line with the vector along which they had initially expected to achieve their objective.

3.1.2.6 – Interaction Decisions

While a particular agent is traveling, there exists the possibility that an encounter occurs with another group. An encounter occurs if either of the two following scenarios transpires during a *TIME SEGMENT*: (1) the *TRAVEL SEGMENTS* of each party intersect; or (2) each party decides to approach, or is already at, the same stockpile. The first of these scenarios is constricted to a one-on-one encounter and the second can become a multi-agent encounter. Agents are restricted to a single encounter during each *TIME SEGMENT* for running time conservation.

If an encounter occurs, specialized decision sets become available for each agent depending on the particulars of the encounter. For example, if two agents have intersecting *TRAVEL SEGMENTS* it is randomly determined that either they see each other simultaneously or one agent sees the other first. If one agent sees the other first, their decision set includes the option of *HIDING* as well as the actions available to both families: *FLEE, RETURN HOME, ATTACK*, *REMAIN NEUTRAL*, and seek to *ALLY*. The determination of this action is largely based on what the agent expects the outcome to be. Therefore, if an agent encounters a group that is perceived to be much stronger the agent will likely seek to avoid confrontation, although if the agent is desperately in need of aid they may still seek to instigate an encounter.

Just as there exists several decisions preceding an encounter, a multitude of possible outcomes are available. One example entails a simultaneous sighting where the weaker, slower family attempts to *FLEE*. If the other family decides that they want to *ATTACK,* it is likely that they will catch the other family and battle ensues. It is very probable that the stronger family wins such a battle and can then raid the supplies of the other party. The *MORALITY* of the winning family determines what percentage of the other family is killed. A ratio of each group's *TRAVEL STRENGTH* decides how many of the winning family are killed, and injuries for all survivors of the battle are determined randomly. These injuries decrease the individual's *HEALTH STATUS* and subsequently their strength. *HEALTH STATUS* can only be regenerated through proper nourishment and avoidance of infection over time.

Another example involves both agents deciding that they would like to perform a *NEUTRAL EXCHANGE* of supplies and information. Relatively equal *MORALS* and perceived *TRAVEL STRENGTHS* are necessary for both families to decide upon a *NEUTRAL EXCHANGE*. *NEUTRAL EXCHANGES* involve the process of haggling which entails the execution of a complex series of decisions. This procedure is described in the following section.

3.1.2.7 – HAGGLING

Haggling is initialized with the computation of the parameter *HAGGLING INTENSITY* for each family. This parameter is calculated from the family traits *TRAVEL INTENSITY*, *TRAVEL STRENGTH*, *MORALS*, and the perceived *TRAVEL STRENGTH* of the other family. The family with a *HAGGLING INTENSITY* of greater magnitude is deemed the more aggressive and initiates and leads the exchange by asking which good the other family would like to trade to receive. This allows the more aggressive family to then set the initial price in terms of the item that they most desire.

RELATIVE DESIRE between goods is a family parameter that is set at the beginning of each day and influences decisions ranging from *DAY STRATEGY* to *EATING RATE*. *RELATIVE DESIRE* for a particular item is influenced by factors such as the number of days it typically takes to find, the current level of availability, the rate of consumption, and how successful recent *SEARCHES* have been.

The decision of what goods are being traded is solved through an iterative process where a family first examines their memory and requests the good with highest *RELATIVE DESIRE*. If the counterparty has this type of good with them they request a certain number of their most desired good to make the exchange. If the counterparty does not have any of the good they counter with an offer of their own.

Price determination is a second iterative process throughout which price is defined in terms of the number of the designated good type in exchange for one of the initially requested item. Each agent determines two prices: asking price, and their low or high limit depending on whether they are trading away or receiving the good by which price is expressed. Each agent's limit price is calculated according to how their circumstances adjust what would be a commonly accepted price.

For example, say that a gallon of water is generally equivalent to a small box of sanitizing wipes, and the agent trading away the water has surplus water and a comfortable amount of sanitizing wipes. Then the base price of 1:1 (water:wipes) would be adjusted slightly since water has a lower importance to the agent than sanitizing wipes. Depending on the exact values of *RELATIVE DESIRE* used in the calculation, a price of 2:1 could be set. If instead the agent had only a slight surplus of water and no sanitizing wipes, a more extreme price of 10:1 may be decided upon.

This process repeats until either the agents execute all desired and feasible trades or until the number of transactions exceeds the time limit for that *TIME SEGMENT*. A time limit is set under the notion that during an epidemic scenario an agent will attempt to minimize its exposure to possible infection.

3.2 – DISEASE PROPAGATION

This work leverages the flexibility of adjustable disease characteristics, which allows for increased simulation versatility and the accurate replication of a disease in a real-world setting.

Disease parameters such as the particular states that the disease may exhibit, overviewed in section 2.1.2.2, are programmed according to a real disease. A strain of smallpox was chosen as the base model for this study. This particular disease has been researched extensively and its characteristics are such that it could conceivably be the basis to an epidemic.

3.2.1 – Disease Overview

There are two know clinical forms of smallpox: variola major, the more severe and common form, and variola minor, which accounts for less than 10 percent of cases. Within the form of variola major, there four types of smallpox each having varying fatality rates, symptoms, and impacted populations (Centers for Disease Control and Prevention, 2012). In this work the most severe strain, of the more common type of smallpox is utilized as the disease in question: hemorrhagic smallpox.

In this simulation package, the states of *HEALTHY, INCUBATION, INFECTED,* and *DEAD* are used to describe the stages of hemorrhagic smallpox. As the rates of infectiousness and the tendency for individuals to display symptoms are typically defined as separate stages of this disease, the stage of *INFECTED* has been subdivided into *SYMPTOMATIC* and *CONTAGIOUS*. Based on this disease's particular characteristics, fatality rates are set to 100 percent.

To understand how differences in decisions, as opposed to differences in genetic traits, impact the extent of infectiousness and when symptoms arise, this particular application does not incorporate the variability between individuals that a disease exhibits. In other words, each individual follows the exact same disease track with the same number of days in each stage regardless of prior health or other characteristics.

Progression through the disease track begins with exposure to the virus. After this, 13 days are spent in the *INCUBATION* period, followed by a short, 3 day period of initial symptoms represented as *SYMPTOMATIC.* The next state is a 20 day period of advanced symptoms, during which the agent is contagious, and therefore is represented as *CONTAGIOUS*; after which the agent becomes deceased. The only built in variability is the day at which an individual dies, which can occur at any time and is based on the characteristics of *HEALTH STATUS* and *STRENGTH*.

As hemorrhagic smallpox is not an airborne virus and cannot survive any considerable amount of time without a host, the base case for this study is transmission via direct contact transmission. However, as the likelihood of an epidemic scenario arising from these exact parameters is miniscule and this study seeks a comprehensive understanding, additional insights are desired. To this effect, all possible methods of transmission types are studied with analysis presented on the resulting differences.

3.2.1.1 – Forms of Disease Transmission

Direct contact transmission is the traditional scenario studied in epidemic modeling; however, diseases may fall in one of four classes in terms of means of transmission: (1) only direct contact, (2) indirect contact, (3) airborne transmission, or (4) both indirect contact and airborne transmission.

As the name implies, direct contact transmission requires actual physical contact between contagious and susceptible individuals. In such a scenario, the likelihood of becoming infected is dependent on the type of contact. For example, shaking hands has a relatively significant probability of passing the infection since people continuously use their hands in a manner that facilitates disease spread: covering a cough, rubbing eyes, etc. However, it is obvious that kissing would have an even higher probability of transferring the virus. The length of exposure is another factor that is significant in becoming infected; however this is relevant to all transmission classes. In this simulation package, the use of *TIME SEGMENTS* accounts for length of exposure.

Similar to direct contact, indirect contact requires interaction between contagious and susceptible individuals. However, indirect contact differs in that the individuals do not have to have physical contact, indeed both individuals do not even have to occupy the same space at the same time. This is the situation for diseases that can survive on a surface without a living host. For example, if a surface was touched by an infected individual, then for as long as the disease can survive without a host, any susceptible individual coming into contact with that area risks infection. As the time from contamination increases, the likelihood of infection decreases.

Airborne transmission allows a virus to be transmitted over any open area, within a certain contamination radius as defined by the disease's characteristics. Thus, a susceptible individual can become infected from simply being within range of a contagious individual. Additional discussion, in terms of how these considerations were implemented within the simulation package, is provided within the following section.

3.2.2 – Transmission

As a preface to the discussion on disease transmission, the distinction between agents and individuals, first defined in section 3.1.1, is of importance. This simulation package determines exposure at the agent, or group, level. The individuals that make up this group are then evaluated individually to determine if they transmit or become infected by the disease. This allows for running time minimization while maintaining robustness by considering the traits of individuals.

The basis to disease transmission is the set of encounters between individuals, across which the virus may spread. As discussed in section 2.1.2, epidemic simulations typically structure the links between all individuals as a contact network with edge weights representing the probability of propagation over that particular connection. This probability is a combination of the likelihood that an encounter occurs between the two individuals and the likelihood that the disease is then transmitted from one to the other. In ABS, the decisions of agents and rules of the environment allow for actual encounters to be determined. This relaxes the dependence on randomness and instead results in a more robust, deterministic model.

In this simulation package, after an encounter occurs the likelihood of catching the infection is dependent on the agent's decisions and the particular individual's traits, within the particular setting. For this study, all disease parameters were held constant except for the transmission class, on which sensitivity analyses were conducted over multiple runs. This section discusses the modeling considerations made for each transmission class, by detailing the three scenarios during which an agent can become infected.

3.2.2.1 – Proximity Transmission

Proximity transmission occurs as a result of an encounter, of which there are two types: two-agent encounters that occur when *travel segments* intersect, and multi-agent encounters which can only occur at stockpiles. For running time and memory conservation, stockpiles are limited to 20 visitors per *time period*. This is a reasonable limitation as it can be assumed that newly arrived agents will avoid a stockpile already having 20 other agents.

In these scenarios, direct contact plays the primary role for disease spread and airborne transmission a secondary, although influential, role. Indirect contact transmission is not applicable in this type of situation. For disease spread to be evaluated, as described in the following subsections, at least one individual making up the agent populations in question must be in the contagious stage.

3.2.2.1.1 – Multi-Agent Encounters

For complexity reduction and running time management, multi-agent encounters are decomposed into a set of two-agent encounters as determined by the decisions of the agents. This is a reasonable as in an epidemic situation it can be assumed that individuals will seek to avoid contact with others when about general business. For instance, assume five agents find a stockpile and four decide to enter. The agent that leaves is not considered for proximity transmission. The four that enter raid the stockpile are all exposed to intermediary transmission, as is further discussed in section 3.2.2.2.

After raiding the available supplies, each of the four agents then consider a variety of factors to determine whether they want to approach another agent and which agent to approach. These factors mainly consist of how successful their raid was, their *risk tolerance*, *morality*, and whether they perceive their *travel strength* to be sufficient to have a successful encounter. After all agents make their decisions, if an agent decides that it would like to leave and no others desire to approach it then it is not further considered. If the agent is approached by another, it is assumed that the confined space of a *stockpile* prohibits escape and a proximity transmission scenario occurs. This situation is executed in the same manner as a two-agent encounter, and upon resolution the agents are exempt for additional encounters during this *TIME SEGMENT*.

3.2.2.1.2 – TWO-AGENT ENCOUNTERS

For two-agent encounters, agents first determine and carry out their corresponding decisions (in the case of reduced, multi-agent encounters these decisions have already been determined). As previously discussed, these include the avoidance tactics of *LEAVE*, *HIDE* or *RETURN HOME*, and the decisions resulting in contact: *ATTACK*, *ALLY*, and *NEUTRAL*. If the situation ends with the agents coming into contact, the simulation package executes the corresponding disease spread logic. This functionality is based on an infection formula that takes into account the agent's traits, disease characteristics, type of encounter, and the stochastic nature of such a situation.

First, the simulation determines whether the agents actually came into direct, physical contact. This represents a decision point where each agent bases its level of concern about physical contact on their *INFORMATION LEVEL*, *RISK TOLERANCE*, and *MEDICAL SUPPLIES*. For instance, assume that an agent has very little knowledge about the disease characteristics and severity. Regardless of its *RISK TOLERANCE*, this agent would have no qualms about touching another. Likewise, an agent with very high *RISK TOLERANCE* would have little concern about physical contact unless their *INFORMATION LEVEL* was such that they understood the disease to be very severe. The presence of *MEDICAL SUPPLIES*, such as a gas mask, gloves, and sanitizing hand solution, increases the probability of contact while also decreasing the agent's susceptibility. Randomness also factors in to the determination of contact according to an inverse relationship dependent on the agents' relative level of concern or care.

If no contact occurs between the agents, then direct contact transmission does not occur, although airborne transmission, if applicable, will still be considered as is discussed subsequently. If contact occurs, then a second series of parameters are examined to determine whether the contagious individual spreads the infection to susceptible individuals making up the other agent's population. These parameters consist of the disease's base infection rate, the level of *MEDICAL SUPPLIES*, current *HEALTH STATUS*, and *STRENGTH* of the susceptible individual.

STRENGTH represents a combined consideration of the fitness and age of the individual, where a healthy, young adult would be less likely to contract the disease than an overweight elderly person. HEALTH STATUS accounts for recent events such as food and water consumption; as such a well fed individual has a lower likelihood of becoming infected than one recently depraved of sustenance.

Regardless of whether agents come into contact or not, if the disease is transmittable by air, then all susceptible individuals involved in the encounter risk infection. The probability of infection, as with direct contact transmission, is based on the level of *MEDICAL SUPPLIES*, current *HEALTH STATUS*, and *STRENGTH*. In terms of proximity transmission, being exposed to airborne transmission is of higher likelihood than direct contact. However, after being exposed, it is also less probable to become infected from airborne transmission than physical contact.

3.2.2.2 – Intermediary Transmission

Intermediary transmission is the method by which indirect contact can spread disease. As only a trivial amount of additional memory is required to store contamination information for a particular location and as *STOCKPILES* attract and are commonly visited by agents, these are assumed to be the only transmission intermediaries.

If the disease can spread via indirect contact, a *STOCKPILE* is considered contaminated from the time that it is visited by an infected individual until the disease life expires. As such all susceptible individuals that visit this *STOCKPILE* over this time period are exposed. Therefore, indirect exposure incidence is typically higher than that of proximity transmission. However, the likelihood of the susceptible individual becoming infected in this scenario is lower and decreases inversely to the time of contamination. The same parameters are considered in the determination of infection after exposure as in the case of airborne and direct contact transmission.

3.2.2.3 – General Airborne Transmission

General airborne transmission is the process by which an individual becomes exposed by simply being within the contamination area of an infected individual. As the home is considered relatively impervious, only agents outside are considered. This process is executed for every contagious agent that is outside during every *TIME SEGMENT*.

In this simulation package wind speed and direction are taken into account for airborne disease spread. In a scenario with no wind, the feasible transmission area around a contagious agent is defined as a circle centered on the agent's location with radius set by disease parameters. This is shown in Figure 3, below.

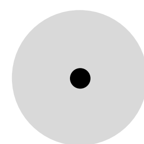

Figure 3: No Wind Airborne Transmission Area

Wind is accounted for by comparison to a maximum value for wind speed. This parameter, *MAXWIND*, is set to 66 mph which represents the average annual wind speed of Goodland, Kansas for the past 54 years (National Environmental Satellite, Data, and Information Service, 2012). Goodland was chosen since a robust data set was available and it is located towards the center of the study's focus area.

In a scenario with slight wind, the feasible transmission area is elongated and the area covered is increased. In addition, the center of the ellipse is shifted from the agent's location towards the direction the wind is blowing in. The relative value of current wind speed to *MAXWIND* determines the magnitude of the shift and elongation. A slight wind instance is depicted in Figure 4.

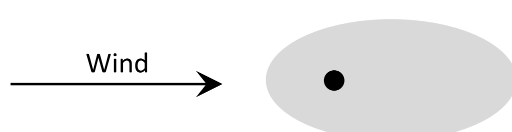

Figure 4: Light Wind Airborne Transmission Area

In a scenario with high winds, the feasible transmission area is elongated and the center of the ellipse is shifted such that the agent's location moves closer to the ellipse perimeter. Assume that the wind speed is equal to *MAXWIND*. In this case, the center of the ellipse is shifted such that the agent's location falls directly on the perimeter, and the ellipse is elongated to the maximum allowed eccentricity of .98. This case is shown in Figure 5.

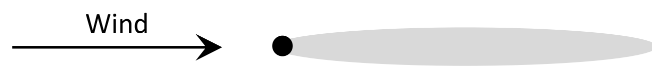

Figure 5: Strong Wind Airborne Transmission Area

As this discussion implies, exposure via general airborne transmission is generally of highest prevalence. If exposure occurs, the same parameters as in proximity airborne transmission are evaluated to determine whether the agent, if susceptible, becomes infected. After exposure, the likelihood of infection via general airborne transmission is the lowest of all methods discussed.

3.3 – Chapter Summary

The incorporation of an ABS simulation core that contains multiple decision points with disease propagation elements that allow for the accurate replication of all general disease types results in a robust simulation package. This represents a successfully expansion to the current modeling frontier in terms of both reduced assumptions and increased functionality. Furthermore, this simulation package adds additional momentum in the paradigm shift towards modeling real-world scenarios as they occur: emergent patterns as the result of the interactions of individual elements. This approach allows for the direct analysis of resulting equilibria and, subsequently, insights as to what decisions increase the likelihood of an individual's survival during an epidemic.

The following chapter discusses the application of this simulation package to a hypothetical epidemic scenario. Based on real world data and parameters representing a plausible virulent outbreak, the findings presented are applicable to a real-world incident and represent additional contributions of this work.

4 – Epidemic Decision Optimization

This study was conducted to gain insight to three main questions: (1) what general family traits increase the likelihood of survival during an epidemic, (2) what responses to common epidemic events increase the likelihood of survival, and (3) what impact the decisions of an individual have on society.

Regarding family traits, the starting population and surviving population were compared according to their relative level of risk tolerance, morality, and self-control. These represent the three primary family traits based on their use in determining an agent's reaction to an event. These traits are represented by decimal values between zero and one, where one denotes a high level of that characteristic. Each parameter was examined in isolation as extrapolating all various combinations exceeds the scope of this work.

The epidemic events analyzed consist of looting/rioting, a government mandate to remain at home, high-levels of sickness in an agent's city, county, and neighboring county, and a family member becoming infected. After the occurrence of an event, each family's decision and whether they become infected over the long-term as a result is recorded. For example, if an agent's city reports high-levels of sickness, infection as a direct result of rushing the stores for supplies is compared to infection as a result of remaining at home until all supplies are exhausted then venturing out.

The decisions of fleeing the area to avoid infection and acting without concern of spreading infection when contagious are the society impacting decisions analyzed. These are evaluated in terms of the number of others that are infected as a result. The choice to rush stores, which leads to looting after a certain threshold value is reached, is an additional decision that impacts society. However, this study does not analyze this scenario since to do so would necessitate an economic evaluation of the damages which exceeds the scope of this work.

The following section introduces general parameters for this specific simulation analysis. The remainder of the chapter provides discussion on the findings for the two disease transmission scenarios studied: the base scenario of direct contact only spread and an extreme case of direct contact, indirect contact, and airborne transmission. Within each section, discussion is provided on family traits and decisions that lead to increased probability of survival and the subsequent impact to society as well as on sensitivity analyses concerning what differences in disease transmission and severity result in. High-level data along with statistical analysis is included to support the conclusions. Additional transmission scenarios were not included in the scope of this study due to time limitations.

4.1 – General Parameters

Due to memory and running time restrictions, the full state of Kansas was not simulated. Instead a 17 county area in northwestern Kansas was selected as the study's concentration, shown as the shaded counties in Figure 6 below. This area is comprised of Cheyenne, Decatur, Gove, Graham, Greeley, Lane, Ness, Norton, Phillips, Rawlins, Scott, Sheridan, Sherman, Thomas, Trego, Wallace, and Wichita counties. 56 towns and small cities are included in this area as well as the rural population.

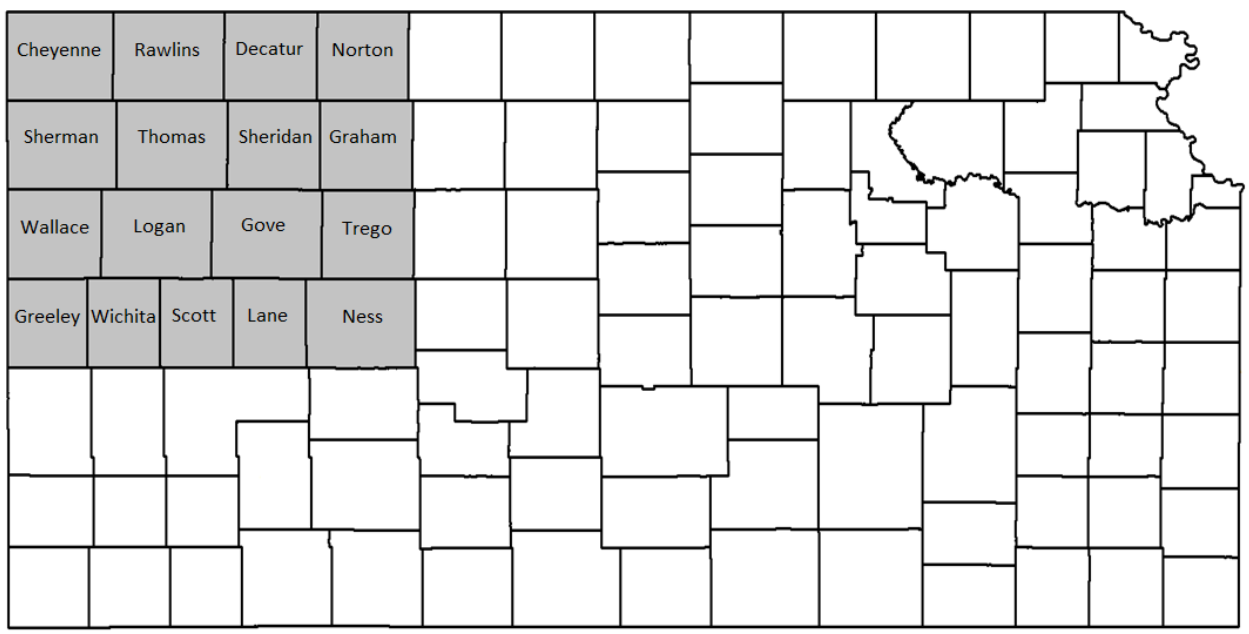

Figure 6: Map of Simulation Area

These counties approximate a square shape spanning roughly 130 miles east to west, 120 miles north to south, and covering 15,741 square miles (United States Census Bureau, 2012). Through basic adjustments to the constant global parameters, the simulation package was altered to model this specific land area and population. The population represented numbers

56,769 individuals separated into 21,325 family groups for an average family size of 2.66. The simulation was limited to 98 iterations representing 14 weeks, during which the disease permeated throughout the population until new infections quit occurring or slowed significantly.

4.2 – Base Scenario: Only Direct Contact Spread

The first scenario analyzed is the base scenario where the disease is assumed to only spread via direct physical contact; subsequent scenarios are extensions of this functionality. From the initial simulation population of 56,769 individuals, 6,353 became infected. This represents 13 percent of the population.

The disease epicenter was on the border of Gove and Logan counties from which it spread to all other counties. Gove county was most heavily impacted, with 36 percent of its population becoming infected, and Wichita county was least infected, having only .2 percent sickened by the disease. The infection rate slowed significantly by day 98, leading researchers to believe the disease was nearing extinction. This scenario had a run time of 5.5 hours, which is equivalent to all other scenarios explored. The simulation package was run on an Intel Core i7 with a 2.67 GHz processor and 6.0 GB of RAM.

4.2.1 – Family Traits

The family trait of *RISK TOLERANCE* was found to be the most influential of the three analyzed due to the large discrepancy in survival rates between the extreme cases. As is shown in Table 1 below, a low *RISK TOLERANCE* was found to be most beneficial with a survival rate of 99 percent. Contrarily, the high *RISK TOLERANCE* of 1 led to a survival rate of just 82 percent. Or as translated to real-world phrasing: a family that has no restraint is 18 times more likely to become infected than a family that is loath to near others, even to trade for needed supplies.

Table 1: Base Scenario Results – Family Traits, Risk Tolerance

	Risk Tolerance				
	0.0	**.25**	**.5**	**.75**	**1.0**
Initial Population	4,214	4,340	4,266	4,223	4,282
Surviving Population	4,164	4,227	3,942	3,686	3,509
Survival Rate	99%	97%	92%	87%	82%

The family trait, *MORALITY*, was found to be the second most relevant based on survival rate differences. From the data in Table 2, it can be inferred that agents with high level of *MORALITY* are more likely to survive in such a scenario. Interestingly, extreme levels of *MORALITY* show the most impact on survival probability with survival rates ranging from a low of 86 percent to 98 percent, whereas between a moral level of .25 and .75 survival rates only range from 90 percent to 92 percent. In part, this suggests that extremely immoral decisions such as attacking weaker groups to raid their supplies are inferior strategies in epidemic survival.

Table 2: Base Scenario Results – Family Traits, Morality

	Morality				
	0.0	**.25**	**.5**	**.75**	**1.0**
Initial Population	4,312	4,351	4,205	4,226	4,231
Surviving Population	3,708	3,936	3,827	3,909	4,148
Survival Rate	86%	90%	91%	92%	98%

The third family trait examined is *SELF-CONTROL* which represents the family's ability to act rationally during a stressful scenario. Families with high *SELF-CONTROL* survived at 92 percent while families with low *SELF-CONTROL* survived at a similar rate of 91 percent, as is shown in Table 3 below. The small difference in survival rates between the high and low cases reflects a small impact of *SELF-CONTROL* on survival.

Table 3: Base Scenario Results – Family Traits, Self-Control

	Self-Control				
	0.0	**.25**	**.5**	**.75**	**1.0**
Initial Population	4,222	4,387	4,331	4,107	4,278
Surviving Population	3,832	4,003	3,976	3,794	3,923
Survival Rate	91%	91%	92%	92%	92%

4.2.2 – Event Responses

In consideration of event responses, the first event examined is infection within the family. As discussed in section 3.1.2.2, there are three reactions available to the family. However, as one of those options is to *ACT WITHOUT WORRY* of infecting others and involves only the sick individuals leaving the house, no additional family members are infected as a result of their decisions. Therefore this reaction is not included in this analysis. Instead the decisions to *SEEK CARE* at the hospital and attempt to provide *HOME CARE* for the sick individuals are compared.

Per the data in Table 4, the decision to *SEEK CARE* results in a likelihood of a second family member becoming infected of 35 percent, while the action of *HOME CARE* has a lower infection rate of only 10 percent. This may be due to the inability to avoid exposures during a trip to the hospital whereas continual care is taken to limit such instances during *HOME CARE*. However, it should be noted that the small data set may result in slightly skewed findings.

Table 4: Base Scenario Results – Family Infection

	Family Infection	
	Seek Care	Home Care
Initial Population	1,667	106
Number Infected	580	11
Infection Rate	35%	10%

The second event explored is rumors/reports of high-level of sickness within various locations as compared to the family in question. This provides interesting insights as to how proximity to the disease outbreak should influence decisions. As shown in Table 5, the action to remain at home and *EXHAUST SUPPLIES* is a superior strategy, more so as infection reports are closer to home. In comparison, *RUSHING STORES* quintuples the likelihood of infection in cases of same city reports and doubles it in same county.

This suggests that when neighbors may already be contagious, avoidance for as long as possible is best. Please note: the number infected values shown in Table 5 have been adjusted to account for subsequent, indirect infections as a result of the decision; due to the relatively small number reported for the same city *IGNORE* reaction, additional scaling was applied.

Table 5: Base Scenario Results – High-Levels of Sickness

	Same City			Same County			Same Region		
	Rush Stores	Exhaust Supplies	Ignore	Rush Stores	Exhaust Supplies	Ignore	Rush Stores	Exhaust Supplies	Ignore
Initial Population	2,103	2,433	249	1,004	992	987	13,522	8,372	25,924
Number Infected	81	26	200	38	16	82	272	261	675
Infection Rate	4%	1%	10%	4%	2%	8%	2%	3%	3%

Looting opportunities arise when there are either a high or very low number of agents seeking supplies. These are represented by *RIOTING/LOOTING* which is triggered by a high number of shoppers, whereas the situation of a government enacting a *24-HOUR CURFEW* is representative of a very low number of shoppers. The determination of infection as a result of these decisions incorporates infection as a result of having to leave the house later in search of necessary supplies. As such, it is possible that choosing to *STAY HOME* to avoid the initial chaos may result in encountering a higher number of infected individuals during subsequent trips to collect necessary supplies.

The results of Table 6 show that the decision to either *LOOT EXPENSIVE* or *LOOT ESSENTIAL* items results in only a slight change in the infected rate. This suggests that the encounters experienced during a looting trip are the cause of infection, not the need to make subsequent trips in search of necessary supplies. The substantially higher rate of infection over the strategy of *STAY HOME* further corroborates this analysis.

Table 6: Base Scenario Results – Looting Opportunities

	Rioting / Looting			24 - Hour Curfew		
	Loot Expensive	**Loot Essentials**	**Stay Home**	**Loot Expensive**	**Loot Essentials**	**Stay Home**
Initial Population	1,216	3,069	11,169	3,964	12,151	44,450
Number Infected	76	199	14	222	705	213
Infection Rate	6%	6%	0.1%	6%	6%	0.5%

4.2.3 – IMPACTS TO SOCIETY

Leveraging the principle of emergence allows for global patterns to be discerned from the interactions of individuals. While such study is largely outside the focus of this research, it is interesting to understand how some individual decisions impact society.

For example, when an individual becomes infected and chooses *ACT WITHOUT CONCERN* of infecting others, on average that initial person infects 1.3 people. Similarly, when a family decides to *FLEE* in response to epidemic rumors, on average 26 percent of families that successfully escape the area bring along one or more infected individuals: people that have been exposed but due to the incubation period of the disease do not yet exhibit symptoms. This will result in over 31 new infections outside the initial contagion region, continuing the spread of the epidemic. Decisions for self-preservation such as these are therefore shown to be a large factor in the spread of a disease.

4.3 – Indirect Contact and Airborne Transmission

The combined impact of spread via direct, indirect, and airborne transmission is examined within this section. From the initial simulation population of 56,769 individuals, 13,045 became infected. This represents a fatality rate of 32 percent, significantly higher than the same disease modeled with only direct contact spread properties as in the base case. The increased transmissibility also caused an increase to the speed at which the epidemic spread. In this scenario the disease almost completely died out, with only 2 individuals remaining in the contagious stage. Due to this it is possible, although highly unlikely, that a resurgence of the epidemic could occur.

The disease epicenter was on the border of Gove and Logan counties from which it spread to all other counties. Cheyenne county was most heavily impacted, with 43 percent of its population becoming infected, and Greeley county was least infected, having only 12 percent sickened by the disease. Similar rates of infection were reported in other counties which reflects a more even spread pattern across the study region when compared to the base case. This suggests that knowledge of disease transmissibility is instrumental to understand disease spread, whereas the locations of towns and common travel patterns are facilitating factors.

4.3.1 – Family Traits

The family trait of *risk tolerance* was again found to be the most influential of the three analyzed due to the large discrepancy in survival rates between the extreme cases. As is shown in Table 7 below, a relatively low tolerance of .25 is shown to be most favorable, having a survival rate of 89 percent. Contrarily, the high *risk tolerance* of 1 led to a survival rate of just 71 percent. Interestingly, somewhere between .25 and .5 seems to be the optimal level as the lowest *risk tolerance* of 0 decreases the probability of survival. This is in contrast to the base scenario where lower *risk tolerance* the more positive the survival outlook.

Table 7: Indirect Contact & Airborne Transmission – Family Traits, Risk Tolerance

	Risk Tolerance				
	0.0	**.25**	**.5**	**.75**	**1.0**
Initial Population	4,214	4,340	4,266	4,223	4,282
Surviving Population	3,295	3,846	3,564	3,229	3,057
Survival Rate	78%	89%	84%	76%	71%

According to the findings reported in Table 8, higher levels of *MORALITY* tend to result in higher survival rates. Medium levels of *MORALITY* appear to be relatively equivalent, as the survival rates are somewhat flat between .25 and .75. Likely due the higher likelihood of negative encounters, low *MORALITY* results in the lowest survival rates. These results follow a similar pattern as found in the base scenario.

Table 8: Indirect Contact & Airborne Transmission – Family Traits, Morality

	Morality				
	0.0	**.25**	**.5**	**.75**	**1.0**
Initial Population	4,312	4,351	4,205	4,226	4,231
Surviving Population	3,190	3,397	3,374	3,352	3,678
Survival Rate	74%	78%	80%	79%	87%

SELF-CONTROL was found to be the least influential in terms of increasing the probability of survival as illustrated by Table 9. This is suggested by the small interval between the high survival rate of 83 percent for *SELF-CONTROL* of .75 and the 77 percent survival rate for *SELF-CONTROL* of .25. Moreover, the probability of survival not increasing or decreasing linearly is suggestive of a lower level of influence from this trait, relative to other factors. Again, these results are closely related to the findings of the base case.

Table 9: Indirect Contact & Airborne Transmission – Family Traits, Self-Control

	Self-Control				
	0.0	**.25**	**.5**	**.75**	**1.0**
Initial Population	4,222	4,387	4,331	4,107	4,278
Surviving Population	3,288	3,392	3,416	3,392	3,503
Survival Rate	78%	77%	79%	83%	82%

4.3.2 – EVENT RESPONSES

Per the data shown in Table 10, the decision to *SEEK CARE* increases the likelihood of infecting a second family member to 75 percent, while the action of *HOME CARE* has a lower infection rate of 71 percent. This parallels the base case, although infection rates of this scenario are substantially higher due to the increased transmissibility.

When the infection rates of Table 10 are compared to infection rates during other events of this scenario, these are found to be significantly higher; the same can be said of the base scenario. This is due to the close proximity of family members to an infected, contagious individual. These results support the real-world tendency of smallpox to spread to family members at a higher incidence than others (Centers for Disease Control and Prevention, 2012).

Table 10: Indirect Contact & Airborne Transmission – Family Infection

	Family Infection	
	Seek Care	**Home Care**
Initial Population	4,403	225
Number Infected	3,296	159
Infection Rate	75%	71%

As shown by the magnitude of the infection rates of Table 11, how an agent responds to rumors/reports of high-levels of sickness play an important role in whether infection occurs as a result. Of highest significance, agents that *IGNORE* same city reports are 4.4 times more likely to become infected than those that immediately *RUSH STORES*. If the infection is already present in the city, however, the best response is to *REMAIN HOME* as long as possible. This results in a probability of survival 28 percent higher than of the decision to *IGNORING* warnings.

Same county results show similar trends although *RUSHING STORES* results in the highest probability of survival. As the disease has not yet become prevalent within the agent's home location, *RUSHING STORES* decreases the likelihood of infection by a third whereas *EXHAUSTING SUPPLIES* results in a decrease to half when compared to *IGNORING* warnings.

Results for same city are in agreement with the base scenario whereas for same county, *EXHAUSTING SUPPLIES* is the superior base case strategy. Please note: the number infected values shown in Table 11 have been adjusted by assumption to account for subsequent infections as a result of the decision. Same region results are largely influenced by the adjustment and therefore, while suggestive that the decisions to *RUSH STORES* or *EXHAUST SUPPLIES* are inferior to *IGNORING* the warnings, findings are not considered conclusive.

Table 11: Indirect Contact & Airborne Transmission – High-Levels of Sickness

	Same City			Same County			Same Region		
	Rush Stores	Exhaust Supplies	Ignore	Rush Stores	Exhaust Supplies	Ignore	Rush Stores	Exhaust Supplies	Ignore
Initial Population	11,033	15,201	2,107	5,667	3,111	2,263	1,960	1,087	2,402
Number Infected	594	463	496	213	180	278	89	89	89
Infection Rate	5%	3%	24%	4%	6%	12%	5%	8%	4%

Table 12 provides strong evidence that avoiding instances of looting significantly increases the probability of survival. This is shown by the similar infection avoidance rates from the decisions to *LOOT EXPENSIVE* or *LOOT ESSENTIAL* items in both scenarios. These results suggest that infection occurs during the looting events and that subsequent excursions for necessary supplies do not significantly increase the likelihood of infection, as was found to be the case in the base scenario.

Analyzing the results of rioting/looting events, it can be inferred that avoiding the large crowds decreases encounters and thus the risk of infection. Further benefit from avoiding possible attacks is also likely. In regards to the 24-hour curfew, as these are only enacted during severe levels of contagion, it is likely that anybody outside their home risks encounter with those that are infected and have no concern of infecting others. This is particularly likely as airborne transmission does not necessitate contact between agents.

Table 12: Indirect Contact & Airborne Transmission – Looting Opportunities

	Rioting / Looting			24 - Hour Curfew		
	Loot Expensive	Loot Essentials	Stay Home	Loot Expensive	Loot Essentials	Stay Home
Initial Population	4,989	12,998	42,409	3,837	8,348	32,896
Number Infected	375	914	116	411	877	217
Infection Rate	8%	7%	0.3%	11%	11%	1%

4.3.3 – Impacts to Society

When an individual becomes infected and chooses act without concern of infecting others, on average 3.9 healthy individuals become infected. When a family decides to flee in response to epidemic rumors, on average 4 percent of families that successfully escape the area bring along one or more infected individuals. This will result in over 250 new infections outside the initial epidemic region based on average spread rates within the simulation area.

In comparison to the base case, this represents a more negative impact to society from a single decision due to the increased transmissibility of the disease. Specifically, in this scenario a single individual acting without concern of infecting others results in 3 times the number of people being infected than in the base case.

In contrast however, the slower more steady disease spread via direct contact results in increased prevalence of exposure before there are enough cases to warrant attention. In other words, the epidemic does not attain a scale to warrant a level of concern that would cause agents to *FLEE* until there are a substantial number of individuals within the exposed state. This is shown by the higher percent of fleeing families in the base case bringing along infected individuals. Specifically, the base case has over 6 times the rate of families leaving the initial epidemic area with an infected individual.

4.4 – Epidemic Survival Guide

Based on the findings discussed above as well as additional understanding developed through review of data and scenarios not explicitly defined within this paper, a set of conclusions can be formed. These are applicable to the disease transmission scenarios analyzed and expected to be appropriate for most variations in disease severity. The following list of general rules and substantiating discussion serves as an epidemic survival guide:

- *Realize that it is too late to prepare for an epidemic after an epidemic has begun.* After warnings of an epidemic are disseminated, people understand that they must remain home — before that though they must gather in enclosed spaces with crowds of people. This is essentially the decision to rush stores and collect the supplies necessary for an extended home stay. However, findings show that the very high number of encounters with others not likely to be infected typically results in increased probability of infection. This is in comparison to venturing out later when there are less people more likely to be infected. Ignoring this rule can increase you likelihood of infection four-fold.
- *Exaggerate carefulness.* The most influential trait leading to survival is having a low risk tolerance. As defined in the simulation package, avoiding others, taking care to be properly protected during interactions with others, and selecting conservative strategies

that limit the possibility of exposure are all decisions which are more likely with a low risk tolerance. Adhering to this principle increases survival likelihood by 12 percent.

- *Avoid the lure of looting, especially superfluous items but also essential supplies.* This is the most statistically significant finding. Staying home when there are crowds of people looting or a government mandate to do so increases the likelihood of survival by a factor of at least 11.
- *Don't make friends with anybody that's infected.* Inter-family/group spread is the most common method by which disease is transmitted. Limiting the number of others that you are continuously exposed to will therefore serve as a primary factor in avoiding infection.
- *Understand that your decisions impact others.* A disease spreads by the interaction of a contagious and susceptible individual. As such, an epidemic can be avoided if all contagious individuals isolate themselves from society. This is a radical measure but the other extreme of acting without any concern of infecting others is excessive and the subsequent infections preventable. Following this rule will not change your likelihood of infection but could decrease your neighbor's to 0.
- *Continuously analyze your specific situation and evaluate all options and possible repercussions before taking action.* As this simulation is based on assumptions and cannot fully account for the impact of all decisions, factors, and events during an epidemic not all superior strategies have been defined. Following this rule will increase your probability of survival by a lot.

While many of these rules may seem obvious, keep in mind that an epidemic situation is a survival event. As such, it is expected that individuals will not act in what would commonly be deemed a rational manner. Instead quick action will likely be considered as a necessary step for survival whereas deliberate action is the superior strategy: follow these rules and increase your likelihood of survival.

4.5 – Chapter Summary

The application of this simulation package to various forms of a hypothetical smallpox outbreak accomplishes two purposes: (1) to provide operational validation of the various functions and components of the simulation, and (2) to gain insight as to the how an individual's decisions can influence their probability of survival and what impact these decisions can have on society as a whole. This meets the objectives on which this study was based. Furthermore, these findings represent investigation into a common topic from a novel perspective; the learnings from which will help to facilitate the development process of subsequent studies.

5 – Conclusion

This work builds upon the knowledge gained from five years of research concerned with the optimization of government-led, epidemic mitigation strategies in rural areas. Prior research and simulation has highlighted two key areas in need of more comprehensive examination, which this work successfully addresses: (1) to more accurately emulate a real-world scenario; and (2) to understand how an individual can exploit knowledge of the equilibria resulting from the cumulative decisions of others.

As such, the objectives maintained throughout the development of this simulation package consist of the following:

- to expand on the functionality of earlier models by incorporating the most advanced epidemic modeling techniques;
- to explore alternate approaches that decrease the number and magnitude of modeling assumptions necessary; and
- to understand how the decisions and interactions of individuals can influence global equilibria.

These objectives were achieved by leveraging linear program optimization techniques and the concept of Agent Based Simulation, to more accurately capture the complexity inherent in most real-world systems via the interactions of individual entities. This has resulted in the development of a 4,000-line computer code simulation. This adaptable simulation can accurately model the interactions of individuals to discern the impact of any general disease type, and can be implemented on the population of any contiguous counties within Kansas.

The application of this simulation package to various types of a hypothetical, although plausible, smallpox outbreak provides valuable insight as to the impact of aggregated decisions. Specifically, the analysis of various responses to particular events achieves this work's objective of determining optimal decisions for an individual during an epidemic. Furthermore, the examination of emergence in regards to the number of others infected because of an individual's decision to *FLEE* or *ACT WITHOUT REGARD* to others, provides an understanding of how the decisions of one can impact all of society.

5.1 – Summary of Findings

To provide operational validation of the various functions of the simulation package and to gain insight as to the how an individual's decisions can influence their probability of survival, a set of disease scenarios were analyzed based on a 17 county area in northwestern Kansas. Specifically, impacts to the probability of survival based on general family traits and responses to common epidemic events were explored.

Risk tolerance, morality, and self-control were family traits examined. Findings show a lower risk tolerance to be most influential in increasing the likelihood of survival while higher morality plays a less impactful role. Self-control was found to be of less relevance.

Additional analysis shows that avoiding encounters with others is fundamental to epidemic survival. Avoiding looting events and limiting the number of people in your family group are examples of such decisions. Another example: while attempting to collect supplies after initial signs of an epidemic is a typical reaction, this generally results in a large number of encounters. As such, it is found to be an inferior strategy to staying home for as long as supplies last.

Additional findings are summarized in chapter 4, along with high-level data and statistical analysis. Section 4.4 is organized as a guide to epidemic survival, and provides a more detailed summary of the main findings.

5.2 – Recommendations for Future Research

As the field of epidemic research is large, diverse, and continually expanding, there are numerous extensions to the research presented in this paper. This section provides discussion on areas of future research, as recommended by the author, by identifying key elements that researchers seeking to undertake similar investigations should be aware of. This discussion includes comments on the major difficulties encountered throughout the development of this simulation package. These recommendations were excluded from the scope of this study due to time constraints.

Throughout the construction of this simulation three key obstacles arose. The first of which was accurately modeling disease propagation throughout a diverse environment while allowing for multiple disease transmission scenarios and infection rates. These issues were assuaged through the use of various assumptions, adjustable disease parameters, and ABS to model agent encounters. However, the severity of diseases is commonly defined in terms of their R_0, which this simulation does not have the functionality to accept as disease parameter input. Incorporating a set of counters to track the average number of encounters each agent experiences depending on their *DAY STRATEGY* and adjusting the disease's infectiousness accordingly would allow for R_0 approximation.

A second difficulty faced was the magnitude of creating an accurate ABS for an epidemic scenario. Specifically, working within memory and running time limitations and incorporating all major functionalities. The final population modeled was a result of computational limitations which was maximized through various efforts for running time and memory reduction. Such techniques include utilizing Dial's implementation, creating a minimalistic environment and parameter sets while still meeting the requisite modeling accuracy, and designing subroutines and loops to eliminated repetition. Efforts to fully incorporate all decisions and interactions available to agents during an epidemic is a massive undertaking, however the functionalities of this simulation package comprise all major actions available allowing for the close representation of such a scenario. Additional accuracy can be achieved by expanding on the capabilities and relaxing the simplifying assumptions of this model.

The third complication confronted was how to discern which decisions led to the infection of an agent. As this understanding is the basis to the findings of this study, this was a major challenge with significant repercussions. The use of events, response decision tracking, and infection occurrence monitoring enabled causation approximation. However, as multiple decisions and factors play a role in the occurrence of infection, a more robust technique that accounts for the influence of multiple variables will provide more detailed insights. As such, it is recommended that future simulations be constructed such the regression analysis techniques can be applied to discern the relative influence of all factors simultaneously.

Sensitivity analyses on the various disease transmission scenarios were conducted. However, expanding the scenarios to include various forms of immunity, situations in which an agent knows it is immune, various disease severity conditions, and across different environments will provide additional insights. Additionally, further examination of how cumulative individual decisions results in emergent trends and what impacts this has on society can be utilized to anticipate likely scenarios such as looting or spreading infection from the disease epicenter. This knowledge can be leveraged in government epidemic preparedness planning.

This work has provided interesting and insightful knowledge from a novel perspective. However, as this is among the first of such studies there is an immense potential for additional information to be gained. As such, the continuation of work in this field will provide a foundation of understanding so that individuals will be able to survive epidemics more successfully than ever before.

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