Intelligent Adversary Risk Analysis:

A Bioterrorism Risk Management Model

Dr. Gregory S. Parnell
Professor of Systems Engineering
Department of Systems Engineering
United States Military Academy at West Point
gregory.parnell@usma.edu

MAJ Christopher M. Smith
Instructor
Department of Mathematical Sciences
United States Military Academy at West Point
christopher.smith@usma.edu

Dr. Frederick I. Moxley
Director of Research for Network Science
Department of Electrical Engineering and Computer Science
United States Military Academy at West Point
frederick.moxley@usma.edu

Abstract:

The tragic events of 911 and the concerns about the potential for a terrorist or hostile state attack with weapons of mass destruction have led to an increased emphasis on risk analysis for homeland security. Uncertain hazards (natural and engineering) have been analyzed using Probabilistic Risk Analysis. Unlike uncertain hazards, terrorists and hostile states are intelligent adversaries who adapt their plans and actions to achieve their strategic objectives. This paper compares uncertain hazard risk analysis with intelligent adversary risk analysis, describes the intelligent adversary risk analysis challenges, and uses a defender-attacker-defender decision analysis model to evaluate defender investments. The model includes defender decisions prior to an attack; attacker decisions during the attack; defender actions after an attack; and the uncertainties of attack implementation, detection, and consequences. The risk management model is demonstrated with an illustrative bioterrorism problem with notional data.

Key words: intelligent adversary risk analysis, bioterrorism, defender-attacker-defender, risk management, terrorism risk analysis

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1. INTELLIGENT ADVERSARY RISK ANALISIS IS DIFFERENT THAN HAZARD RISK ANALYSIS

Risk analysis has helped public and private organizations assess, communicate, and manage the risk posed by uncertain hazards (i.e. natural hazards and engineered systems) (Henley, E. and Kumamoto, H., 1996, Ayyub, B., 2003, and Haimes, 2004). The U.S. government has been informed on preparation for natural events and potential engineered system failures by credible and timely risk analysis. In probabilistic risk analysis (PRA), the uncertain hazards have been modeled using probability distributions for threats, vulnerabilities, and consequences. The data has been obtained from statistical analysis of past events, tests, models, simulations, and assessments from subject matter experts. Risk analysts have used PRA techniques including event trees, fault trees, attack trees, systems dynamics, and Markov models to assess, communicate, and manage the risk of uncertain hazards.

The nuclear power industry, perhaps more than any other risk application area, has integrated the use of PRA for risk assessment, risk communication, and risk management. The original PRA process was developed in the commercial nuclear power industry in the 1970s (USNRC, 1975). The U.S. Nuclear Regulatory Commission and the nuclear power industry jointly developed procedures and handbooks for PRA models (USNRC, 1983, and Vesely, 1981). Today, the nuclear power industry is moving toward risk-based regulations, specifically using PRA to analyze and demonstrate lower cost regulations without compromising safety (Davison and Vantine, 1998, Frank, 1988). Research in the nuclear industry has also supported advances in human reliability analysis, external events analysis, and common cause failure analysis (USNRC, 1991, Mosleh, 1993, and USNRC, 1996).

More recently, leaders of public and private organizations have requested risk analyses for problems that involve the threats posed by intelligent adversaries. For example, in 2004, the President directed the Department of Homeland Security (DHS) to assess the risk of bioterrorism (HSPD-10, 2004). Homeland Security Presidential Directive 10 (HSPD-10): Biodefense for the 21st Century, states that "[b]iological weapons in the possession of hostile states or terrorists pose unique and grave threats to the safety and security of the United States and our allies" and charged the DHS with issuing biennial assessments of biological threats, to "guide prioritization of our on-going investments in biodefense-related research, development, planning, and preparedness." A subsequent Homeland Security Presidential Directive 18 (HSPD-18): Medical Countermeasures against Weapons of Mass Destruction directed an integrated risk assessment of all chemical, biological, radiological, and nuclear (CBRN) threats. The critical risk analysis question addressed in this paper is: are the standard PRA techniques for uncertain hazard techniques adequate and appropriate for intelligent adversaries? Our answer is an emphatic no. We will show that treating adversary decisions as uncertain hazards is inappropriate because it provides the wrong assessment of risks.

In the rest of this section, we describe the difference between natural hazards and intelligent adversaries and demonstrate, with a simple example, that standard PRA does not properly assess the risk of an intelligent adversary attack. In the second section, we describe a canonical model for resource allocation decision making for an intelligent adversary problem using an illustrative bioterrorism example with notional data. In the third section, we describe the illustrative analysis results obtained for model and discuss the insights they provide for risk management. In the fourth section, we describe the benefits and limitations of the model. Finally, we discuss future work and our conclusions.

1.1. Intelligent adversary risk analysis requires new approaches

We believe that risk analysis of uncertain hazards is fundamentally different than risk analysis of intelligent adversaries. Others have found that there are differences between risks from intelligent adversaries and other risk management decisions (Willis, 2006). Some of the key differences are summarized in the Table 1 below (NRC, 2008). A key difference is historical data. For many uncertain events, both natural and engineered, we have not only historical data of extreme failures or crises, but many times we can replicate events in a laboratory environment for further study (engineered systems) or analyze using complex simulations. Intelligent adversary attacks have a long historical background, but the aims, events, and effects have incomplete documentation.

Both risk of occurrence and geographical risk can be narrowed down and identified concretely.

Table 1: Uncertain Hazards vs. Intelligent Adversaries

	Uncertain Hazards	Intelligent Adversaries
Historical Data	*Some historical data:* A record exists of extreme events that have already occurred.	*Very limited historical data:* Events of September 11, 2001, were the first foreign terrorist attacks worldwide with such a huge concentration of victims and insured damages.
Risk of Occurrence	*Risk reasonably well defined:* Well-developed models exist for estimating risks based on historical data and experts' estimates.	Considerable ambiguity of risk: Adversaries can purposefully adapt their strategy (target, weapons, time) depending on their information on vulnerabilities. Attribution may be difficult (e.g. anthrax attacks).
Geographic Risk	*Specific areas at risk:* Some geographical areas are well known for being at risk (e.g., California for earthquakes or Florida for hurricanes).	All areas at risk: Some cities may be considered riskier than others (e.g., New York City, Washington), but terrorists may attack anywhere, any time.
Information	*Information sharing:* New scientific knowledge on natural hazards can be shared with all the stakeholders.	Asymmetry of information: Governments sometimes keep secret new information on terrorism for national security reasons.
Event Type	*Natural event:* To date no one can influence the occurrence of an extreme natural event (e.g., an earthquake).	*Intelligent adversary events:* Governments may be able to influence terrorism (e.g., foreign policy; international cooperation; national and homeland security measures).
Preparedness and Prevention	Government and insureds can invest in well-known mitigation measures.	Weapons types are numerous. Federal agencies may be in a better position to develop more efficient global mitigation programs.

Modified form Kunreuther, H. and Michel-Kerjan, E (2005), "Insuring (Mega)-Terrorism: Challenges and Perspectives", in OECD, Terrorism Risk Insurance in OECD Countries, July (modified first two columns).
Parnell, G. S., Dillon-Merrill, R. L., and Bresnick, T. A., 2005, Integrating Risk Management with Homeland Security and Antiterrorism Resource Allocation Decision-Making, The McGraw-Hill Handbook of Homeland Security, David Kamien, Editor, pp. 431-461.

Intelligent adversary targets vary by the goals of the adversary and can be vastly dissimilar between adversary attacks.

Information sharing between the two events differs dramatically. After hurricanes or earthquakes, engineers typically review the incident, publish results, and improve their simulations. Sometimes after intelligent adversary attacks, or near misses, the situation and conduct of the attack may involve critical state vulnerabilities and protected intelligence means. In these cases, intelligence agencies may be reluctant to share complete information even with other government agencies.

The ability to influence the event is also different. Though we can prepare, we typically have no way of influencing the natural event to occur or not occur. On the other hand, governments may be able to affect terrorism attacks by a variety of offensive and defensive measures. Additionally, adversary attacks can take on so many forms that one cannot realistically defend against all types of attacks.

We believe that PRA still has an important role in intelligent adversary risk analysis for assessment of vulnerabilities and consequences, but we do not believe we should assess probabilities of adversary decisions. With uncertain hazards, the systems (e.g. hurricanes, nuclear reactors, or space systems) do not make decisions so the uncertainties can be assigned a probability distribution based on historical data, tests, models, simulations, or expert assessment. However, when we consider intelligent adversary risk analysis, the adversary will make future decisions based on their objectives, our actions, and future information about their ability to achieve their objectives that is revealed during a scenario. Instead, we believe the probabilities of adversary decisions should be an output of not an input to risk analysis models (NRC 2008).

1.2. An Illustrative Bioterrorism Example

In order to make our argument and our proposed alternative more explicit, we use a bioterrorism illustrative example. In response to the 2004 HSPD, in October 2006, the DHS released a report called the Bioterrorism Risk Assessment (BTRA) (BTRA, 2006). The risk assessment model contained 17 step event tree (18 steps with consequences) that could lead to the deliberate exposure of civilian populations for each of the 27 most dangerous pathogens that the Center for Disease Control tracks (emergency.cdc.gov/bioterrorism) plus one engineered pathogen. The model was extremely detailed and contained a number of separate models that fed into the main BTRA model. The BTRA resulted in a normalized risk for each of the 28 pathogens.

The National Research Council conducted a review of the BTRA model (NRC, 2008) and provided 11 specific recommendations for improvement to the model. In our example, we will use four of the recommendations: model the decisions of intelligent adversaries, include risk management, and simplify the model by not assigning probabilities to the branches of uncertain events, and do not normalize the risk. The intelligent adversary technique we illustrate is defender-attacker-defender model (NRC 2008, Appendix E) solved with decision trees (NRC 2008, Appendix D. Since the model has been simplified to reflect the available data, the model can be developed in a Commercial off the Shelf (COTS) software package, such as the one we used to for modeling, DPL (www.syncopation.org). Other decision analysis software would work as well[1].

1.3. Event Trees Do Not Properly Model Intelligent Adversary Risk

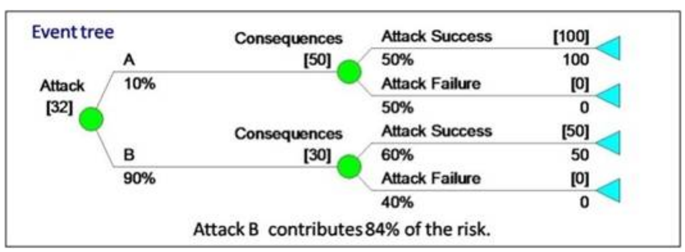
Event trees have been useful for modeling uncertain hazards (Pate-Cornell, 2002). However, there is a difference in the modeling of intelligent adversary decisions that event trees do not capture. The attacker makes decisions to achieve his objectives. The defender makes resource allocation decisions before and after an attack to try to mitigate vulnerabilities and consequences of the attacker's actions. This dynamic sequence of decisions made by first defender, then an attacker, then again by the defender should not be modeled by assessing probabilities of the attacker's decisions. For example, when the attacker looks at the defender's preparations for their possible bioterror attack, they do not assign probabilities to their decisions; they choose the agent and the target based on their perceived ability to acquire the agent and successfully attack the target that will give them the effects they desire to achieve their objectives. In the 911 attack, the terrorists decided to attack the World Trade Center and targets in Washington DC using airplanes loaded with fuel to achieve their

[1] A useful reference for decision analysis software is located on the ORMS website (http://www.lionhrtpub.com/orms/surveys/das/das.html).

objectives. Furthermore, they choose flights and timing to maximize their probability of success. They did not assign probabilities to these decisions.

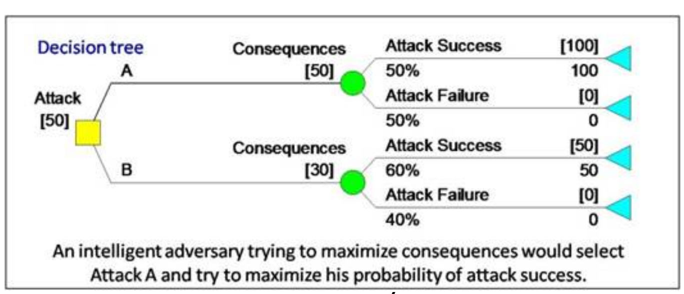
Representing an attacker decision as a probability can result in a fundamentally different and flawed risk assessment. Consider the simple bioterrorism event tree given in Figure 1 with notional data. For each agent (A and B) there is a probability that an adversary will attack, a probability of attack success, and an expected consequence for each outcome (at the terminal node of the tree). The probability of success involves many factors including the probability of obtaining the agent and the probability of detection during attack preparations and execution. The consequences depend on many factors including agent propagation, agent lethality, time to detection, and risk mitigation. Calculating expected values in Figure 1, we would assess expected consequences of 32. We would be primarily concerned about agent B because it contributes 84% of the expected consequences (30*0.9=27 for B of the total of 32).

Figure 1: Event Tree Example



However, adversaries do not assign probabilities to their decisions; they make decisions to achieve their objectives, which may be to maximize the consequences they can inflict (Golany et al.,

Figure 2: Decision Tree Example

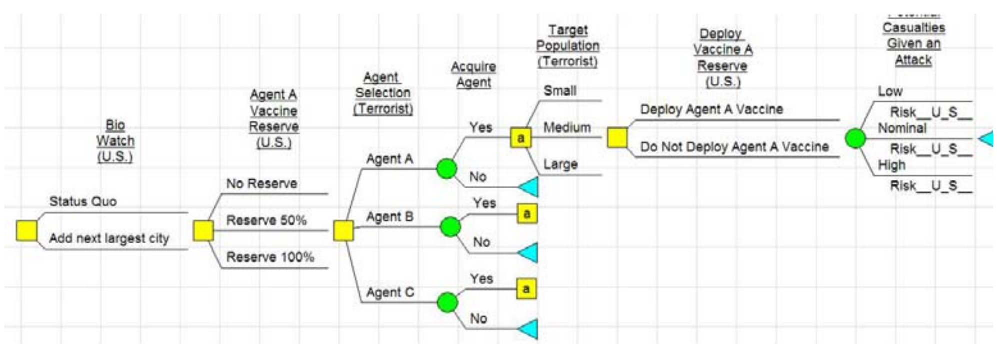


2009). If we use a decision tree as in Figure 2, we replace the initial probability node with a decision node since this is an adversary decision. We find that the intelligent adversary would select agent A, and the expected consequences are 50, which is a different result than with the event tree. The expected consequences are greater and the primary agent of concern is now A. Clearly, event trees underestimate the risk and provide the wrong risk ranking. However, while providing an important insight into the fundamental flaw of using event trees for intelligent adversary risk analysis, this simple decision tree model does not sufficiently model the fundamental structure of intelligent adversary risk.

2. CANONICAL INTELLIGENT ADVERSARY RISK MANAGEMENT MODEL FOR BIOTERRISM

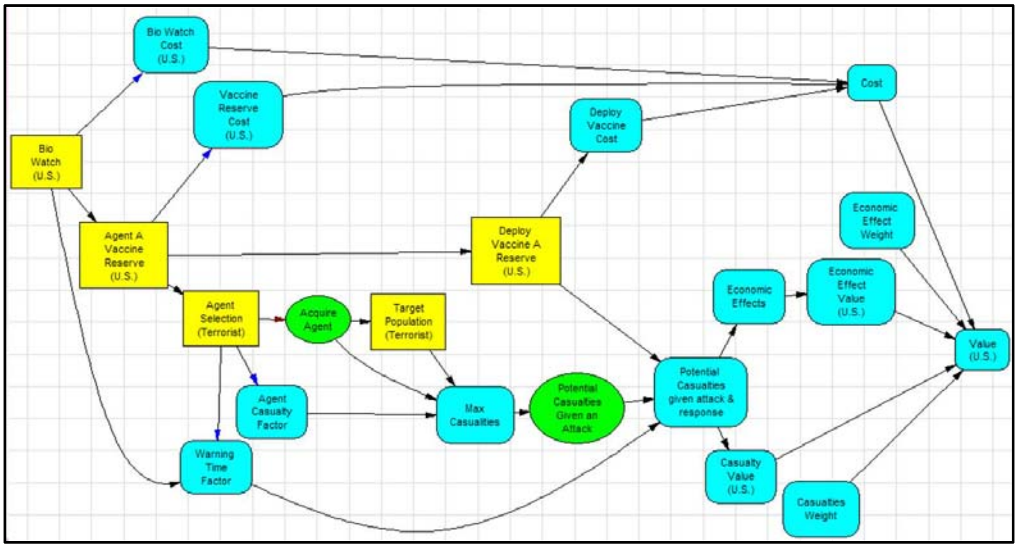
We believe the canonical risk management model for bioterrorism homeland security must have at six components: the initial actions of the defender to acquire defensive capabilities, the attacker's

Figure 3: Canonical Bioterrorism Decision Tree



uncertain acquisition of the agents (e.g., A, B, and C), the attacker's target selection and method of attack(s) given agent acquisition, the defender's risk mitigation actions given attack detection, the uncertain consequences, and the cost of the defender actions. In general the defender decisions can provide offensive, defensive, or informational capabilities. We are not considering offensive decisions such as preemption before an attack; however, we are considering decisions that will increase our defensive capability (e.g. buy vaccine reserves) (BioShield, 2004) or provide earlier or more complete information for warning of an attack (add a Bio Watch city) (BioWatch, 2003). In our defender-attacker-defender decision analysis model, we have the two defender decisions (buy vaccine, add a Bio Watch

Figure 4: Canonical Bioterrorism Influence Diagram



city), the agent acquisition is uncertain, the target and method of attack are attacker decisions, the consequences (fatalities and economic) are uncertain, and the costs are known. The U.S. risk is defined as the probability of adverse consequences and is modeled using a multiobjective additive model similar to multiobjective value models (Kirkwood, 1997). The defender minimizes the risk and the attacker maximizes the risk. We implemented a decision tree (Figure 3) and an influence diagram (Figure 4) using DPL. The mathematical formulation of our model and the notional data are provided in the appendix.

2.1. Defender.

The illustrative decision tree model (Figure 3) begins with decisions that the defender (U.S.) makes to deter the adversary by reducing the vulnerabilities or be better prepared to mitigate a bioterrorism attack of agents A, B, or C. We modeled the agents to represent notional bioterror agents using the CDCs agent categories in Table 2 below. For example, agent A represents a notional agent from category A. Table 3 provides a current listing of the agents by category. There are many decisions that we could model, however for our simple illustrative example, we chose to model notional decisions about the Bio Watch program for agents A and B and the BioShield vaccine reserve for Agent A.

Table 2: CDC BioTerror Agent Categories

Category	Definition
A	The U.S. public health system and primary healthcare providers must be prepared to address various biological agents, including pathogens that are rarely seen in the United States. High-priority agents include organisms that pose a risk to national security because they: can be easily disseminated or transmitted from person to person; result in high mortality rates and have the potential for major public health impact; might cause public panic and social disruption; and require special action for public health preparedness.
B	Second highest priority agents include those that: are moderately easy to disseminate; result in moderate morbidity rates and low mortality rates; and require specific enhancements of CDC's diagnostic capacity and enhanced disease surveillance
C	Third highest priority agents include emerging pathogens that could be engineered for mass dissemination in the future because of: availability; ease of production and dissemination; and potential for high morbidity and mortality rates and major health impact.

Center for Disease Control website. Bioterrorism Agents/Diseases Definitions by category. Avai http://www.bt.cdc.gov/agent/agentlist-category.asp, Accessed February 10, 2009.

Bio Watch is a program that installs and monitors a series of passive sensors within a major metropolitan city (BioWatch, 2003). The BioShield program is a plan to purchase and store vaccines for some of the more dangerous pathogens (BioShield, 2004). The defender first decides whether or not to add another city to the Bio Watch program. If that city is attacked, this decision could affect the warning time, which influences the response and ultimately the potential consequences of an attack. Of course the BioWatch system does not detect every agent, so we modeled agent C to be the most effective agent that the BioWatch system does not sense and therefore will give no additional warning. Adding a city will also incur a cost in dollars for the U.S.

The second notional defender decision is the amount of vaccine to store for agent A. Agent A is the notional agent that we have modeled that exceeds the other agents in probability to acquire and

Table 3: Pathogens

National Institutes of Health National Institute of Allergy and Infectious Diseases (NIAID) Category A, B and C Priority Pathogens		
Category A	Category B	Category C
• Bacillus anthracis (anthrax) • Clostridium botulinum toxin (botulism) • Yersinia pestis (plague) • Variola major (smallpox) and other related pox viruses • Francisella tularensis (tularemia) • Viral hemorrhagic fevers • Arenaviruses • LCM, Junin virus, Machupo virus, Guanarito virus • Lassa Fever • Bunyaviruses • Hantaviruses • Rift Valley Fever • Flaviruses • Dengue • Filoviruses • Ebola • Marburg	• Burkholderia pseudomallei • Coxiella burnetii (Q fever) • Brucella species (brucellosis) • Burkholderia mallei (glanders) • Chlamydia psittaci (Psittacosis) • Ricin toxin (from Ricinus communis) • Epsilon toxin of Clostridium perfringens • Staphylococcus enterotoxin B • Typhus fever (Rickettsia prowazekii) • Food and Waterborne Pathogens • Bacteria • Diarrheagenic E.coli • Pathogenic Vibrios • Shigella species • Salmonella • Listeria monocytogenes • Campylobacter jejuni • Yersinia enterocolitica) • Viruses (Caliciviruses, Hepatitis A) • Protozoa • Cryptosporidium parvum • Cyclospora cayatanensis • Giardia lamblia • Entamoeba histolytica • Toxoplasma • Microsporidia • Additional viral encephalitides • West Nile Virus • LaCrosse • California encephalitis • VEE • EEE • WEE • Japanese Encephalitis Virus • Kyasanur Forest Virus	Emerging infectious disease threats such as Nipah virus and additional hantaviruses. *NIAID priority areas:* • Tickborne hemorrhagic fever viruses • Crimean-Congo Hemorrhagic fever virus • Tickborne encephalitis viruses • Yellow fever • Multi-drug resistant TB • Influenza • Other Rickettsias • Rabies • Prions* • Chikungunya virus* • Severe acute respiratory syndromeassociated coronavirus (SARS-CoV)

The list of potential bioterrorism agents was compiled from both CDC and NIH/NIAID websites available at http://www.bt.cdc.gov/agent/agentlist-category.asp and http://www3.niaid.nih.gov/topics/emerging/list.htm [accessed Feb. 10, 2009].

potential consequences. The defender can store a percentage of what experts think is 100% of what we would need in a full scale biological agent attack on the maximum number of people. The more of agent A vaccine the U.S. stores, the fewer consequences we will have if the adversaries use agent

A and we have warning time to deploy the vaccine reserve. However, as we store more vaccine, the costs for purchasing and storage increase.

2.2. Attacker.

After the defender has made their investment decisions, the attacker makes two decisions: the type of agent and the target. We will assume that the attacker has already made the decision to attack the United States with a bioterror attack. In our model, there are three agents they can choose, though this can be increased to represent the other pathogens listed in Table 3. As stated earlier, if we only looked at the attacker decision, agent A would be the best choice. Agent B and C are the next two most attractive agents to the attacker. Again, agent B can be detected by BioWatch while agent C cannot be detected by BioWatch. The attacker has a probability of acquiring each agent. If the agent is not acquired, he cannot attack with that agent. Additionally, each agent has a lethality associated with it, represented by the agent casualty factor. Finally, each agent has a different probability of being detected over time. Generally, the longer it takes for the agent to be detected, the more consequences the U.S will suffer.

The adversary also decides what population they would target. Generally, the more population they target, the more potential consequences that could result. The attacker's decisions impact the maximum possible casualties from the scenario. There is a probability of actually attaining a low, medium or high amount of those potential casualties. This sets the stage for the next decisions by the defender.

2.3. Defender.

After warning of the attack of agent A, the defender decides whether or not to deploy the agent A vaccine reserve. The decision depends upon how much of the vaccine reserve the U.S. chose to store, whether the attacker used agent A, and the potential effectiveness given the attack warning. Additionally, there is a cost associated with deploying the vaccine reserve.

2.4. Consequences.

In our model (Figure 4) we have two consequences: causalities and economic impact. Given the defender-attacker-defender decisions, the potential casualties given an attack and the economic impact are assessed. Casualties are based on the maximum potential casualties, the warning time given to the defender, and the effectiveness of vaccine for agent A. Economic effects are modeled with a linear model with a fixed economic effect no matter the number of casualties and a variable cost of the number of casualties times the dollars per casualty. Of course, the defender would like potential consequences (risk) given an attack to be low, while the attacker would like the potential consequences (risk) given an attack to be high.

Our economic consequences come from Wulf, Haimes and Longstaff's paper (2003) on economic impact of terrorism. For example, experts estimate that there was a negative $6 billion effect on the economy due to the Anthrax letters of 2001 (World at Risk, 2008, p. 8). This attack only infected 17 and killed 5. Therefore, we modeled the impact as a linear function with the $10 billion as the constant and a cost per casualty also based on their work. They give an upper bound of the casualties and economic impacts of a full scale biological attack.

2.5. Budget.

Each U.S. defender decision incurs a dollar cost. The amount of money available to homeland security programs is limited by a budget determined by the President and Congress. The model will track the costs incurred and only allows spending within the budget (see appendix). We considered notional budget levels of 10M, 20M and 30M.

2.6. Risk.

Normally, a decision tree is solved by maximizing or minimizing the expected attribute at the terminal branches of the tree. In our model, the attribute is defender risk which depends on the casualty and economic consequences given an attack. We use multiple objective decision analysis with an additive value (risk) model to assign risk to the defender consequences[2]. The defender is minimizing risk and the attacker is maximizing risk. Therefore, we assign a risk of 0.0 to no consequences and a value of 1.0 to the worst case consequences in our model. We model each consequence with a linear value function (constant returns to scale) and a weight (See Appendix). The risk functions measure returns to scale on the consequences. Of course, additional consequences

Table 4: Modeling Assumptions

Categories	Our Assumptions	Possible Alternative Assumptions
Uncertain Variables	Probability of acquiring the agent, Detection time varies by agent	Other indications and warning
Decisions	Add Bio Watch city for agent A and B	Additional detection and warning systems
	Increase vaccine reserve stocks for agent A	Increase stocks of multiple agents
	Deploy vaccine A	Other risk mitigation decisions
Consequence Models	One casualty model for all three agents	Different casualty models for different agents
Risks	Casualties and economic consequences	Additional risk measures
	Defender minimizes risk and attacker maximizes risk	Other optimization assumptions
	Solve decision tree at various budget levels	Other solution approaches

could be included and different shape risk curves could be used.

2.7. Assumptions.

Some of the key assumptions in our model are listed in Table 4 (the details are in the Appendix) and some possible alternative assumptions. Given different assumptions, the model may produce different results.

[2] We define risk to be a weighted expected value using an additive value model instead of a probability of a bad outcome.

We model uncertainty in probability that an adversary acquires an agent and we vary detection time by agent. Clearly, other indications and warning exist to detect possible attacks. These programs could be included in the model.

We model three decisions: add Bio Watch for agent A and B, increase vaccine researve for agent A, and deploy agent A. Additionally, we assume limited decisions (i.e., 100% storage of vaccine A, 50% storage, 0% storage), but there decisions that could be modeled (e.g., other levels of storage, storing vaccines for other agents, etc).

We used one casualty model for all agents. There are other casualty and economic models that could be used.

Finally some risk assumptions that our model makes are listed. First, we assume that the risks important to the defender are the number of casualties and the economic impact but additional measures could be used. Second, we assume defenders and attackers have a diametrically opposed view of all of the objectives. Finally, we made some budget assumptions, which could be improved or modified. We assumed a number for a budget, but this budget could be modeled with more detailed cost models (e.g., Instead of adding a set amount to adding a city to the Bio Watch program, the budget could reflect different amounts depending upon the city and the robustness of the sensors installed).

2.8. Number of Strategies.

The canonical model has 108 different strategies to evaluate (Table 5). This is important because one

Table 5: Total number of strategies

Owner	Decision	# Strategies
U.S.	BioWatch	2
U.S.	BioShield	3
Attacker	Agent Selection	3
Attacker	Target	3
U.S.	Deploy Reserve	2
Total # of Strategies		**108**

can see that with more complexity, the number of strategies the model would need to evaluate can grow significantly.

3. ILLUSTRATIVE DECISION ANALYSIS RESULTS

3.1. Modeling Insights.

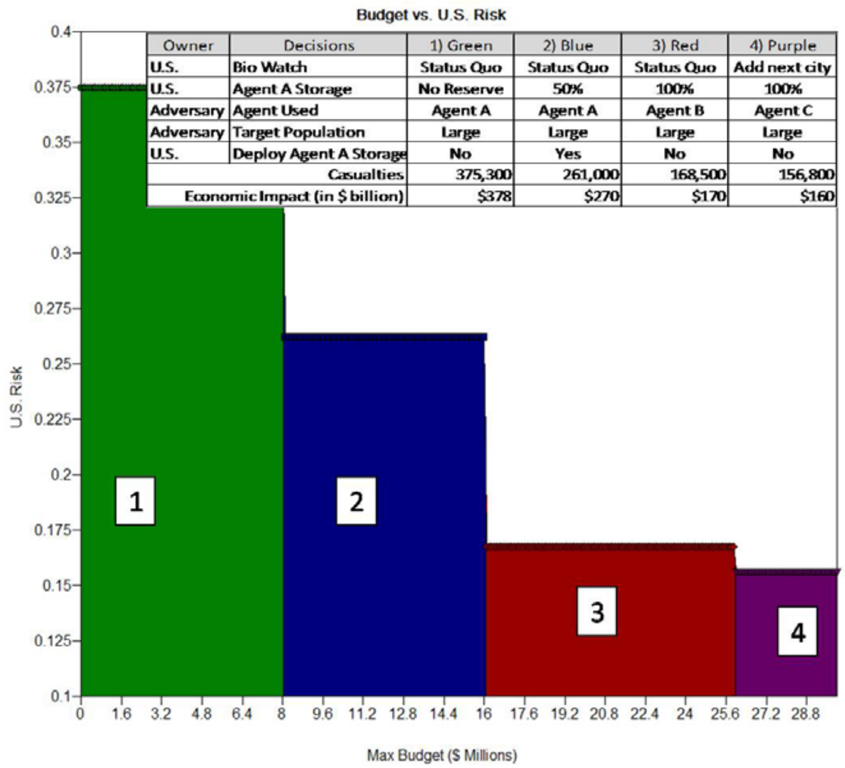
After modeling the canonical problem, we obtained several insights. First, in our model economic impact and casualties are highly correlated. Higher casualties will result in higher economic impact. In addition, other consequences, e.g. psychological consequences, could also be correlated with casualties. Second, there could be a large economic impact (and psychological impact), even if casualties are low.

3.2. Analysis Results of Risk versus Budget

The major risk analysis results are shown in Figure 5. Risk shifting is occurs in our decision analysis model. In the baseline, (no defender spending) Agent A is the most effective agent for the attacker to select and the defender to consider spending resources to reduce vulnerability and/or consequences. As we improve our defense against agent A, at some point the attacker will select another agent, B. The high risk agent has shifted from agent A to B. Finally, as the budget level increases, the defender adds a city to the BioWatch program and the attackers choose to attack with agent C which Bio Watch cannot detect. We use notional data in our model, but if more realistic data were used, the defender could determine the cost benefit of additional risk reduction decisions. This decision model, using COTS software allows DHS to conduct risk management. They can quantitatively evaluate the potential risk reduction of options and make cost benefit decisions.

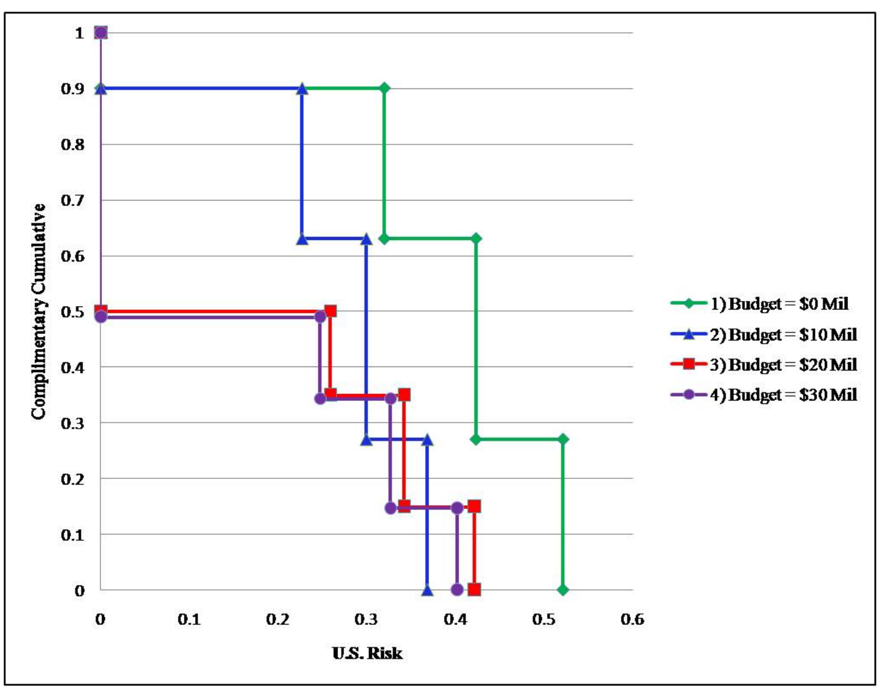
Figure 5 provides a useful summary of the expected risk. However, it is also very useful to

Figure 5: Budget vs. U.S. Risk



look a the complementary cummumative distribution (Figure 6) to better understand the risks of

Figure 6: Complimentary cumulative distribution

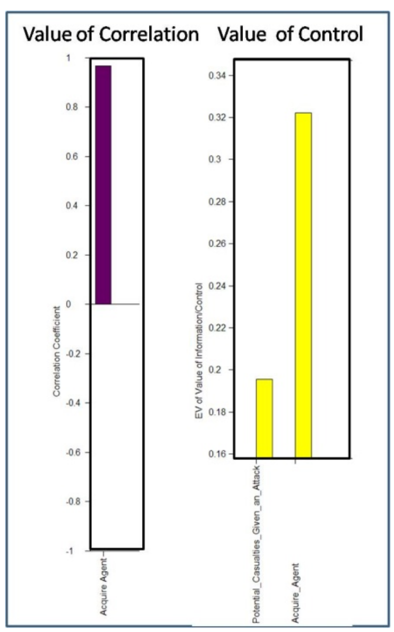


extreme outcomes. The best risk management result would be that option 4 deterministically or stochastically dominates (SD) option 3, 3 SD 2, and 2 SD 1. The first observation we note from Figure 6 is that options 2, 3, and 4 stochasically dominate 1 since there is a lower probability for each risk outcome. A second observation is that while 4 SD 3, 4 does not SD 2 since 4 has a 0.15 proability of a risk of 0.4. This illustrates a possibly important relationship necessary for understanding how the budget might affect the defender's risk.

3.3. Value of Information/Control.

Risk managers can run a value of control or value of correlation diagram to see which nodes most directly affect the outcomes and which are correlated (Figure 7). Since we only have two uncertainty nodes in our canonical model, the results are not surprising. The graphs show that the ability to acquire the agent is positively correlated with the defender risk, and that it is the most important variable that defender risk managers would want to control. Admittedly, this is a basic

Figure 7: Value of Information/Control

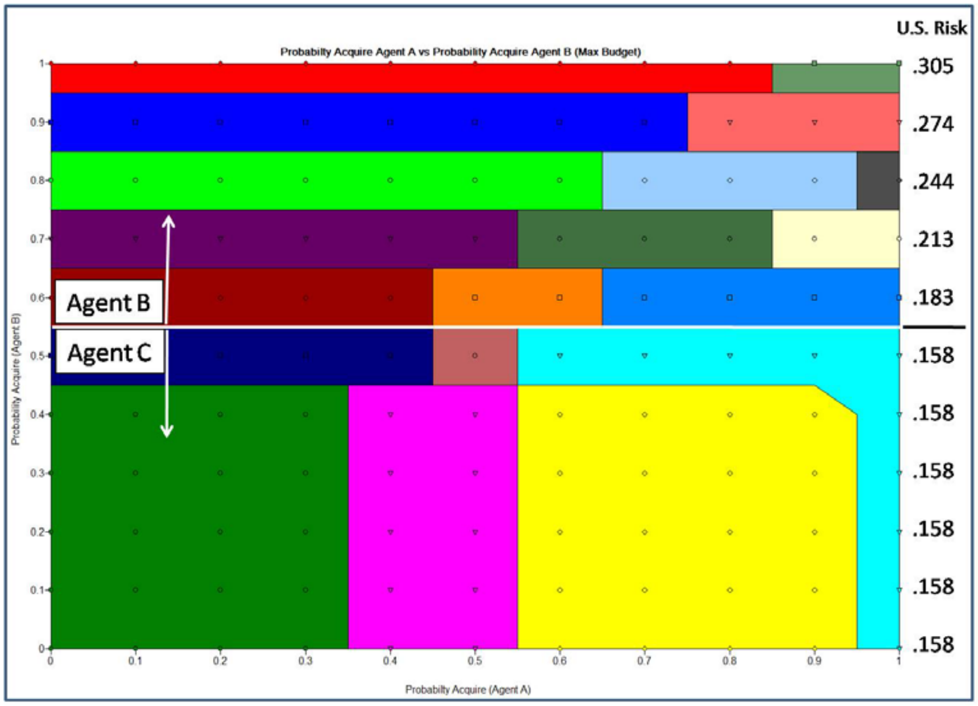


example, but with a more complex model, analysts could determine which nodes are positively or negatively correlated with risk and quantitatively which nodes we would most want to exercise control over or gather information about the outcomes.

3.4. Sensitivity Analysis.

Using COTS software also allows us to easily perform sensitivity analysis on key model assumptions. From the value of correlation and control above, the probability the attacker acquires the agent they choose is an important variable. COTS software allows us to perform sensitivity analysis like a rainbow and strategy region diagrams. The strategy region diagram (Figure 8) allows us to see changes in strategy as our assumptions about the probability of acquiring agent A and agent B change. The different colored/shaded regions represent a change in decisions, both the attacker and the defender. If our assumption about the ability to acquire agent A is wrong, we see the effects. Currently we notionally assigned the value of probability of acquiring agent A and B are .9 and .5 respectively. The diagram was run with the model at maximum budget and it shows that if the probability of acquiring agent B rises to .6, the attackers would choose to use agent B instead of agent C. One can also see the level of defender risk rising as the probability of acquiring agent B increasing. In addition, we see that as the probability of acquiring agent A increases, there is no overall change in risk unless the probability of acquiring agent B also increases.

Figure 8: Rainbow Diagram Probability of Acquiring Agent A vs. Agent B



4. BENEFITS AND LIMITATIONS OF DEFENDER-ATTACKER DECISION ANALYSIS MODEL

4.1. Benefits.

The defender-attacker-defender decision analysis model provides four important benefits. First, it provides a more accurate risk assessment. Second, it provides information for risk-informed decision making. Third, using COTS software that takes advantage of the existing sensitivity analysis tools. Fourth, the risk analysis can be conducted by one risk analyst with an understanding of decision trees and optimization and training on the features of the COTS software.

Risk analysis of intelligent adversaries is fundamentally different than risk analysis of uncertain hazards. As we demonstrated in Section 1.3, assigning probabilities to the decisions of intelligent adversaries underestimates the potential risk and provide an incorrect ranking of the threats. Decision tree models of intelligent adversaries provide more accurate risk assessment.

The defender-attacker-defender decision analysis provides essential information for risk management decision making. These models provide insights about resource allocation decisions to reduce risk and risk shifting. Additionally, with budget set to 0 you can assess the baseline risk. As you increase the budget, the analyst can clearly show the best risk management decisions and the risk reduction.

This model significantly simplifies the DHS BTRA model and enables the use of COTS risk analysis software. In addition, the use of COTS software enables the use of standard sensitivity analysis tools to provide insights into areas that the model should be improved or expanded.

Currently, the DHS BTRA event tree requires extensive contractor support to run, compile, and analyze results (NRC 2008). The defender-attacker-defender decision analysis model is usable by a single risk analyst who can provide real-time analysis results to stakeholders and decision makers. This risk analyst must understand decision trees, optimization, and have training in the COTS tool.

4.2. Limitations

Some of the limitations are actually the same as using event trees. There are limitations on the number of agents used in the models. We easily modeled 28 bio agents with reasonable run times, but there are always more agents that could be modeled. Additionally, there are challenges in assessing the probability of the uncertain events, e.g., the probability that the attacker acquires Agent A. Next, there is a limitation in modeling of the multiple consequences. Another limitation may be that in order to get more realistic results, we may have to develop "response surface" models of more complex consequence models. These are the limitations that event trees and decision trees share.

There are some decision tree limitations that are different from event trees. First, there are a limited number of risk management decisions that can realistically be modeled. Care must be used to choose the most appropriate set of potential decisions. Additionally, there may be an upper bound in the number of decisions or events the COTS software can model. In this case, an alternative would be large scale optimization software (Brown, 2005). Finally, successful model operation and interpretation requires trained analysts who understand decision analysis and defender-attacker-defender optimization.

5. FUTURE WORK

This paper has demonstrated the feasibility of modeling intelligent adversary risk analysis using defender-attacker-defender decision analysis. Table 4 and the discussion in section 2.7 identified several alternative modeling assumptions that could be considered. We can modify and expand our assumptions to increase the complexity and fidelity of our canonical model. The next step is to use the model with the best data available on the agents of concern and the potential risk management options.

6. CONCLUSION

These defender-attacker-defender recommendations do not require a major intelligent adversary research program; they require the willingness to change (NRC, 2008). Much of the data used for event tree models can be used in the decision analysis model. Assessing probabilities of attacker decisions will not increase our security but defender-attacker-defender decision analysis models can provide a sound assessment of risk and the essential information our nation needs to make risk-informed decisions.

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APPENDIX: MODEL FORMULATION

This model is a multi objective decision analysis / game theory model that allows for risk management at the U.S. governmental level in terms of budgeting and certain bio terror risk mitigation decisions. The values for probabilities as well as factors are notional and could easily be changed based on more accurate data. It uses the starting U.S. (defender) decisions of adding a city to the Bio Watch program (or not) and the percent of storing an agent in the nation's vaccine reserve program to set the conditions for an attacker decision. The attacker can choose which agent to use as well as what size of population to target. There is some unpredictability in the ability to acquire the agent as well as the effects of the agent given the defender and attacker decisions. Finally, the defender gets to choose whether to deploy the vaccine reserve to mitigate casualties. The model tracks the cost for each U.S. decision and evaluates them over a specified budget. The decisions cannot violate the budget without incurring a dire penalty. The objectives that the model tracks are U.S. casualties and impact to the U.S. economy. They are joined together using a value function with weights for each objective.

We outline our model using a method suggested by Brown and Rosenthal (2008).

Table 5: Notional data for variable nodes

	0%	50%	100%
Agent A reserve factor (ar_v)	0	0.3	0.6
Vaccine Reserve cost factor ($vrcf_v$)	0	0.5	1
	Agent A	**Agent B**	**Agent C**
Warning time factor (wf_a)	0.87	0.7	0.8
Agent casualty factor (af_a)	0.9	0.5	0.4
	Small	**Medium**	**Large**
Target population factor (pop_t)	0.001	0.1	1
	Low	**Nominal**	**High**
Potential casualties factor (pcf_c)	0.6	0.8	0.99
Weight of Casualties (w_1)	0.5		
	Agent A	**Agent B**	**Agent C**
Probability of acquiring agent *a* ($P(ac_a)$)	0.9	0.5	0.49

Table 6: Notional Data for probability of potential casualties *c* with agent *a*

Probability of potential casualties *c* with agent *a* ($P(pc_{ac})$)	Agent A	Agent B	Agent C
Low	0.3	0.3	0.3
Nominal	0.4	0.4	0.4
High	0.3	0.3	0.3

Indicies

w = add Bio Watch city {0, 1}
v = store vaccine A at percent {0%, 50%, 100%}
a = agent {A, B, C}
t = target population {Small - .0001 Million, Medium - .1 Million, Large - 1 Million}
c = potential casualties given an attack {Low, Nominal, High}
d = deploy reserve vaccine {0, 1}
i = risk measure {1, 2}

Data

ac_a = agent acquired {0, 1}

w_i = weight of $_i$ value measure $\{w_1, 1\text{-}w_1\}$

Probability Data

$P(ac_a)$ = probability acquire agent *a*

$P(pc_{ac})$=probability of potential casualties *c* with agent *a*

Casualty Data

bwf = bio watch factor {.9}

ar_v= Agent A reserve factor

wf_a= warning time factor

af_a= agent casualty factor

pop_t= target population factor

mpop = max population targeted {1 Million people}

pcf_c=potential casualties factor

Economic Impact Data

eif = economic impact of attack (fixed) {$10 Billion}

dtc = dollars to casualty effect ratio {1 Million $/person}

Cost Data

mbw=maximum bio watch cost {$10 Million}

mcvr = maximum cost for vaccine reserve {$10 Million}

$vrcf_v$ = vaccine reserve cost factor

mcd = maximum cost to deploy 100% of vaccine A {$10 Million}

mb = maximum budget (U.S.) {$30 Million or variable}

cbp = cost greater than budget penalty = 1

Equations

Casualty Equations

wt_{aw} = warning time factor (U.S.)

$$wt_{aw} = wf_a \times b_w$$

mc_{at} = maximum casualties given an attack

$$mc_{at} = ac_a \times popd_t \times af_a$$

pc_{atc} = potential casualties given attack

$$pc_{atc} = mc_{at} \times pcf_c$$

drf_{vd} = deploy reserve factor

$$drf_{vd} = \text{if } dr_d \leq 0 \text{ then } drf_{vd} = 1, \text{otherwise } drf_{vd} = (1 - ar_v)$$

x_1 = U.S. casualties due to bioterrorism attack given response

$$x_1 = \begin{cases} if\ agent_a = agent\ A\ then,\ pc_{atc} \times wt_{aw} \times drf_{vd} \\ if\ agent_a = agent\ B\ then,\ pc_{atc} \times wt_{aw} \\ if\ agent_a = agent\ C\ then,\ pc_{atc} \end{cases}$$

Economic Impact Equations

mei = maximum economic impact

$mei = eif + dtc \times mpop$

x_2 = U.S. economic effects due to a bioterrorism attack

$x_2 = ac_a \times (eif + x_1 \times dtc)$

Cost Equations

bwc_w = bio watch cost (U.S.)

$bwc_w = \text{if } b_w = 0, \text{then} = 0, \text{otherwise} = mbw$

vrc_v = vaccine reserve cost (U.S.)

$vrc_v = mcvr \times vrcf_v$

$drcf_{av}$ = deploy reserve cost factor

$$drcf_{av} = \text{if agent}_a < 1 \text{ then } (\text{if } ar_v <= .1 \text{ then } drcf_v = mb + 1, \text{otherwise } drcf_v = ar_v) \text{otherwise } drcf_{av} = mb + 1$$

cd_{avd} = deploy vaccine cost (U.S.)

$cd_{avd} = \text{if } dr_d = 1 \text{ then } drcf_{av} \times dr_d \times mcd, \text{otherwise} = 0$

$cost_{awvd}$ = U.S. cost to prepare and mitigate a potential bioterrorism attack

$cost_{awvd} = b_w + vrc_v + cd_{avd}$

Decision Variables

b_w = bio watch decision (U.S.)

r_v = vaccine reserve decision (U.S.)

$agent_a$ = agent selection decision (Terrorist)

$popd_t$ = target population decision (Terrorist)

dr_d = deploy reserve decision (U.S.)

Objectives

$r_1(x_1)$ = risk function for U.S. casualties due to bioterrorism attack

$$r_1(x_1) = \frac{x_1}{mpop}$$

$r_2(x_2)$ = risk function for U.S. economic effects due to a bioterrorism attack

$$r_2(x_2) = \frac{x_2}{mei}$$

r(x) = Risk to the United States

r(x) = if $cost_{awvd} \leq$ mb then $\sum_{i=1}^{n} w_i r_i(x_1)$, else cbp

$$\min_{w}(\min_{v}(\max_{a}(\sum_{a} Prob(ac_a) \cdot \max_{t}(\min_{d} \sum_{ac} Prob(pc_{ac}) \times r(x))))))$$

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