Chapter I

All Hazards Analysis: A Complexity Perspective

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Abstract

With the increase in the complexity of terrorism's networks and activities, the advances in chemical and biological warfare, and the use of organized criminal activities, it is becoming apparent that dealing with this complexity is not possible with traditional problem-solving approaches. The artificial complexity area (Artificial Life, or ALife), complex systems and agent-based distillation (ABD) provide a new perspective to the problem and emphasize the importance of modeling the interaction between system components to tackle these issues. This chapter presents an introduction to Cellular Automota and ABD, and then reviews and critiques how these approaches specifically have been used to model aspects of bushfires, epidemics, biological warfare and terrorism. This chapter then extends upon previous works to present an overview of the possible use of artificial complexity models to the larger field of security and safety applications.

Introduction

Australia and other countries are currently facing new security challenges. Possible terrorism can take a variety of forms, which is compounded with the fact that each country is characterized with its own eco, political and social systems. These influence the nature of risk and, hence, the risk management techniques needed to address those threats. We identify two types of generic hazards: disasters and terrorist attacks.

Disasters relate more to the ecological and social context within a country. For example, native forests comprise 21% of the Australian land-mass (Australian Bureau of Statistics, 2003). This represents both a major boon and threat to the Australian economy. In December 2002, one of the worst bushfires in Australian history occurred in Canberra. The impact of this bushfire is described here: "... ACT bushfire disaster that struck the national capital on Saturday 18 January was arguably the worst on record in Australia. Over 400 homes lost, at least four people dead, the ACT pine plantations wiped out, the Mount Stromlo Observatory national heritage treasure lost, thousands of businesses affected (including AusIssues) and a rebuilding debt of hundreds of millions of dollars" (AusNews.Com, 2003).

Another source of hazard is the spread of epidemics. The latest SARS disease raised public awareness of the potential for an epidemic to spread quickly throughout a population. When that potential is combined with the high relative proportion of overseas tourists into a country such as Australia (in 2001-2002, there were nearly 5 million incoming tourists, compared to a resident population of nearly 20 million; Australian Bureau of Statistics, 2003), it is obviously necessary to plan for potential epidemics.

Complex systems have successfully been used to model the behavior of both bushfires and epidemics. This introductory chapter will consider the characteristics of those models and outline some characteristics of nuclear, biological and chemical terrorism that the same modeling approaches may be adapted to. In the context of studies such as those by Kupperman and Smith (1993), which find that one gram of anthrax is sufficient — if its spores were distributed appropriately — to kill more than one-third of the population of the United States (U.S.) (Purver, 1995), the importance of work in this area is apparent.

Terrorist attacks are our second category of hazards. This type of threat is different in that it usually requires a group to act and is usually directly targeted at people, populated infrastructure or critical infrastructure.

To deal with any of these hazards, we can identify three stages:

- **Pre-attack:** During the pre-attack stage, the organization of the threat takes place. For example, the start of summer can be seen as the pre-attack stage for a natural bushfire disaster. Another example is the time before September 11, where the terrorist network was building up and planning for the attack. Obviously, the optimal resolution is to deal with the hazard during this stage. However, it is very difficult to predict the hazard accurately.
- **In-attack:** If dealing with the hazard was not successful or possible during the pre-attack stage, the hazard takes place. The in-attack stage is the time frame of the hazard. For example, the Canberra bushfire in-attack stage lasted about 1 month. The tsunami in the Asian-pacific area was another global disaster and is an example of a natural mass destruction that lasted less than a day.
- **Post-attack:** The major impact of a hazard takes place after the hazard occurs. Afterwards, the problems of homeless people, destroyed infrastructure and the mental consequences of the hazard must be dealt with. After the tsunami, *The Australian Newspaper* reported, "As survivors were evacuated from stricken areas across Asia, horrific accounts of the carnage wrought by the tsunami emerged; babies torn from their parents' arms, children and the elderly hurled out to sea, entire villages swept away" (Australian Newspaper, 2004).

In all three stages, large-scale simulation models can be used to assist the decision maker during planning, design and implementation phases. This chapter will present an overview of work from the literature on the possible use of complexity techniques for security and safety models. It also will identify new areas where the complexity field may make new contributions. In particular, this chapter will cover the following topics:

- **Disaster models:** In particular, bushfire and epidemic models, and their potential use regarding nuclear, biological and chemical warfare.
- **Terrorism models:** In particular, the possible use of artificial complexity simulations for modeling terrorism attack plans, estimating terrorism network size and checking biometric system reliability.

The rest of this chapter is organized as follows: The next section presents background materials, where a simple introduction is given to cellular automata and agent-based distillation models. Bushfire models are then introduced, followed by epidemics models and a discussion of nuclear, biological and chemical incidents. Terrorism models are then presented and conclusions are drawn.

Background Materials

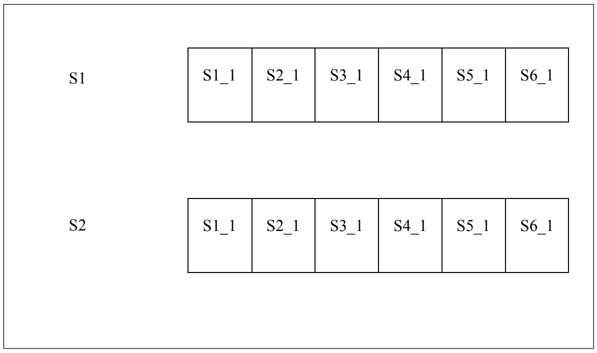
Cellular Automata

Cellular automata (CA) were introduced by von Neumann in the 1950s to model biological self-reproduction. CA are a class of mathematical systems that model spatially and temporally discrete deterministic systems. These systems are inherently parallel and characterized by local interactions. Despite their simplicity, CA feature many of the characteristics a complex system may exhibit, including: the emergence of global behavior through simple rules that define local interaction, the existence of a phase transition between order and disorder or chaos, and that complexity exists within the aforementioned phase transition (known as the edge of chaos).

The majority of CA systems in the literature are one-, two- or three-dimensional lattices of cells, where each cell has a number of discrete states. Cells are also homogenous; that is, any cell can be in one of the states belonging to all possible states. Further, a cell changes its state based on a rule set that defines the new state of the cell given the state of other cells in its local neighborhood. Finally, cells can change their states synchronously (simultaneously) or asynchronously (one/some at a time).

For example, consider Figure 1. It shows a CA at two timesteps, S1 and S2. At step S1, each cell, Si_1 will be at one of the states in set S_all. For example, assume S_all is the set {0,1,2,3,4,5,6}. During each time step, a consistent rule is applied to each cell. The cell addresses in rules are relative. For example, a rule could be (if (Si_t < 3) Si_t+1 = 5, else Si_t+1 = (int) (S(i-1)_t * 0.4 + Si_t * 0.2 + S(i+1)_t * 0.4)). Thus, at each new step, every new Si_t+1 will be determined by the application of one rule, to its neighboring cells during the previous step.

Figure 1. A CA in 2 timesteps, S1 and S2



Agent-Based Distillation and Military Operations

Multi-agent systems fall between two extremes: pure cognitive and pure reactive agents. On one hand, pure cognitive agents (known as high-fidelity agents) use powerful representations and are able to reason their behaviors. However, they are computationally very expensive and do not scale well. On the other hand, pure reactive agents are known as low-fidelity agents, since they are simple and scale well but are abstract. An example of the former is the *Belief Desire Intention* (BDI) architecture, while an example of the latter is *Agent-Based Distillation* (ABD). In modeling military operations such as attrition, the military has found ABDs to be very beneficial. Some features that distinguish ABDs from traditional simulations include: their simplicity, which make them easy to scale up to thousands of agents; abstraction, which makes the representation generic enough to achieve the desired goals without needing to get into too many details; and their relationship with complex systems. ABDs have much to do with the field of embodied cognition, although no study has yet contrasted these fields together. Both fields focus on the fact that agents' behaviors are determined through the interaction between the agents and the environment. A scenario is modeled through representations of the involved entities (known as agents) and the relationships between those entities, which, hence, define the nature and scope of interaction between agents. The analyst then examines multiple runs of the simulation in order to search for patterns that emerge over time. ABDs have received considerable interest from sectors of the Operational Analysis community in the last two to three years. This is attributable to a number of factors:

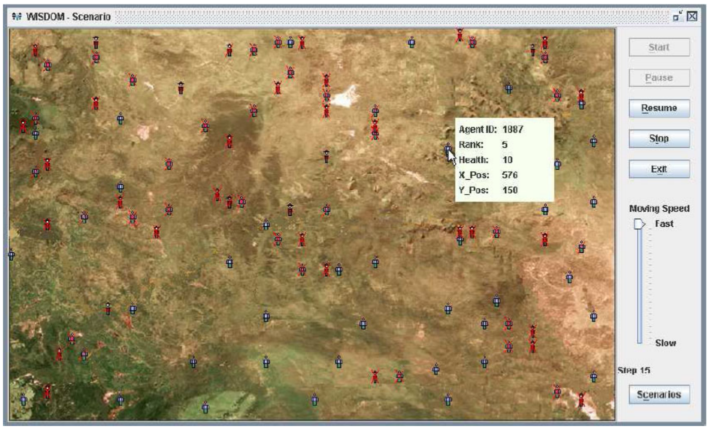
- **Rapid Prototyping:** The ability to rapidly explore a large parameter space to obtain insights necessary to guide more detailed analysis.
- **Nonlinearity:** The ability of distillations to capture the essential and well-known non-linearity of modern battles.
- **Intangibles:** The potential of ABDs to begin to quantify the effects of intangibles such as training, morale and leadership on battle outcomes.
- **Co-evolution:** The ability of ABDs to see the actions of both sides, to alter in response to their perception of the actions of opponents. That is, agents do not make decisions in isolation, but are influenced by their knowledge of both teammates' and enemies' actions.

In modeling attrition, the military used to depend on a set of coupled ordinary differential equations known as Lanchester equations. Despite their usefulness, Lanchester equations were insufficient for modeling heterogeneous forces, the dependency between firing rates and opposing force levels, and situational awareness, to name a few. One of the major disadvantages of these equations is the linearity assumption. Modern warfare is nonlinear by nature; therefore, Lanchester equations have been found insufficient (Ilachinski, 1996, 2000).

Toward the end of the 20th century, the U.S. Marine Corps started what is known as Project Albert to overcome the drawbacks and limitations of Lanchester equations. Ilachinski (1996) proposed the use of complex systems for modeling warfare. This resulted in a series of software systems by the U.S., New Zealand and Australia. These systems modeled attrition using agent-based distillation and complex adaptive systems. Some of these systems include *Irreducible Semi-Autonomous Adaptive Combat* (ISAAC) (Ilachinski, 2000), *Enhanced ISAAC Neural Simulation Toolkit* (EINSTein), *Map Aware Non-uniform Automata* (MANA) (Lauren, 2000; Lauren & Stephen, 2000, 2001), *Conceptual Research Oriented Combat Agent Distillation Implemented in the Littoral Environment* (CROCADILE) (Barlow & Easton, 2002) and the *Warfare Intelligent System for Dynamic Optimization of Missions* (WISDOM) (Yang, Abbass & Sarker, 2004). It is important to note that CROCADILE used a continuous representation of the environment, while all the other systems used a grid representation.

With the techniques of cellular automata and agent-based systems, the artificial complexity area has contributed to the solution of how to model more complex, spatial interactions. Both these techniques hold common that rather than representing one homogeneous population, the system is segmented into a

Figure 2. A screen dump of Wisdom Scenario Player V1.0



number of sub-components representing sub-parts of the population, each performing their own calculations, and so together contribute to an overall complex behavior.

To illustrate how these models have been applied, we will first consider how to model bushfire and epidemic patterns. After establishing these approaches, we will then consider how the models could be adopted to model aspects of nuclear, biological and chemical warfare.

Bushfires

Given the self-evident risks and costs associated with bushfires, it is not surprising that effort has been made to model their behavior.

A major early influence was the fire spread equations by Rothermel (1972). These equations considered the fire in a single location, and by considering the characteristics of this location (including its fuel type, wind and slope), the behavioral characteristics of the fire is generated. These results could be extrapolated to predict future behavior.

The problem with this approach is the assumption that the fire's environment is homogenous. In contrast, in general, when a CA models a fire incident, a spatial area is simulated as a series of cells. Each of these cells then manages certain information regarding its flammable inventory, slope, moisture level or amount of wind, and the status of fire within it. At each timestep of the algorithm, the amount of fire in a cell and the nature of its inventory will change based on its state and the state of neighboring cells at the previous timestep.

CAs have been used on a variety of scales and with different levels of details in the modeling of fire. For example, some work has focused on modeling fire such that it mimics the behavior of fire under laboratory conditions. Muzy, Wainer, Innocenti and Santucci (2002) developed a CA capable of simulating a fire as it spreads across a level, windless approximately $1m^2$ bed of pine needles. In their work, the simulation's results were compared with experimental laboratory results.

At a larger scale, Li and Magill (2003) developed a fire-modeling system that they described as agent-based. Their work considered whether there was some form of bush in each cell; if there was, the bush could then be assigned some particular density and flammability. Each cell could also be assigned a particular height. Furthermore, an overall wind could be specified, where the wind would have some given strength and direction. In their experiments, they showed that the spread of fire behaved in overall terms as would be expected; that is, the fire spread further both uphill and in the presence of strong, stable wind. However, these results were not normalized or compared with historical fire data.

On an even larger scale, Veach, Coddington and Fox (1994) describe a CA where each cell represented 400 square feet of land. Thus, each cell was characterized by information about its type of fuel, fuel moisture, slope, wind direction and wind strength. The equations they used to model the spread of the fire were adapted from Rothermel's equations. However, these results were not compared with specific or historic fire data, but the issue of matching the simulated cell characteristics to real-life data was considered.

It would be worthwhile to develop a realistic CA-based fire simulator that normalizes its behavior in-live with historic field data. With today's satellite data, organizations such as the CSIRO in Australia (www.sentinel.csiro.au) are interpreting satellite data to automatically and digitally determine the location of fires. Data sourced from such and other origins could provide the requisite data. A model normalized to historic data would provide tremendously valuable capabilities to bushfire fighting organizations. Not only could it provide insight during the in-attack phase in terms of determining likely characteristics and movements of fire fronts, but it also could provide valuable training and planning abilities during the pre-attack phase. Once a model had been normalized for the natural spread of fire, the effect of interventions could be studied, including the effect of fire breaks, water bombing and assignment of ground fire-fighting teams. This would be valuable both in the planning of defensive measures such as fire breaks, back-burning in the off-danger season and bush thinning, and also in a training/what-if mode, where fire-fighting commanders could practice their skills at the employment of fire-fighting capabilities and/or could develop new strategies for the employment of those capabilities.

Epidemics

Another largely natural threat occurs in the form of epidemics. Similar to bushfires, sets of differential equations were first used to model epidemics. These were first elaborated by Kermack and McKendrick (1927) in their SIR model, which assumed a homogeneous population divided into three groups: those that were susceptible (S), infected (I) or retired (R). The size of these three groups would be adjusted according to two parameters: b, the rate at which infected organisms would infect susceptible ones; and g, the rate at which infected individuals would either attain immunity or become deceased. Over time, variants of this model have been created that allow for more sophisticated modeling, such as spatial models and variants on the way in which infection may occur. However, these approaches are limited in that the more complicated the algorithms of the model become, the harder they are to solve.

In general, when cellular automaton are used to model epidemics, each cell of the automaton represents a particular spatial region. The cells in the automaton then store information about the individuals in and the progress of the epidemic within itself. At each timestep, the state of the cell is modified according to some formula that takes into account the current state of the cell and the states of the neighboring cells. In broad terms, this means that an epidemic can start in one cell and infect its neighbors, which then infect their neighbors, and so on.

A range of research with differing levels of cell complexity has been explored. At one extreme of the range, Ahmed and Elgazzar (1998, 2001) used a one-dimensional CA, where each cell represents an individual. They present a number of variants that cover aspects such as latency (an individual that is sick, but not infecting), incubation periods (when an individual is not sick, but is infecting) and variable levels of susceptibility of individuals within the population. In particular, they have studied the interaction of these factors to characterize under which conditions an infection will spread,or be contained.

More commonly, a two-dimensional CA is used. Researchers have customized each CA in order to characterize particular conditions. For example, Johansen (1996) used a two-dimensional CA where each cell represented an individual that could be susceptible, infected or absent. Essentially, after an individual was sick they were removed from the system, and after some time they were replaced by a new susceptible individual. This allowed the study of recurrent diseases, where a disease could pass through a region of the CA and return later.

Rousseau, Giorgini, Livi and Chate (1997) gave each cell an infection vector that indicated which neighboring cell it would deterministically infect. These vectors all rotated at the same rate and in the same direction, but by altering the variation of the initial vectors, the distribution and rate of infection could be varied.

In some CAs, each cell does not represent a single individual. Sirakoulis, Karafyllidis and Thanailakis (2000) considered a CA cell to contain a sub-population that might contain more than one individual; consequently, they also stored the percentage of a population that was infected in each cell. This setup meant that an individual could move from one cell to another cell. This system then allowed analysis of how infections varied according to how much individuals move. This system was also used to study the effect of vaccines.

Even more complex, Maniatty and Caraco (1999) had an individual and one or more parasites in each cell. These components then evolved as the algorithm developed. In particular, this system had been studied in order to understand the interaction between parasites that could strongly reproduce with the side effect of harming the host and those that were more passive but in doing so permitted a healthier host. It also studied the interaction of competing parasites on a particular host.

The most complex modeling of epidemics has been performed by agent-based systems. In these, a virtual world is defined where each modeled organism follows some particular rule-set describing its behavior and infection status. For example, Bagni, Berchi and Cariello (2002) defined a simulated farm where simulated cows passed through the various parts of the farm during their life, possibly becoming infected at various times. Bagni's system also differed from the other epidemic models discussed, because as it was meant to model the occurrence of Bovine Leukemia on Italian farms, it was extensively normalized to ensure that its model realistically matched the real-world behavior of a particular disease in a particular setting.

Weapons of Mass Destruction

The models discussed above may be adapted to various aspects of nuclear, biological and/or chemical warfare. Some work, such as the BioWar system, has already been initiated. BioWar (Yahja, 2002) is an agent-based system that models the population of a city as it undergoes a series of epidemics of either national or deliberate origins. Similar to the Burn system, the modeled data is based on real-world surveys and the U.S. 2000 census.

Many other models would be useful in this context. First, biological attacks fall into one of two categories: that of living microorganisms and that of toxins (chemicals) produced by living organisms. The first type of attack, depending on the microorganism, may have a possibility of reproducing. In such a case, agent-based systems to determine the characteristics of the resultant epidemic would be valuable. A related approach is that of determining whether a particular epidemic is of natural or artificial origins. Effective models would allow the study of epidemics with different origins; for example, those originating because of a local entry of an infected individual, a truck driven around a city with an aerosol dispensing a biological agent or from an aerially mounted biological dispersing aerosol. The study of these models would give valuable insights and could also give information regarding the inverse problem; namely, given some epidemic, what were its origins and were they natural or an attack?

Many biological agents undergo stress in the open atmosphere, so to minimize exposure before an agent reaches a target, biological attacks may be conducted in an enclosed space, such as a building or subway system. Writers have done some characterization of the effects of attacking sports stadiums (Berkowitz et al., 1972) or subways (Karisch, 1991). The Canadian Security Service, in its Biological Terrorism document (Purver, 1995), cites a number of passive means that aim to minimize the effect of a biological attack. In particular, it lists, "building disinfectant aerosols into air-conditioning systems of large buildings." This raises the possibility of building complex simulations of buildings viewed as likely targets. Thus, by modeling the behavior of people within the building and the spread of an aerosol-based attack, the effect of that attack and the effect of potential defensive means could be investigated and characterized. Particularly in enclosed spaces, some of these approaches may be adapted to modeling chemical attacks.

Another potential complex modeling problem relates to the modeling of nuclear attack. Cordesman (2001) states that, "there are no reliable models of nuclear weapons effects in major urban areas." He is concerned with some studies that have shown that large buildings reduce the effect of nuclear weapons, but the overall effect of this is uncertain. To further complicate matters, the effects of a nuclear attack at ground level in the center of an urban area will be different from a similar attack from the air. This is a significant difference, given that if a terrorist initiates a nuclear attack, there is a substantial likelihood that it would be ground-based rather than air-based. CA could potentially give greater insight into these processes. A two- or three-dimensional CA could model a particular region, and have main rules that dictate how that region (and the level and direction of blast in that region) would change in relation to levels and direction of blast in neighboring regions. If successful, this could give response teams critical information about relative radiation dangers and likely casualty figures.

Terrorism Models

September 11 was the starting point to redirect our attentions to a different type of hazard: terrorism. The topic of terrorism received attention in the literature of security before September 11. However, September 11 offered a different perspective on terrorism: The move was well-planned, the organization was distributed in a network structure and the weapons used were airplanes. This event not only marked a day of shame in human history, it turned many of our views of terrorism upside down.

Post September 11, there has been a great increase in interest for means with which to study unconventional and asymmetric attacks and warfare, particularly those focused on non-military targets. The focus of different studies changed from looking at terrorism as:

- an unorganized group of people to a self-organized network with very different characteristics from traditional organization structures;
- an activity being carried out by a group of uneducated people to an activity that involves highly educated, young, seemingly normal, hard-to-predict groups of people;
- an activity that primarily targets military objectives to an activity that primarily targets civilian infrastructures and public propaganda.

Tsvetovat and Carley (2002) state, "It has been widely noted that terrorist organizations (as well as many other secret or illegal organizations) are very rarely built on the same organizational principles as legitimate organizations (Garreau, 2001). While legitimate organizations tend towards building hierarchical structures and chains of command, the illicit organizations must strive to maximize secrecy and security." This statement has strong implications for complex systems research. Estimating and understanding the network structure behind terrorist organizations (see Dombroski & Carley, 2002) can benefit from the large literature on complex systems and social networks.

ABD is ideal for modeling artificial attacks and then testing and evaluating countermeasures. They also have the potential of training to practice and determine the best potential countermeasures. The possibility also exists for modeling nuclear attacks at ground level in heavily built-up areas.

Previous attempts to use ABD models (Barlow & Easton, 2002; Ilachinski, 1996, 2000; Lauren, 2000; Lauren & Stephen, 2000, 2001; Yang, Abbass & Sarker, 2004; Yiu, Gill & Shi, 2003) have focused on modeling peacekeeping operations and attrition. However, the potential of these systems for use in security and safety applications is enormous. ABD provides a framework that can be as simple as a cellular automaton or as complex as a complete maneuver scenario. It is therefore apparent that these models have the potential to be used for modeling bushfires or the spread of epidemics, or as scenario-planning tools for dealing with terrorism attacks.

Despite the previous advantages ABD offered for modeling terrorism attacks, potentially one drawback needs to be considered: Reasoning is not easy within an ABD environment, in contrast to a BDI architecture. However, we need to note that the resultant gain from losing direct reasoning is the ability to scale the simulation to thousands of agents. What really matters in an ABD framework is the global emerging behavior, not necessarily a detailed representation of the rationality of each individual's behavior. One way to capture this global emerging behavior is to use spatial and temporal data mining models. Another way is through visualization techniques. The work on WISDOM (Yang, Abbass & Sarker, 2004) was done on version 1.0. However, the new version of WISDOM has reasoning capabilities more related to the military environment but which can be generalized very easily to other environments.

In summary, ABD offers a rich mechanism for simulating different scenarios, whether for bushfires, epidemics or a terrorist attack.

Conclusion

In this chapter, we have presented an overview to the use of artificial complexity models to security and safety applications. A short review was given to each possible application area, including bushfires, modeling epidemics, biological and chemical warfare, and terrorism attacks. It is clear that artificial complexity can provide significant tools to the security and safety fields. However, the field is still emerging, and the potential exists for improving those models reported in the literature in order to become of real practical use. It is also important to be able to use the right data farming tools. For example, with ABD models, each scenario needs to be run hundreds of times, and thus, there is a requirement to be able to identify patterns across these runs; hence, the importance of spatial and temporal data mining techniques is apparent.

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