Critical Infrastructure Integration Modeling and Simulation

William J. Tolone[1], David Wilson[1], Anita Raja[1], Wei-ning Xiang[2], Huili Hao[2], Stuart Phelps[2], and E. Wray Johnson[3]

[1] Department of Software and Information Systems, College of Information Technology
University of North Carolina at Charlotte, 9201 University City Blvd, Charlotte, NC 28223
{wjtolone,davils,anraja}@uncc.edu
[2] Department of Geography and Earth Sciences, College of Arts and Sciences
University of North Carolina at Charlotte, 9201 University City Blvd, Charlotte, NC 28223
{wxiang,hhao}@uncc.edu, sphelps@carolina.rr.com
[3] IntePoint Solutions, LLC. 9201 University City Blvd, Charlotte, NC 28223
Wray.Johnson@IntePoint.com

Abstract. The protection of critical infrastructures, such as electrical power grids, has become a primary concern of many nation states in recent years. Critical infrastructures involve multi-dimensional, highly complex collections of technologies, processes, and people, and as such, are vulnerable to potentially catastrophic failures on many levels. Moreover, cross-infrastructure dependencies can give rise to cascading and escalating failures across multiple infrastructures. In order to address the problem of critical infrastructure protection, our research is developing innovative approaches to modeling critical infrastructures, with emphasis on analyzing the ramifications of cross-infrastructure dependencies. This paper presents an initial overview of the research and of the modeling environment under development.

1 Introduction

The protection of critical infrastructures, such as electrical power grids, has become a primary concern of many nation states in recent years - particularly within the U.S. Critical infrastructures involve multi-dimensional, highly complex collections of technologies, processes, and people, and as such, are vulnerable to potentially catastrophic failures (intentional or unintentional) on many levels. A pointed recent example can be seen in the August 2003 blackout in the northeastern U.S. and eastern Canada. A series of unintentional events led to a loss of power for millions of businesses and homes. Moreover, failure in the electrical power infrastructure had serious impacts on other critical infrastructures. For example, the loss of power also led to a loss of water in many communities, as water systems depend heavily on power to operate the pumping systems that deliver water for consumption. The tight couplings within and across infrastructures and the brittleness that can result were clearly evident in the length of time it took to restore power to the affected region. It also was evident that failure isolation is a difficult task within complex infrastructures, let alone across infrastructures. While the August 2003 blackout may not be considered catastrophic from a human perspective, it was clearly catastrophic from an economic perspective.

H. Chen et al. (Eds.): ISI 2004, LNCS 3073, pp. 214–225, 2004.

Given the breadth and depth of critical infrastructures, one can readily observe characteristics that make the problem of protecting a nation's critical infrastructures, in general, intractable. Key among these characteristics is the inherent complexity of the infrastructures, each defining a unique field of research with numerous open problems regarding organization, operation, and evolution. For example, electric power systems are complex, semi-redundant networks of power generation, transmission, and distributions facilities relying upon technologies that may vary in age in excess of twenty years. Rinaldi et. al. [22] refer to such infrastructures as complex adaptive systems. Furthermore, many of these critical infrastructures were designed and constructed over several decades with few, if any, security considerations in mind. Aside from nuclear power generation facilities, this is particularly true of the energy sector. As a result, each of these critical infrastructures faces a clear and present danger of failure by accident or design.

Magnifying these challenges and the dangers that arise are numerous inherent interdependencies that exist among critical infrastructures. Electric power systems depend upon transportation networks to deliver fuel to generation facilities. These same generation facilities often depend upon water systems for cooling purposes. In addition, electric power systems depend heavily upon telecommunication networks to support the **S**upervisory, **C**ontrol **a**nd **D**ata **A**cquisition (SCADA) systems that manage power transmission and distribution. The list of interdependencies among the critical infrastructure sectors is long and in some cases, poorly understood. Furthermore, many interdependencies are very strong, time-sensitive, and essential. The result is a brittle "system of systems" that could lead to catastrophic occurrences as a failure (intentional or unintentional) cascades and escalates across infrastructures.

Our research is helping to address the crucial and daunting task of infrastructure protection by developing innovative infrastructure modeling approaches in order to help identify and understand vulnerabilities. In particular, we are interested in explicitly modeling and exposing the impact that failures in one infrastructure may have on connected and related infrastructures. Our approach also contributes to current understanding of the design and application of intelligent agent-based systems as applied to geographic information system (GIS) environments. This paper presents an initial overview of our work in developing a modeling and simulation environment to help nations, states, and regions better understand the vulnerabilities within their critical infrastructures, particularly those vulnerabilities that are due to cross infrastructure dependencies. Section 0 provides a brief background on the notion of critical infrastructure and highlights the current research in modeling and simulating cross-infrastructure dependencies. Section 0 presents our approach to this challenging modeling and simulation problem, including a brief overview of the simulation architecture. Section 0 demonstrates our initial results via an example simulation scenario, and Section 0 summarizes our work and identifies future research opportunities.

2 Background

We begin by developing a working definition of what constitutes a critical infrastructure and providing some background on infrastructure modeling. We have chosen to adopt the definition put forth by the U.S. Patriot Act, which identifies a critical infrastructure to be:

> systems and assets, whether physical or virtual, so vital to the United States that the incapacity or destruction of such systems and assets would have a debilitating impact on security, national economic security, national public health or safety, or any combination of those matters [2]

Under this definition, critical infrastructures may be organized according to the following sectors: agriculture, food, water, public health, emergency services, government, defense industrial base, information and telecommunications, energy, transportation, banking and finance, chemical industry and hazardous materials, postal and shipping, and national monuments and icons [2].

The problem of understanding the behavior of critical infrastructures and their interdependence is an integral part of many well-established disciplines, such as urban and regional planning, civil and environmental engineering, operations research, landscape architecture, and emergency management [14]. More recently, as a key area of inquiry, it is receiving increasing attention from the emerging field of geographic information science and technology (GI S&T) [24, 26].

Researchers in the GI S&T community have primarily approached the study of the behavior and spatial interdependence of critical infrastructures from three distinct vantage points. The first stream of inquiry examines the interdependence of critical infrastructures with tools from spatial statistics and econometrics, and identifies their approach as spatial data analysis (SDA) [6, 13]. The second approach depicts geographic correlations among critical infrastructure components by using traditional map overlay methods for spatial data aggregation in GIS environments [4, 10, 11]. The third approach uses rule-based inference engines, usually fueled by human expert's knowledge, in the delineation and manipulation of interdependence [12, 28]. Each of these approaches, while informative, does not in isolation adequately address the problem regarding the impact of critical infrastructure interdependencies.

Consequently, many respected authors, such as Getis [9] and Sinton [24], have advocated a multi-dimensional approach to the study of behavior and spatial interdependence of critical infrastructures. Instead of "divide-and-conquer," they suggested a strategy that combines strengths of the three intellectual streams of inquiry and investigates the matter of interdependence from all three vantage points. Despite some genuine efforts [1, 7, 9, 18], progress along this route has yet to meet the advocates' expectations. The status quo is exemplified by some most recent publications in which little if any multi-dimensional results were reported [16, 29].

Thus, the problem of understanding the behavior of critical infrastructures and their interdependence remains a difficult, open problem. The limitations of single-dimensional approaches are by no means trivial. Multi-dimensional approaches, while theoretically promising, have produced few results. In the following sections, we present our approach to cross-infrastructure modeling and simulation, which leverages the strengths of a multi-dimensional approach. We believe our approach provides an appropriate foundation for multi-dimensional analyses of critical infrastructure interdependencies. We include some initial results to demonstrate the kinds of analyses and subsequent understandings to be gained from our work.

3 Our Approach

In this section, we present our approach to infrastructure and cross-infrastructure modeling and simulation. Fundamentally, the problem of enabling cross-infrastructure simulations is one of proper integration of individual critical infrastructure behavior models. Different approaches were considered regarding how to perform this integration. The approaches and the problem of integration can be considered along two dimensions: the *level of integration* and the *methodology of integration*. Linthicum describes the problem of integration [15] in terms of four levels: data level, application interface level, method (i.e., business process) level, and the user interface level. These levels represent common practices of enterprise integration.

Data level integration is a bottom-up approach that creates "integration awareness" at the data level by extending data models to include integration data. For example, infrastructure models are extended to include explicit infrastructure interdependency data. Application level integration creates "integration awareness" at the application level, which in our case refers to the infrastructure models. At this level, behavioral analysis constructs for each infrastructure are adapted to recognize and interact with other infrastructures. Method level integration develops "integration awareness" external to the infrastructure models - that is, infrastructure models remain unaware of one another. This cross-infrastructure awareness is encapsulated and managed at a level above the infrastructures. The final level of integration creates "integration awareness" at the user interface level. This level of integration, through techniques such as "screen scraping," is often used to integrate legacy systems. In our work, we need to draw on a potentially diverse set of individual infrastructure models, which has led us to adopt a method level approach.

The methodology dimension of integration refers to the method by which integration occurs given an integration level. Integration methodologies may be partitioned into two categories: peer-to-peer integration and brokered integration. Peer-to-peer integration is most common and effective for data and application level integration. These methodologies essentially support fire-and-forget or request-response remote procedure calls among applications. Brokered integration is most common and effective for method level integration. Different approaches to brokered integration include agent-based integration and workflow-based integration. Each of these approaches depends upon meta-knowledge to enable the integration. Agent-based integration utilizes contextual meta-knowledge represented in the form of facts and rules while workflow-based integration utilizes procedural knowledge represented in the form of process models. Because user interface level integration is a technique for opening up legacy systems, this level may participate equally within both methodology categories (see Table 1). In our work, the focus on cross-infrastructure interaction has led us to adopt a brokered approach.

Table 1. Level and Methodology of Integration

	Data	Application	Method	User Interface
Peer-to-peer	X	X		X
Brokered			***X***	X

In particular, our approach to integrating critical infrastructures for the purpose of cross-infrastructure modeling and simulation utilizes an intelligent agent-based, brokered methodology designed for method level integration. The following sections detail and motivate our design choices and present our architecture for agent-based critical infrastructure integration.

3.1 Intelligent Software Agents for Integration, Modeling, and Simulation

In order to ground the discussion of our agent-based approach, we first clarify the notion of agents as employed in our research. The term software agent, though commonplace, does not have a common definition. Many definitions have been proposed, often reflecting the purpose(s) of their application. Our preferred definition is an adaptation of Weiss [27] and Franklin and Graesser [8].

> *Definition 1.* A **software agent** is an autonomous program, or program component, that is situated within, aware of, and acts upon its environment in pursuit of its own objectives so as to affect its future environment.

Software agents can be further categorized, according to Weiss [27], by their degree of autonomy and intelligence, and the type of environment within which they may be situated. *Autonomy* refers to an agent's ability to sense and act upon its environment without intervention (e.g., human intervention) - the more autonomous an agent, the less need for intervention. *Intelligence* refers to an agent's ability to be reactive, proactive, and social (i.e., converse with other agents). *Agent environments* are characterized based on issues of accessibility, determinism, dynamism, continuity, and their episodic nature (i.e., whether agents must consider past and future actions when reasoning about current actions). These environment characteristics shape an agent's required capabilities[1].

Our decision to utilize intelligent software agents to support critical infrastructure integration, modeling, and simulation is based primarily on three motivating factors. First, we examined the types of critical infrastructure models we desired to integrate. It was clear from this examination that neither data nor application level integration would provide the appropriate level of extensibility and scalability that our modeling and simulation environment requires. Data and application level integration could be accomplished for specific infrastructure models that are well-scoped and fully populated. However, we desire an ability to perform simulations across multiple, potentially sparse infrastructure models. As such, method level integration, and therefore brokered integration, is the most promising approach.

Second, we examined the meta-knowledge necessary to support cross-infrastructure simulations. This examination focused on the contextual versus procedural characteristics of the meta-knowledge and revealed that infrastructure interdependency data are highly contextual. Our conclusion is further supported by the contention that agent-based systems are a promising approach to modeling complex adaptive systems

---

[1] Another characteristic frequently discussed is agent mobility - the ability of an agent to migrate among machines. We view agent mobility as an architectural characteristic derived from agent environment characteristics such as accessibility.

[22]. Consequently, we capture meta-knowledge using a rule-based, declarative approach rather than a procedural representation such as hierarchical state transition diagrams or Petri nets.

Third, we examined the desired simulations. This examination revealed a strong need for multiple types of simulations. We organize these simulation types along the following three dimensions of analyses. Each has been shown to be supported effectively by agent-based solutions. The nature of these analyses also suggests an agent design that embodies a strong notion of intelligence as previously described.

1. Predictive ("what if") and prescriptive ("goal-driven") analyses - these types of analyses are complementary and often used simultaneously. They are used during simulations to determine the consequences of vulnerability exploitation or if there are vulnerabilities that might lead to an undesirable outcome. [5, 19, 20, 23]
2. Discovery based analyses - these types of analyses examine infrastructure models and the supporting meta-knowledge to discover new knowledge (e.g., uncover unidentified infrastructure interdependencies) and identify data set inconsistencies. [17, 25]
3. Probabilistic analyses - these types of analyses introduce variability into simulations in order to provide better approximations of infrastructure behavior. [3, 21]

Thus, in order to best address the problem of critical infrastructure integration, modeling, and simulation, we are developing an intelligent agent-based system that provides a brokered methodology for method level integration. This system will afford a better understanding of critical infrastructure vulnerabilities, particularly those due to cross-infrastructure dependencies, as a means to provide better protection to a nation's critical infrastructures. In the following, we provide an overview of our system architecture and demonstrate our current results via an example simulation.

3.2 Modeling and Simulation Architecture

The architecture of our modeling and simulation environment (see Fig. 1) is designed to allow end users to execute simulations seamlessly within the context of a GIS environment. Users initiate simulations by selecting and disabling infrastructure features and then viewing the impacts of those actions through the GIS visualization support.

In order to support cross-infrastructure simulations, we have developed a community of intelligent software agents that register interest in the critical infrastructure models of concern. These agents collectively sense changes within infrastructures, reason about the changes using meta-knowledge that includes cross-infrastructure dependency data, communicate within the community of agents, and based upon the outcome of the collective reasoning, potentially affect change back to and across the infrastructures of concern.

Currently, two types of change may be affected by the agents. First, agents, having sensed an infrastructure state change (e.g., a transmission line has failed due to contact with a tree branch), may reason about the impacts of this event upon all infrastructures based upon the meta-knowledge available and affect changes in state within and across infrastructures. Second, agents, having sensed change, may utilize GIS supported network analyses to reason about and affect changes within infrastructures. This latter feature allows agents to leverage specialized functionality to enhance simulations.

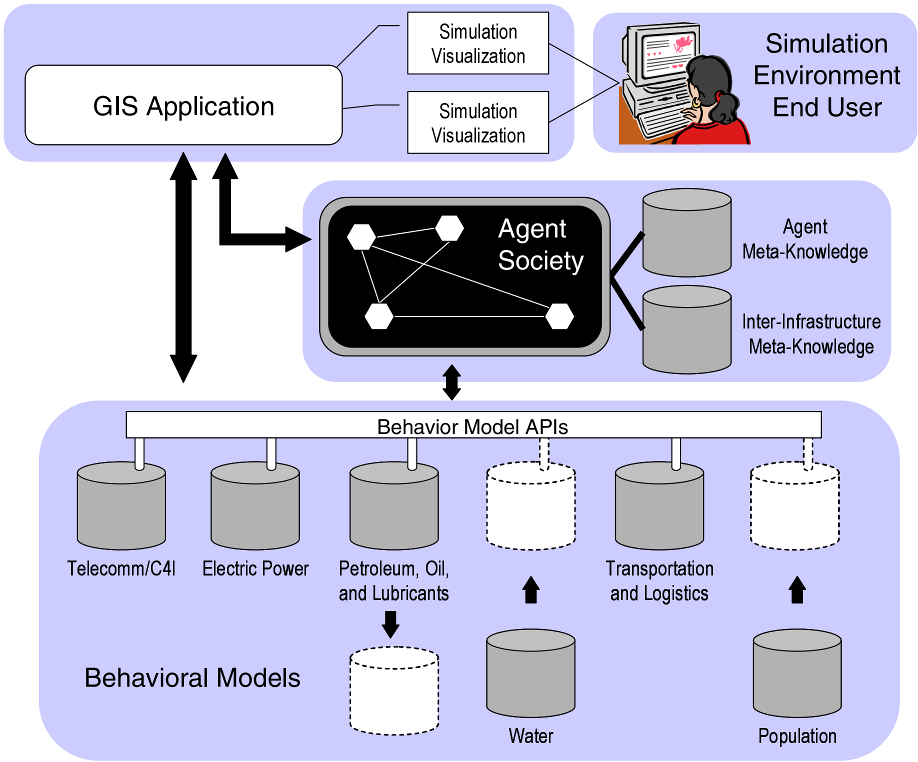


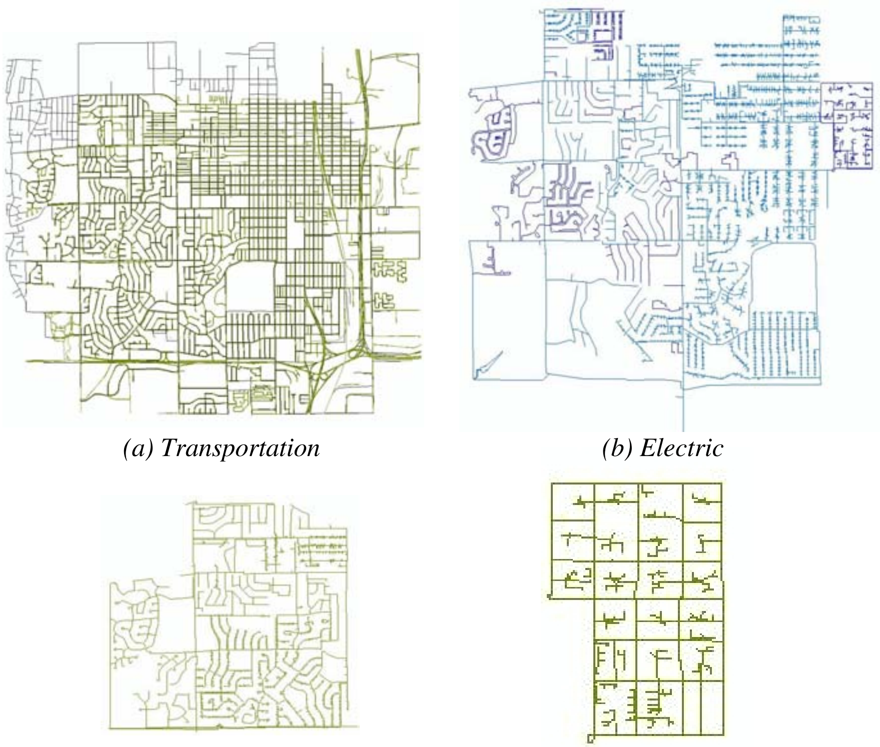
Fig. 1. Simulation Environment Architecture

Three important characteristics of our architecture are its flexibility, scalability, and extensibility. Our architecture is *flexible* in that it allows the 'plug and play' of different models of the same infrastructure for a given region. Our architecture is *scalable* in that multiple models of the same infrastructure type (e.g., models of adjacent transportation systems) may simultaneously participate in a single simulation. Our architecture is *extensible* in that new infrastructure model types may be easily incorporated into the simulation environment.

4 Example Results

In this section we provide a demonstration of our simulation environment. We begin by discussing the critical infrastructure models in question. This example simulation contains four critical infrastructures for a fictional town: electrical power transmission and distribution, gas distribution, telecommunications, and transportation (see Fig. 2).

The land area for the region in question is roughly four square miles. However, we have successfully conducted simulations on regions with land area well in excess of 500 square miles. In fact, our simulation environment operates independent of region size. Furthermore, it is not a requirement that the infrastructure models completely overlap one another. Infrastructure models may overlap very little, if at all.



(a) Transportation (b) Electric

(c) Petroleum (d) Telecom

Fig. 2. Example simulation infrastructures

For simplicity in presentation, we further scope the example simulations by focusing our simulation on an area roughly eight city blocks in size and limit the number of infrastructures to two: gas and electric power. Fig. 3 contains four screen captures of the example simulation. While both the electric power and gas distribution infrastructures are visualized in all four screen shots, we have configured the GIS display to depict the electric power impacts and gas distribution impacts separately. Thus, Fig. 3 (a) and (b) are time sequenced visualizations of changes to the electric power infrastructure while Fig. 3 (c) and (d) are time sequenced visualizations of changes to the gas distribution infrastructure.

The type of simulation presented in this example is a predictive (i.e., “what-if”) analysis. To begin the simulation, the end user selects and disables a feature of interest. Fig. 3 (a), identifies this feature as a small segment of the power distribution network. Once disabled, the feature is highlighted through color change and increased thickness. This change to the infrastructure, which is part of the agent environment, is sensed by the agent community. The agent community reasons that downstream power distribution might be affected and thus requests the GIS network analysis support to analyze the downstream impacts. These downstream impacts are accepted and rendered (see Fig. 3 (b)).

(a) (b) (c) (d)

Fig. 3. Example cross infrastructure simulation

At the same time, the agent community reasons that disabling that same initial power distribution feature may also impact gas distribution infrastructure due to a nearby electric powered gas pump. Thus, the agent community affects the gas infrastructure by disabling the gas pump. Once the gas pump is disabled the agent community reasons that downstream gas distribution may be affected and requests the GIS network analysis support to analyze downstream impacts. These downstream impacts are accepted and rendered (see Fig. 3 (c)). The agent community further reasons that downstream power disruptions, as depicted in Fig. 3 (b), impact additional gas distribution due to cross-infrastructure dependencies. As a result, additional segments of the gas distribution infrastructure are disabled and subsequent analyses renders downstream effects as shown in Fig. 3 (d). Thus, disabling a small segment of the electric power infrastructure has left a small region without power, but an even larger region without gas. Such a conclusion may not be easily predicted without the aid of proper modeling and simulation support.

Other visualization techniques are also possible. For example, depicts an elevated rendering of three of the critical infrastructures (gas, electrical power, and transportation - top to bottom). Such renderings are supported by many GIS systems. By augmenting this visualization with extruded renderings of the disabled infrastructure, additional perspective and understanding may emerge.

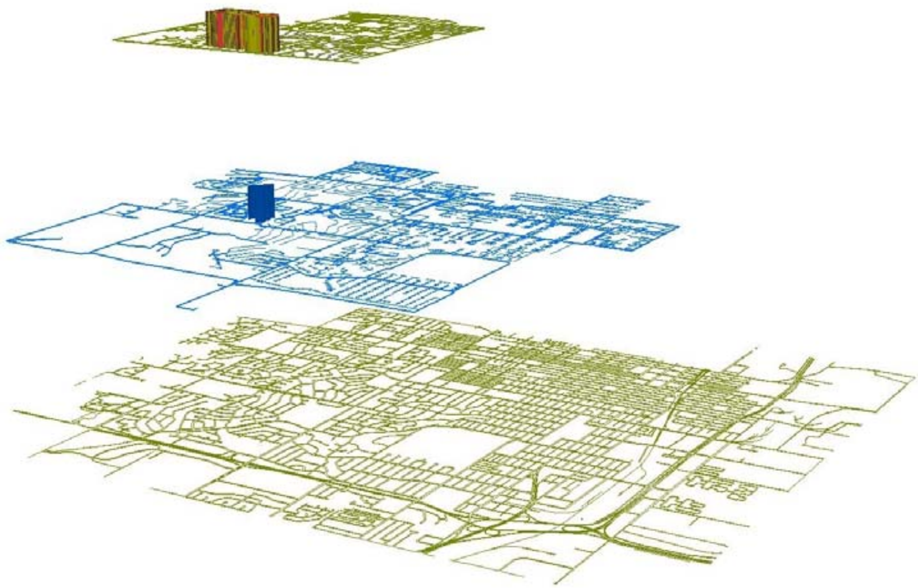


Fig. 4. Three-dimensional, extruded renderings for additional analyses

5 Summary and Future Work

Protecting critical infrastructures remains a difficult open problem, in part due to the multitude of complex interdependencies that exists among infrastructures. Our research is helping to address the crucial and daunting task of infrastructure protection by developing innovative infrastructure modeling approaches in order to help identify and understand vulnerabilities. In this paper, we presented the initial results of our approach, which utilizes communities of intelligent software agents to model and simulate cross-infrastructure dependencies. We demonstrated, by way of an example, that the behavior of critical infrastructures may be better understood through multi-infrastructure simulations.

We have identified several areas of future work based upon the initial research presented here. First, we are expanding our environment to support discovery-based analyses such as constraint-based conformance analyses to identify inconsistencies within and across infrastructure models and their representations. Furthermore, we plan to investigate additional discovery-based analyses including: i) case-based reasoning, which can extract meta-knowledge from simulation execution, and ii) spatial inference analysis, which draws upon the correlation, or even causal relationship, between land use patterns for an area and the spatial patterns of infrastructure networks.

A second area of future work is to incorporate probabilistic representations of infrastructure dependencies and failures, where the fuzzy effects of probabilistic events will require agents to use more complex reasoning processes. We also plan to scale our approach to common cause failures, where multiple infrastructures are disabled because of a common cause. These studies will provide us a good understanding of the nature of cascading and escalating failures among critical infrastructures. In addition, we expect to use our work to study the possible organizations of agents, their communication protocols, and resource-bounded adaptive behavior.

A third area of future investigation is the interface between our simulation models and decision-making or plan-making models that various government agencies and private organizations use in their practice of homeland security planning, emergency management, and counter-terrorist drills. This requires an approach that brings together a broader spectrum of knowledge, skills, and expertise to study the policy impacts of critical infrastructure assessment, management, and planning. The outcome will be recommendations for developing sound support systems for critical infrastructure planning and management.

Finally, ongoing research is required to validate not only the meta-knowledge that agents utilize, but also the methodology for representing, organizing, and reasoning about that knowledge. We believe that these studies will eventually lead to our long term goal of better protecting critical infrastructures.

Acknowledgements

The authors would like to thank the following people for their contributions to the project: Bei-tseng Chu, Mirsad Hadzikadic and Vikram Sharma of the Department of Software and Information Systems, UNC Charlotte; Mark Armstrong, Michael Russell, and Robert Vaessen of IntePoint Solutions, LLC; and Qianhong Tang of the Department of Geography and Earth Sciences, UNC Charlotte.

References

1. Anselin, L., Getis, A.: Spatial statistical analysis and geographic information systems. Annals of Regional Science. Vol. 26 (1992) 19-33
2. As cited in: The President's National Strategy for Homeland Security (2002)
3. Bar-Shalom, Y.: Multitarget Multisensor Tracking: Advanced Applications. Artech House (1990)
4. Burrough, P.A.: Methods of spatial analysis in GIS. International Journal of Geographical Information Systems. Vol. 4. No. 3. (1990) 2-21
5. Chu, B., Long, J., Tolone, W.J., Wilhelm, R., Peng, Y., Finin, T., Matthews, M.: Towards intelligent integrated planning-execution. International Journal of Advanced Manufacturing Systems. Vol. 1. No. 1. (1997) 77-83
6. Cressie, N.: Statistics for Spatial Data. John Wiley, Chichester (1991)
7. Flowerdew, Green: A real interpolation and types of data. In, FotheringHam, S. and Rogerson, P. (Editors), Spatial Analysis and GIS Taylor & Francis, London (1994) 121-145

8. Franklin, S., Graesser, A.: Is it an agent, or just a program?: a taxonomy for autonomous agents. 3rd International Workshop on Agent Theories, Architectures, and Languages. Springer-Verlag, (1996)
9. Getis, A.: Spatial dependence and heterogeneity and proximal databases. In, Fothering-Ham, S. and Rogerson, P. (Editors), Spatial Analysis and GIS Taylor & Francis, London (1994) 105-120
10. Goodchild, M.F., Kemp, K.K.: NCGIA core curriculum. University of California at Santa Barbara, CA (1990)
11. Greene, R.W.: Confronting Catastrophe: a GIS Handbook. ESRI Press, Redlands CA (2002)
12. Gronlund, A.G., Xiang, W.-N., Sox, J.: GIS, expert systems technologies improve forest fire management techniques. GIS World, Vol. 7. No. 2. (1994) 32-36
13. Haining, R.: Spatial data analysis in the social and environmental sciences. Cambridge University Press, Cambridge, UK (1990)
14. Kaiser, E.J., Godschalk, D.R., Chapin, F.S., Jr,: Urban Land Use Planning. 4th Edn. University of Illinois Press, Urbana, IL (1995)
15. Linthicum, D.S.: Enterprise Application Integration. Addison-Wesley, New York (2000)
16. Mitchell, A.: The ESRI Guide to GIS Analysis. ESRI Press, Redlands, CA (1999)
17. Moukas, A., Maes, P. Amalthaea: an evolving multi-agent information filtering and discovery systems for the WWW. Autonomous agents and multi-agent systems. Vol. 1. (1998) 59-88
18. Openshaw: Two exploratory space-time-attribute pattern analysers relevant to GIS. In , FotheringHam, S. and Rogerson, P. (Editors), Spatial Analysis and GIS Taylor & Francis, London (1994) 82-104
19. Pearl, J.: Probabilistic Reasoning in Intelligent Systems: networks of plausible Inference. Morgan Kaufmann, San Mateo, CA (1988)
20. Peng, Y., Finin, T., Labrou, Y., Cost, S., Chu, B., Tolone, W.J., Long, J., Boughanam, A.: An agent-based approach to manufacturing integration: the CIIMPLEX experience. Applied Artificial Intelligence, An International Journal. Vol. 13. No. 1-2. (1999) 39-64
21. Rao A.S., Georgeff, M.P.: Modeling rational agents within a BDI-architecture. In J. Allen, R. Fikes, and E. Sandewall, editors, Proceedings of the Second International Conference on Principles of Knowledge Representation and Reasoning. Morgan Kaufmann (1991) 473-484
22. Rinaldi, S.M., Peerenboom, J.P., Kelly, T.K.: Identifying, understanding, and analyzing critical infrastructure interdependencies. IEEE Control Systems Magazine. December (2001) 11-25
23. Russell, S.J., Wefald, E.H.: Do the Right Thing: Studies in Limited Rationality. MIT Press, Cambridge, MA (1991)
24. Sinton, D.F.: Reflections on 25 years of GIS. GIS World. Vol. 5. No. 2. (1992) 1-8
25. Sycara, K., Decker, K., Pannu, A., Williamson, M., Zeng, D.: Distributed intelligent agents. IEEE Expert. Vol. 11 No. 6. (1996) 36-46
26. University Consortium for Geographic Information Science (2003)
27. Weiss, G. ed.: Multiagent Systems. MIT Press (1999)
28. Xiang, W.-N.: Knowledge-based decision support by CRITIC. Environment and Planning B: Planning and Design, Vol. 24. No. 1. (1997) 69-79
29. Zeiler, M.: Modeling Our World: the ESRI Guide to Geodatabase Design. ESRI Press, Redlands, CA (1999)