MODELING CRITICAL INFRASTRUCTURE INTERDEPENDENCIES

CHOOSING A MODELING TECHNIQUE

Finn Olav Sveen[1], Jose. M. Torres[1], Jose M. Sarriegi[1], Jose J. Gonzalez[2], Adriana M. Ortiz[1]

[1]*Tecnun (University of Navarra)*

[2]*University of Agder and NISlab (Gjøvik University College)*

Abstract

Modern critical infrastructures (CIs) are becoming increasingly more interdependent, locally, regionally and globally, constituting a system of systems. The nature of large scale, cross-border crises in these systems of systems is not easily understood. Multiple actors, multiple legal environments, time delays, cascading effects and unintended consequences of well meant actions create a complexity that overwhelms. Researchers have therefore turned to computer modeling and simulation to understand such systems. We present an overview of some of the most common modeling and simulation techniques used to assess vulnerabilities and their consequences arising from CI interdependencies. This includes Input-Output models, models based on mathematical Network theory, Agent-Based models and System Dynamics models. We find that the modeling techniques offer different advantages and disadvantages and in general they are all useful to understand different aspects of the problem. A crucial question is whether to model the system of systems using a bottom-up or a top-down approach.

Keywords: Modeling and Simulation, Critical Infrastructure, System Dynamics, Agent-Based, Networks, Input-Output models

Introduction

The recent EU 7th framework programme ICT and Security Joint Call FP7-ICT-SEC-2007-1, focused on cross-border security crises in Europe. It is possible to conceive of a wide range of such scenarios affecting critical infrastructures (CIs). The unfolding of a particular crisis depends on its origin, severity, involved parties and a host of other factors. Traditional cross border crises involve natural disasters or military conflict between nations. Individual countries were more or less self sufficient. Today that is no longer true. For example: The EU depends on energy supplies that are mostly not produced within the EU.

“One of the most frequently identified shortfalls in knowledge related to enhancing CI protection capabilities is the incomplete understanding of interdependencies between infrastructures”

---

[1] Tecnun (University of Navarra), Manuel de Lardizábal 13, 20018 San Sebastián, Spain. Email: {fosveen, jmsarriegi, jmtorres, amortiz}@tecnun.es

[2] University of Agder, Service Box 509, 4898 Grimstad, Norway and NISlab, Gjøvik University College, 2802 Gjøvik, Norway. Email: jose.j.gonzalez@uia.no

(Mussington 2002). Consequently, failing to understand these interdependencies and their dynamics will result in ineffective response and poor coordination between decision makers and agencies responsible for rescue, recovery and restoration (Pederson et al. 2006). It is not only the incomplete understanding that is problematic, but also emergent interdependencies owing to fast CI interconnection growth rate (Likar, Fatur, and Krizaj 2001). As CIs do not exist in isolation of one another, we need a “system of systems” perspective to analyse them. Furthermore, owing to the last decade’s trend of deregulation, these CI systems are no longer centrally controlled.

New technologies and evolving operational modes generate unfamiliar risks, that have “emergent character”: they derive from interdependencies and circumstances that have not been anticipated by the designers and the users of CIs. I.e., they are risks that are shaped in novel ways by the different man-technology-organization-relationships (Schneier 2000).

When we lack experience we must turn to other methods to predict and prepare for crises and their possible consequences. One way is through computer simulation. To achieve success the simulation environment must be able to realistically describe the strategic environment of a cross-border crisis. Furthermore, crises involve transient, dynamic phenomena, which may have a significant impact on the unfolding of the crisis, and must be represented.

Another issue is the unpredictable nature of crises. Although, one may know broadly what kind of crises one can expect, one does not know exactly where they will strike or how they will unfold. The number of potential crisis scenarios is so great that to create specific simulation models of all of them is unfeasible. Furthermore, the underlying CI systems are always changing; a perfect model of the system today would be obsolete tomorrow. Hence, point prediction of specific real world variables is an unrealistic, unfruitful approach. However, by focusing on the qualitative relationships of interconnected system variables it is possible to train crisis managers to handle a wide range of different scenarios.

Over the years a variety of simulation paradigms have been developed and used to study strategic problems. This paper has two purposes: 1) To show some of the applications of simulation modelling to interdependent CI. 2) To assess the applicability of four modelling paradigms to crises in interdependent CI. The modelling paradigms include Network models, Input-Output (I-O) models, Agent-Based (A-B) models and System Dynamics (SD) models.

Common Modelling Techniques

Network Models and Derivatives

These models build on mathematical network theory. CI is represented as a network of vertices (nodes) interconnected by edges (links).

Albert et al. (2000) investigated the Internet and found that it is a scale-free graph. In scale-free graphs, rather than all the nodes having the approximate same number of connections, only a few of the nodes are central communication hubs, other nodes having few connections. These kinds of networks exhibit strong robustness in the face of random errors, as the probability of selecting a highly connected node is low in the face of random error. However, scale-free graphs are vulnerable to targeted attacks on key nodes, i.e., nodes which are highly connected with many other nodes. Such attacks, if successful, may lead to catastrophic failure.

Grubesic and Murray (2006) presented a linear integer programming approach to evaluate two North-American Internet backbones, WorldCom and ICG. Both of these extensive networks cover most of the United States. They are considered to be hub-and-spoke networks where a selected number of vital nodes carry most of the connections for the system and are often constructed because of the prohibitive cost of truly redundant network structures. These networks have properties approximating those of scale-free networks. Analysis indicates that removal of only a few key nodes in the system would severely degrade communications capability. E.g., in the ICG network, the removal of only three vital nodes, Cleveland, Newark and Dallas, would disconnect the whole Mid-South and the ICG network would be splintered into sub-graphs (sub-networks). Removal of one more vital node led to cascading failures.

Holmgren (2006) studied the North-American western states power grid and the Nordic power grid. He found that the networks exhibit small-world phenomena and have exponential degree distributions like random graphs. They are thus not exactly scale-free graphs but exhibit many of the same properties. The power grid networks fragmented considerably faster when vertices were removed deliberately rather than randomly. The results indicate that the Nordic power grid is slightly more vulnerable than the North-American one. However, both disintegrated faster than the theoretical random and scale-free graphs used for comparison.

Svendsen and Wolthusen (2007) present a connectivity model that can be used to represent and investigate interdependent CIs. The model is able to account for buffering, e.g. storage of petroleum in a tank, which would lessen the dependency on continuous supply. A small interconnected network of electricity, natural gas and ICT is examined. Although the network is a theoretical example it is based on real world counterparts. The model shows how error propagates through the system of systems as nodes are removed, significantly degrading the performance of all three infrastructures.

Input-Output Models

The original static Input-Output model was proposed by W. Leontief (1951; 1951), a work for which he won the Nobel Prize in economics in 1973. His model and derivatives have since been used extensively. I-O models build on the premise that output from one industry sector is input for one or more others and that there is equilibrium conditions between these. I-O models consider the structure of the economy and the flow of resources between the different sectors. I-O models can therefore produce a detailed picture of the economy.

Moore et al. (2006) used a spatial Input-Output model, SCPM2 to study the economic impacts of infrastructure failure in Los Angeles in Southern California. The model is a development of SCPM1, which is a combination of a traditional Input-Output model with a Garin-Lowry model. Travel and freight flows throughout the region are modelled. A scenario assuming a one month power loss affecting 10% of the cities in the region was simulated. They found that “The impacts that infrastructure failures impose on the urban economy are (a) widespread, but (b) do not seem to include adverse income distribution effects.”

The Inoperability Input-Output (IIM) model was proposed by Santos and Haimes (2004). The concept of inoperability is defined as the “*percent of output reduced from the ideal output*” (Lian and Haimes 2006). Inoperability is triggered by demand reduction. IIM is a static model and Lian and Haimes propose a dynamic version of the model, the DIIM, which is then used to assess the inoperability and economic cost caused by hypothetical terrorist attacks. A limitation of both the IIM and DIIM is that they deal only with economic loss (2006).

Agent-Based Models

A-B modelling is a simulation methodology coming from the field of complexity science (Schieritz and Gröbler, 2002). A-B systems are comprised of multiple idiosyncratic agents and are useful to study complex systems. A-B models represent complex system behavior as consequences of local interactions between agents and their environment. This approach is suitable to study CI as there are infrastructures that interact with their users and other networks. Amin (2001) states that: “The relationships and interdependencies are too complex for conventional mathematical theories and control methods. Infrastructures that interact with their users and other networks (for example, an automatic switching system for telephone calls) create additional complexity because the interaction of their elements further increases the number of possible outcomes.” Because of this he proposes A-B modelling as a suitable technique to study interdependent CIs. Amin also identifies cascading failure as the main vulnerability in CI networks.

The main benefits of using A-B models are the possibility to represent heterogeneous agents, capture emerging behaviour and create a space where the agents interact according to distance. (Bonabeau 2002; Borshchev and Filippov 2004). Borshchev and Filippov (2004) indicate that another advantage is that A-B provides for construction of models in the absence of knowledge about global interdependencies.

To construct an A-B model it is necessary to specify three main types of elements; agents, rules and the environment. The agents are people or entities of the artificial societies. The environment is the framework or abstract space where the agents can interact, and the rules are behaviour patterns for the agents and the environment. These rules can take the relationship forms of agent-environment, environment-environment and agent-agent. An insight of A-B models is that complex behaviour can arise from quite simple rules. Behaviour is said to be emergent, i.e. it arises endogenously and there is an element of surprise to the behaviour. As opposed to traditional economic analyses, A-B models do not focus on a system's stable state, its equilibrium. Rather, they focus on the time period preceding equilibrium, which many real systems is unlikely to reach. The advent of object oriented programming and high performance computers have made A-B modelling and simulation feasible.

A-B models should be used when the interactions among agents are complex; nonlinear, discontinuous or discrete, when the population is heterogeneous or each individual is potentially different; when its localization in the space is key in the problem; or when the agents exhibit complex behaviours including learning or adaptation.

Aspen is a Monte Carlo simulation of the US economy, with agents representing various segments, such as households, banks, industries and the Federal Reserve (Barton et al. 2000). The simulator was developed by Sandia National Laboratories in the US. Aspen-EE builds on the Aspen model, but it has been extended with new agents to include interdependencies in electrical infrastructure. These include among others: producers of electricity, market structures that control the production of electricity and a supplier of electricity utility requirements.

The Idaho National Engineering and Environment laboratory (INEEL) also developed A-B simulation models of CI (Dudenhoffer, Permann, and Sussman 2002). The efforts of INEEL are directed towards modelling multiple infrastructures centred around a single facility and the functional capabilities therein. An initial study was made of the Idaho Nuclear Technology and Engineering Center.

Panzieri et al. (2004) developed CISIA (CI Simulation by Interdependent Agents). One of the key problems in simulating the interdependence of CI is the vast amounts of numerical data needed. "While it is relatively easy to obtain, at least via expert interviews, qualitative information on them, it is a hard challenge to discover quantitative and precise information." To overcome this problem Panzieri et al. adopt the use of fuzzy logic. CISIA is capable of simulating infrastructure interdependencies on a quite detailed level. In a simple proof of concept case study they model the power infrastructure, air-conditioning and information infrastructure of the university campus of one of the authors.

Balducelli et al. (2005) created a model that simulates the effects of a power outage on hospital staff and patient arrival. Staff and patients have to take the railway to get to work. The interdependence between the power and transportation infrastructure means that a power outage will have consequences for staff arrival and may create problems at the hospital. However, not everyone travelling to the hospital will react in the same way. For example, students may choose to skip some lectures and go home instead. Balducelli et al., like Panzieri et al. adopt fuzzy logic to overcome this problem. The model is able to show the effects and duration of disturbances.

Tolone et al. (2004) present a hybrid model that couples A-B modelling with behavioural models and Geographic Information Systems and Technology (GI S& T). The model can simulate areas as small as just a few city blocks or large models on the order of hundreds of square miles. The model is capable of showing the geographical extent of propagating failures. An example simulation shows how a relatively minor loss of parts of the electrical power infrastructure caused a more widespread loss of functionality in the natural gas distribution network.

System Dynamics Models

System Dynamics (SD) has been heavily shaped by the Human Sciences and is used to study complex social systems. Its record proves that SD is appropriate to study any kind of complex, non-linear dynamic system, even pure technological systems. But one of its main advantages is its ability to effectively model socio-technical systems, which CIs certainly belong to; they consist of human, organizational and technological parts. The philosophical stance behind SD models is that complex systems are in essence feedback systems. That is, closed-loop relationships are ubiquitous in those systems: X affects Y, which in turn, directly or indirectly, affects X. Much of the mathematical foundation for modelling such systems comes from control theory and can be traced back to Norbert Wiener’s foundations of cybernetics. Differential or integral equations are used to specify the mathematical relationships between variables. Since non-linear equations often are too complex to solve analytically it is necessary to use a computer to simulate these systems.

SD is used when the individual properties are not decisive and high-level aggregation is desired or required for management purposes. This is typically the case for management strategies and long-term planning (“long-term” being a relative concept in relation to the system’s lifecycle). The objects being modelled (human resources, events, processes, etc) are aggregated and they are represented as stocks that change through inflows and outflows. The flows are in turn influenced by information arising from the dynamics of the system (the stocks, flows and management interventions). SD models assume the endogenous posture: The causal structure of the system is responsible for its dynamic behaviour. SD models capture the propagation of causes and effects in terms of reinforcing and balancing feedback. The SD method accounts for time delay, nonlinearity and recognizes that crucial aspects are often “soft” – motivation, reputation, etc – and must be present in the model despite their fuzzy nature, since its omission would make the model useless. A distinctive feature of SD models is their ability to capture unintended side-effects of interventions and to help identify policies to minimize the impact of unintended repercussions. This is crucial, since experience teaches that many strategies that initially seem to work often have disastrous unintended long-term consequences (Dörner 1989, 1997; Forrester 1968; Maani and Cavana 2000; Richardson and Pugh 1981; Sterman 2000).

Beyeler et al. (2004) model the dependencies of port operations on telecommunications, electricity and transportation. The SD model used to simulate port operations relies on a discrete-event simulation model called N-SMART to provide input to the telecommunication part of the model. E.g., to simulate effects such as call blocking. Both models have been developed as a part of the US NISAC (National Infrastructure Simulation and Analysis Center) initiative. The port model is able to show how a three week interruption and recovery of telecommunications caused a two month disruption to port operations. The model was also able to show the increased cost per container caused by e.g., increased ship idle time.

The CIP / DSS (CI Protection / Decision Support System) project at Argonne, Los Alamos and Sandia national laboratories has developed a risk informed decision support system (Conrad et al. 2006). The system has been implemented as a SD model in the software package Vensim. The CIP / DSS Metropolitan Model is able to simulate the impact of disturbances in a wide variety of sectors in a metropolitan area. Conrad et al. (2006) give an example of the impact of a power blackout on telecommunications and emergency services. Today, most homes have wired phones which continue to function during a blackout. Consequently, there is little cascading failure and adverse effects on emergency services. This is because wired phones are powered through the phone line from the telephone provider’s headquarters, where they have emergency generators. More and more people are switching to mobile phones and no longer have wired access, and consequently, can no longer call 911. Cell towers only have batteries as backup and they typically last for only four hours. The simulation indicated that there would be increased deaths and costs in such a future scenario. Dauelsberg and Outkin (2005) also give example runs of the model. They investigate different policies under an infectious disease outbreak.

Pasqualini et al (2006) present a model of a potable water distribution system (PWDS). It is also part of the CIP / DSS suite of models. The model addresses the effects of contaminated water and recovery procedures in an area. On interdependencies Pasqualini et al. writes: “There are a number of interdependencies between the potable water infrastructure and other infrastructures. The PWDS model is coupled with other infrastructure such as metropolitan energy, transportation, and economic. For example, the ability to repair a damaged water system depends on the availability of transportation, energy, and labour force; the treated process also depends on the availability of energy. In the case of a scenario the interdependency between PWDS and public health also needs to be considered….”

Discussion

Purpose of the Modelling Effort

As the previous section shows the four modelling paradigms discussed in this paper have all been applied to CI problems at various levels. While some have modelled individual institutions others have modelled whole economies. In many cases these models overlap and it is not a given which modelling paradigm one should choose for a given problem.

Before we go on it is appropriate to think about the meaning of a model. A model is always a simplification of reality (Sterman 2000, p. 89-90). When we build models we do our best to include the most important aspects, but there will always be something that must be left out. If not the model would be huge and unmanageable, and therefore lose its value as a model that can help us make sense of a complex reality. Different paradigms make different omissions; hence no modelling paradigm is suited for every purpose. Below we discuss some aspects of modelling and how they relate to critical infrastructures and training of crisis managers. We start with the different paradigms ability to handle dynamic phenomena.

Traditional Network models fail in this regard. They only show what the network would be if a node is added or removed. They are not able to represent the transition from one state to the other. Although network analysis is very useful in building robust CI networks (or for bad guys, in choosing the attack target), it is not able to represent the transition from non-crisis to crisis to end-of-crisis. The model by Svendsen and Wolthusen (2007) is a departure in this regard. Their model is able to account for, e.g., buffering, giving it some ability to handle transient phenomena. Another downside of Network models is that they are very data intensive. You need to know how every node is connected to every other node. This is also a problem with Input-Output models.

In addition to being data intensive, further criticism has been directed at Input-Output models (Vargas et al. 1999). 1) Prices and production means are fixed, and 2) production is demand driven, i.e., it assumes that all necessary input to satisfy needs for production will be supplied once demand is established (Miller and Blair 1985). The IIM model shares these assumptions and the impact of a disruptive event is a reduction in demand which is treated as an exogenous event (Santos and Haimes 2004). Kujawski (2006) states that: “These assumptions are not realistic for disruptive events. Disruptive events damage or destroy production facilities, and therefore they may reduce the output capacity below the demand and lead to a shift in production and price changes.” Kujawski (2006) proposes that to study disruptions to CI one must consider the dynamics of the system.

Dauelsberg and Outkin (2005) compare SD simulations with that of economic Input-Output models. “Thus the goal is to investigate and understand the non-equilibrium, non-linear dynamics of the system. Our SD models with multiple feedback structures are well suited for such a task. This is a point of departure from the input-output (I/O) approaches where equilibrium conditions are implied. However, during a disruptive event there are no apparent reasons why the equilibrium, as it is normally defined in economics, should occur. In general the incidents that are modelled by this system are transient in nature, often lasting no longer than a few weeks. I/O models are most often calibrated to annual data and intend to capture permanent changes and long term trends, smoothing out short term dynamics." Input-Output models therefore do not seem appropriate for modelling when the purpose is to understand the dynamics of the problem. However, I-O models would be appropriate if the goal is to see which sectors of the economy might be affected. "Given the limitations of the I-O based models, we conclude that they are more appropriate as a tool for guidelines to potential effects than for quantitative economic predictions." (Kujawski 2006)

A-B models are, as SD models, able to handle non-linear dynamics. Both A-B and SD models are causal models of the studied systems' microstructure. The approach to modelling is somewhat different in each paradigm. SD models work on integral (or differential) equations that define causal structure. Although it is possible in SD to model individual entities, usually groups of entities are modelled. A-B models define agents who interact with each other according to each agent's rule set. As such A-B models are a form of bottom-up modelling, while SD models usually choose a higher aggregation level and can therefore be considered top-down modelling. It must be noted that top-down and bottom-up are relative concepts. In an SD model the level of aggregation (or dis-aggregation) must be sufficient to reproduce the behaviour of the system under study, hence one might have to model the system quite detailed in some cases. However, the goal is to find the maximum level of aggregation possible. In A-B modelling agents are not always individual persons, but can be e.g. households, individual companies and so on.

In SD models feedback is explicitly represented, and a strength is that the system's feedback structure can be easily visualized through diagramming techniques. A-B models also handle feedback, but instead of explicit representation it emerges based on the agents' interactions. The ability of SD to explicitly represent feedback in diagrams give it an advantage presentation-wise, while being able to follow individual actors and their actions is an advantage of A-B.

Both SD and A-B modelling paradigms stress the importance of bounded rationality, a feature which is important to understand socio-technical systems in crisis situations. No one has the full overview in a crisis. The information that forms the basis for managers' decisions is usually incomplete and delayed.

Validity

So far, despite the philosophical difference between bottom-up and top-down, A-B and SD seems equally suited to handle the modelling task at hand. And we have also seen in the previous section that both modelling paradigms have been successfully applied to CI problems. What then is each paradigm's approach to validation? After all, if the model is to be used to train crisis-managers it must be able to give a sufficient representation of reality. But, how do we determine whether that representation is sufficient? We can not say whether a model is true or false. The nature of modelling defeats such an attempt. As mentioned above something is always left out in a model. There is always a danger that what is left out is important. Verification, as we understand it, is the process of establishing whether all the important bits are in the model and validation makes sure that the model satisfies behaviour tests for the right reasons. The ultimate question is: Is the model useful (Forrester 1961), i.e. is it good enough for our purpose ? (Coyle and Exelby 2000)

Although there are many aspects to model validation, it can principally be thought of as two main issues: 1) Behavioural validity and 2) structural validity. Behavioural validity is concerned with whether the model adequately reproduces the behaviour of the real system. This involves comparing historical data with the output of the model. It can be done in more or less sophisticated ways. However, in the case of cross-border crises in interdependent CI there is one major problem. Since the level of interconnections on a regional and global scale now has reached unprecedented levels there are few historical crises that can be used as data sources. Hence, statistical validation against historical data is largely inapplicable. Instead we must establish whether the produced behaviour makes sense.

Structural validity is a prerequisite for behavioural validity. A model may reproduce the desired behaviour with an unrealistic structure. In the case of SD models, getting the model to reproduce the right behaviour is only a matter of adding enough terms to the integral equations (Forrester 1961, p 117). This goes for A-B models too. The reproduction of behaviour only shows that the decision rules in the model is sufficient to reproduce that behaviour, not that they are necessary (Epstein 1999), and, more importantly, whether it adequately approximates the system's real structure. This is important because the goal is ultimately to find a better policy for how to handle crises. If the model structure is different from the real structure the normal behaviour might be the same, but the behaviour under a changed policy might be different. Both SD and A-B struggle with this issue. Establishing structural validity can be done in various ways but it must be rigorous and is thus time consuming. The greater the scope of the model and its level of detail, the more difficult it is to validate. We find no philosophical differences between the paradigms in this regard.

The Model Building Process

Most textbooks on modelling, whether it is SD or A-B, concentrate on the technical aspects of model building and interpretation of its result. However, modelling, as any other scientific activity, is inherently an iterative process. A model is built and tested against the real world. I.e. it is subjected to refutability. If the model is found lacking a new model is developed based on new field data. As such the modelling oscillates between laboratory experiments (simulations) and data gathering in the field. Unfortunately there is no such thing as a standard model building process. Each new model that is to be built poses new challenges. At best we can say that there is a common framework. Both the A-B and SD paradigms are subject to this. Indeed any simulation model building paradigm suitable for the construction of causal models is subject to this iterative process. Philosophically there is no difference.

Practitioners of SD have developed a Group Model Building (GMB) approach, which allows for rapid model development and increased stakeholder involvement in the modelling process (See e.g.Vennix 1996). The graphical notation of SD lends itself readily to collective model building. Building models in groups is especially an advantage in environments where knowledge about the problem is highly fragmented and dispersed between many different actors. We are not aware of similar model building approaches in other paradigms.

Final Comments

We can not say whether one paradigm is better than another paradigm in general, however for specific purposes some are better than others. If knowing what is impacted is important, but not how it is impacted, i.e. the dynamics of the crisis is not of interest, then Network and Input-Output models are suitable. SD and A-B models are both suited for handling the dynamics of a crisis. For purposes that require a strategic overview of the situation it makes sense to use SD, in part because its presentation tools are clearer than the tools currently available in A-B modelling. If it is important to understand how individual agents interact to form a larger macro-behaviour, A-B modelling is suitable.

References

Albert, Reka, Hawoong Jeong, and Albert-Lazlo Barabasi. 2000. Error and Attack Tolerance of Complex Networks. *Nature* 406 (378-382).

Amin, Massoud. 2001. Towards Self-Healing Energy Infrastructure Systems. *IEEE Computer Applications in Power*:21-28.

Balducelli, Claudio, Sandro Bologna, Antonio Di Pietro, and Giordano Vicoli. 2005. Analysing interdependencies of critical infrastructures using agent discrete event simulation. *International Journal of Emergency Management* 2 (4):306-318.

Barton, Dianne C., Eric D. Eidson, David A. Schoenwald, Kevin L. Stamber, and Rhonda K. Reinert. 2000. Aspen-EE: An Agent-Based Model of Infrastructure Interdependency. Albuquerque, NM and Livermore, Ca: Sandia National Laboratories.

Beyeler, Walter E., Stephen H. Conrad, Thomas F. Corbet, Gerard P. O'Reilly, and David D. Picklesimer. 2004. Inter-Infrastructure Modeling—Ports and Telecommunications. *Bell Labs Technical Journal* 9 (2):91-105.

Bonabeau, E. 2002. Agent-Based Modeling: Methods and Techniques for Simulating Human Systems. *Proceedings of the National Academy of Sciences of the United States of America* 99 (10):7280-7287.

Borshchev, A., and A. Filippov. 2004. From System Dynamics and Discrete Event to Practical Agent Based Modeling: Reasons, Techniques, Tools. In *The 22nd International Conference of the System Dynamics Society*. Oxford, UK.

Conrad, Stephen H., Rene J. LeClaire, Gerard P. O'Reilly, and Huseyin Uzunalioglu. 2006. Critical National Infrastructure Reliability Modeling and Analysis. *Bell Labs Technical Journal* 11 (3):57-71.

Coyle, R.G., and D. Exelby. 2000. The validation of commercial system dynamics models. *System Dynamics Review* 16 (1):27-41.

Dauelsberg, Lori, and Alexander Outkin. 2005. Modeling Economic Impacts to Critical Infrastructures in a System Dynamics Framework. In *The 23rd International Conference of the System Dynamics Society*. Boston, Ma, USA.

Dörner, Dietrich. 1989. *Die Logik des Misslingens*. 1st ed. Reinbek bei Hamburg: Rowohlt.

———. 1997. *The Logic of Failure*. 1st ed. Reading, Massachusets: Addison-Wesley.

Dudenhoffer, Donald D., May R. Permann, and Eliot M. Sussman. 2002. A Parallel Simulation Framework for Infrastructure Modeling and Framework. In *Proceedings of the 2002 Winter Simulation Conference*.

Epstein, Joshua. 1999. Agent-Based Computational Models and Generative Social Science. *Complexity* 4 (5):41-60.

Forrester, J.W. 1961. *Industrial Dynamics*. Cambridge, MA: Productivity Press.

Forrester, Jay Wright. 1968. *Principles of Systems*. Cambridge MA: Productivity Press. Original edition, Wright-Allen Press and MIT Press.

Grubesic, Tony H., and Alan T. Murray. 2006. Vital Nodes, Interconnected Infrastructure and the Geographies of Network Survivability. *Annals of Association of American Geographers* 96 (1).

Holmgren, Åke J. 2006. Using Models to Analyze the Vulnerability of the Electric Power Network. *Risk Analysis* 26 (4).

Kujawski, Eduoard. 2006. Multi-Period Model for Disruptive Events in Interdependent Systems. *Systems Engineering* 9 (4).

Leontief, W. W. 1951. Input-output Economics. *Scientific American*:15-21.

———. 1951. *The Structure of the American Economy 1919-1939: An Empirical Application of Equilibrium Analysis*. 2nd ed. New York: International Arts and Sciences Press.

Lian, Chenyang, and Jacov Y. Haimes. 2006. Managing the Risk of Terrorism to Interdependent Infrastructure Systems through the Dynamic Inoperability Input–Output Model. *Systems Engineering* 9 (3).

Likar, B., P. Fatur, and D. Krizaj. 2001. *Innovation Management (in slovene)*. FM: Faculty of Management, Koper.

Maani, Kambiz, and Robert Y. Cavana. 2000. *Systems Thinking and Modelling: Understanding Change and Complexity*. Softcover ed. Auckland, New Zealand: Pearson Education.

Miller, R.E., and P.D. Blair. 1985. *Input-output: Analysis foundations and extensions*. Englewoods Cliffs, NJ: Prentice-Hall.

Moore, James E., Richard G. Little, Sungbin Cho, and Shin Lee. 2006. Using Regional Economic Models to Estimate the Costs of Infrastructure Failures. *Public Works Management and Policy* 10 (3):256-274.

Mussington, David. 2002. Concepts for Enhancing Critical Infrastructure Protection Relating Y2K to CIP Research and Development: RAND's Science and Technology Policy Institute.

Panzieri, S., R. Setola, and G. Ulivi. 2004. An Agent-Based Simulator for Critical Interdependent Infrastructure. In *Securing Critical Infrastructures*. Grenoble.

Pasqualini, Donatella, Perry C. Klare, Paolo Patelli, Marc S. Witkowski, and Catherine A. Cleland. 2006. A Model for a Water Potable Distribution System and its Impacts resulting from a Water Contamination Scenario. In *The 24th International Conference of the System Dynamics Society*. Nijmegen, Nl.

Pederson, P., D. Dudenhoeffer, S. Hartley, and M. Permann. 2006. Critical Infrastructure Interdependency Modeling: A Survey of U.S. and International Research. Idaho Falls, Idaho: Idaho National Laboratory Critical Infrastructure Protection Division.

Richardson, George P., and Alexander L. Pugh, III. 1981. *Introduction to System Dynamics Modeling*. Portland, OR: Productivity Press.

Santos, J. R., and Y. Y. Haimes. 2004. Modeling the Demand Reduction Input-Output (I-O) Inoperability due to Terrorism of Interconnected Infrastructures. *Risk Analysis* 24:1437-1451.

Schneier, Bruce. 2000. *Secrets & Lies: Digital Security in a Networked World*: Wiley.

Sterman, John D. 2000. *Business Dynamics: Systems Thinking and Modeling for a Complex World*. Boston: Irwin/McGraw-Hill.

Svendsen, Nils Kalstad, and Stephen D. Wolthusen. 2007. Connectivity of Models of Interdependency in Mixed-Type Critical Infrastructure Networks. *Information Security Technical Report* 12:44-55.

Tolone, William J., David Wilson, Anita Raja, Wei-Ning Xiang, and E. Wray Johnson. 2004. Applying Cougaar to Integrated Critical Infrastructure Modeling and Simulation. In *Proceedings of the Open Cougaar Conference*.

Vargas, E., D. Schreiner, G. Tembo, and D. Marcouillier. 1999. Computable general equilibrium modeling for regional analysis: Regional Research Institute, West Virginia University.

Vennix, Jac A. M. 1996. *Group Model Building: Facilitating team learning using System Dynamics*. Chichester, England: John Wiley and Sons.

Author Biographies

Finn Olav Sveen is currently undertaking PhD studies at the University of Navarra, San Sebastian, Spain. He resides in the Industrial Management Department. He has a bachelor degree in Computer Science from Buskerud University College, as well as a Master of Science degree in Industrial and Information Management from Agder University College (Now University of Agder), both in Norway. His principal research interest is information security management with focus on incident reporting and learning. To learn about and solve these problems he applies System Dynamics modelling and simulation.

Jose M. Torres (Industrial Engineer 2003, PhD 2007) is a lecturer of Information systems and Electronic Commerce at the University of Navarra Engineering School. His research interests include information systems security management and complex systems modeling. He has published several papers in international conferences.

Jose M. Sarriegi is a Professor of Information Systems, Knowledge Management and Modelling and Simulation at the University of Navarra Engineering School. His research interests include information systems security, knowledge management and complex systems modelling. He has led several research projects in all these topics. He has published several papers in journals and international conferences.

Jose J. Gonzalez is a Professor of System Dynamics and Information Security at the Faculty of Engineering and Science at the University of Agder, Norway. He leads the Security and Quality in Organizations group with two Postdoctoral fellows and two PhD fellows. In addition to numerous publications in the fields of system dynamics and information security, he was co-founder of Powersim and developer of one of the leading system dynamics tools.

Adriana Ortiz is a PhD candidate in industrial engineering at the University of Navarra Engineering School. Her research interests are multi method modeling (System Dynamics, Discrete Event, Agent-Based and Econometrics), soft variables, complex systems modeling and knowledge management. She presented her PhD Viva on July 2006 and she did a PhD exchange stay at Brunel University (London, UK).