Decision Making for Extreme Events: Modeling Critical Infrastructure Interdependencies to Aid Mitigation and Response Planning

Nicholas Santella
Southern Methodist University

Laura J. Steinberg
Syracuse University

Kyle Parks
Southern Methodist University

Abstract

Recent tragedies such as Hurricane Katrina, 9/11, and the 2008 Sichuan Earthquake have revealed a need for methods to evaluate and plan for the impact of extreme events on critical infrastructure. In particular, awareness has been raised of the threat that a major disruption will lead to cascading failures that cross boundaries between interdependent infrastructure sectors, greatly magnifying human and economic impacts. To assist in planning for such extreme events, researchers are developing modeling tools to aid in making decisions about how best to protect critical infrastructures. We present some of the capabilities of this modeling approach as well as some of the challenges faced in developing such applications based on our experience with the Critical Infrastructure Protection Decision Support System (CIPDSS) model, developed for use by the Department of Homeland Security. A set of disruptions to road and telecommunication infrastructures is implemented in CIPDSS and the modeled disruptions to the original infrastructure as well as cascading effects on other infrastructure sectors are discussed. These simulations provide insights into the potential of this approach.

KEY WORDS: critical infrastructure, disaster and risk management, infrastructure interdependencies, systems dynamics modeling, urban studies

Introduction

In the wake of 9/11 and the devastating natural disasters of recent years, the impact of major disruptions to critical infrastructure (e.g., telecommunications, transportation, emergency services) is receiving increased attention from the scientific research and policy communities. Of concern is the threat that the inherent interdependencies of critical infrastructures can lead to cascading failures which cross boundaries between both technological and social structures (NIPP, 2006; O'Rourke, 2007).

This type of vulnerability was tragically illustrated by the extensive indirect effects of the September 11 attacks (Mendonca & Wallace, 2006; O'Rourke, Lembo, & Nozick, 2003), for example, extensive disruption to telecommunications caused by ruptured water mains, and of Hurricane Katrina (Gray & Hebert, 2007; Moore & Kellogg, 2007).

The high degree of dependency (unidirectional) and interdependency (bidirectional) that exists between sectors of infrastructure requires that the whole system be considered when assessing the impacts of such events or evaluating methods of intervention (Little, 2004). Examples of such dependency-related issues arising from the aftermath of Hurricane Katrina are the failure of oil pipelines and

© 2009 by The Policy Studies Organization. All rights reserved.

telecommunication systems due to loss of power; the slowed reopening of New Orleans due to contamination of the city's water distribution system; and the difficulty of responders in organizing rescue and relief efforts in the light of inoperable communication and data-gathering equipment.

In the case of oil pipelines and cellular telecommunication systems, legislative attempts to address this vulnerability by mandating backup power capacity for these facilities were faced with the difficult trade-offs (and resulting controversy) between the risk demonstrated by Katrina and the cost and difficulty in making changes to such ubiquitous infrastructure. Similar difficulty is raised in determining how best to improve security of the very large number of individual facilities that make up many other critical infrastructures (e.g., chemical plants, water treatment facilities). To best protect public welfare, such policy and investment decisions related to critical infrastructure must be made within an objective framework that takes into account all available information including the dependencies and interdependencies within and across infrastructures.

Because of the complex and interlinked nature of critical infrastructure, models of these systems and their interdependencies have been proposed as useful tools to aid decision making by government and infrastructure managers (Conrad et al., 2006; Min et al., 2007). Modeling systems can potentially provide a number of benefits in the process of risk assessment and evaluation of risk mitigation methods. Through combining the knowledge of many subject-matter experts, and data from multiple sources, models make available a greater range of quantitative information and knowledge of system connectivity and behavior than it would be otherwise practical for one person to acquire or use effectively. This is particularly important when assessing the interdependence of critical infrastructure where a large number of infrastructure systems interact, sometimes in nonlinear ways. In addition, indirect effects may not be well known to individual expert in a single area of infrastructure and without significant study these interdependencies may be difficult to quantify. For example the processes and degree by which loss of telecommunications reduces the level of function of emergency services or business is of vital importance for planning emergency response, or estimating economic impacts of a telecom disruption, but could probably not be easily quantified by a manager in any of these three fields.

To describe impacts across multiple infrastructures requires large amounts of descriptive data from each infrastructure and expertise from many disciplines. When such multidisciplinary problems need to be addressed, the convening of a panel of experts is a common approach used to develop a comprehensive assessment for planning. Table-top exercises are used to address a similar need for expertise from multiple critical infrastructure components, as well as serve to improve communication and coordination. However, such group exercises are difficult and costly to carry out, and so cannot be applied to every question that encompasses multiple infrastructures. Models of critical infrastructure interaction which have been sufficiently validated, ideally against real-world data, but also through review of subject matter experts, can supplement and, in some cases, replace panels of experts, as well as inform table-top exercise scenarios. In these applications, the use of models provides the advantage of allowing a user with general-subject knowledge to answer complex questions within a consistent and quantitative framework, which allows for comparison between different types of hazard events and potential mitigations. However, when applied to a type of analysis or scenario, which is not well-established, expert judgment is still necessary to understand limitations imposed by the model's methodology or assumptions and to guide model development and refinement as needed to answer new questions.

Our interest in systems frameworks for risk management resulted in our performing, as an independent third party, an evaluation of the predictive accuracy of the Critical Infrastructure Protection Decision Support System (CIPDSS) when applied to post-Katrina conditions in Baton Rouge, LA. This article describes our reflections on the potential of such modeling tools, informed by this experience. We describe the CIPDSS model and the way in which it attempts to meet the need for information about complex interactions between critical infrastructures. Two sets of simple emergency scenarios implemented using CIPDSS are used to demonstrate the potential utility of this type of modeling system. Challenges faced in developing such applications as well as a critique of some aspects of the CIPDSS model are also presented. For these analyses, the late-2005 version of the CIPDSS software was used; the software undergoes continual review and improvement.

The CIPDSS Model

CIPDSS is a modeling application that has been developed through collaboration between Los Alamos, Sandia, and Argonne National Laboratories, sponsored by the Science and Technology Directorate of the U.S. Department of Homeland Security DHS. It is presently one of the modeling capabilities of DHS's National Infrastructure Simulation and Analysis Center (NISAC). While many other models exist for the simulation of various aspects of critical infrastructure behavior (see Pederson et al., 2006, for a review and comparison of recent efforts in critical infrastructure modeling), CIPDSS is unique in providing an aggregate-level model of all critical infrastructure sectors and their major interdependencies. CIPDSS is intended as a tool to allow government (federal, state, and local) and industry decision makers to determine what consequences might be expected from disruptions to infrastructure, explore the mechanisms behind these consequences, and evaluate mitigations for a particular risk. It is intended for analysis of high-level behavior of metropolitan or regional infrastructure. CIPDSS does not replace more detailed sector specific models but enables analysis which takes into account the way disruptions in one infrastructure sector may propagate to other infrastructure systems.

DSS encompass a broad range of computer applications which organize and present information in order to facilitate decision making (Power, 2002). Simulation models are one class of DSS and have been widely applied in business and engineering management. CIPDSS is a system dynamics simulation model of all critical infrastructure sectors as defined by Homeland Security Presidential Directive 7 (e.g., water, public health, emergency services, telecom, energy, transportation) and their major interdependencies at an aggregate level. Although not evaluated in this analysis, CIPDSS also incorporates multiattribute utility functions derived from interviews with infrastructure decision makers, which can be used as an aid in evaluating potential mitigation strategies.

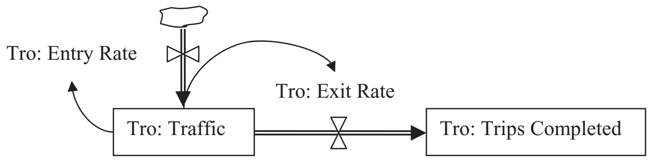

Figure 1. Simplified Example of CIPDSS System Dynamics Framework for Road Traffic

At present CIPDSS is intended for deployment by its developers or other expert users, but easy to use interfaces for exploring specific questions have been developed as well (LeClaire et al., 2007). The developers of CIPDSS have applied it to a variety of scenarios. In one study, it was used to model an influenza outbreak and evaluate the impact of interventions and public behavior on spread of the infection (Fair et al., 2007). In another application, it was used to quantify the impact of blackouts on telecommunications and emergency services (Conrad et al., 2006). Other unpublished applications implemented by the national labs quantified the cost and benefits of various mitigations for a toxic chemical release and predicted the impacts of displaced people on Baton Rouge subsequent to Hurricane Katrina. Order of magnitude prediction accuracy was the initial operational goal for CIPDSS with improvements expected after deployment.

The system dynamics approach used by the CIPDSS model is a methodology for studying complex systems involving feedbacks or interdependencies. A system is broken down into simple objects or processes which interact to produce complex behaviors. To produce a system dynamics model, feedback loops, stocks, and flows are used to represent the system under study based on the knowledge of a subject-matter expert. Feedback loops indicate connection and direction of effects between objects. Stocks represent quantities or states of the system, the levels of which are controlled over time by flow rates between stocks. A simplified example of these components taken from the CIPDSS model of road traffic is illustrated in Figure 1. In the small segment of the model pictured, the volume of traffic present on the road (Tro: Traffic) is a stock controlled by flows determined by the entry and exit rate of vehicles, which are dependent on a number of other variables not pictured. Through a series of steps not shown, a feedback loop is set up between Tro: Traffic and the entry rate decreasing entry to the roads under heavy traffic conditions. The number of people successfully completing trips (Tro: Trips Completed) is calculated by multiplying the exit rate by the average number of occupants per vehicle (variable not shown).

In order to create a quantitative system dynamics model, formulas are developed to calculate a value for each variable. The model is tested to verify that it reproduces the behavior of interest in the system and it then provides a framework to quantify the effects of hypothetical events, and to compare proposed interventions. It may also serve to identify inconsistencies between processes which occur in reality and the mental models used by decision makers. This type of model has been applied in academic research (see for example the publication *System Dynamics Review*) as well as business, supply-chain, and operations management. In economic applications, models developed using the system dynamics approach have been used to answer such questions as what the impacts of regulation, investment choices, and pricing might be on profitability as well as optimization of manufacturing and retail stocking.

CIPDSS has been programmed in Vensim, a commercial system dynamics modeling software package. In the late 2005 version of CIPDSS, which is the subject of this investigation, 14 critical infrastructure systems are modeled. Teams of one to three analysts created the software code for each infrastructure system, with collaboration between the teams occurring to model system interdependencies. Overall the model utilizes more than 2,250 variables. Infrastructure systems are subdivided into more than 100 subsectors; for example, bus, road, and subway subsectors are created within the transportation system. This results in over 5,000 potential interactions between infrastructure subsectors; as this number of potential interactions is too large to evaluate, expert judgment was used to identify and represent only the most significant interactions between subsectors.

Systems within each subsector are modeled at an aggregate level. For example, within the metropolitan scale model discussed here, all roads within a city are treated as an aggregate entity with properties similar to a single road. This contrasts with the approach used, for example, in a metropolitan travel demand model where individual roads are represented. An aggregate approach makes it possible to directly parameterize the dependency of traffic flow on other subsectors, for example, availability of electricity, and also reduces the need for finely resolved site-specific data and analysis. However when applying the model to a specific location aggregate data describing local infrastructure (e.g., population, number of hospital beds, electricity production) must be obtained which may represent a significant task.

Because of the complexity of the systems and interactions, identification and parameterization of dependencies can be challenging. In addition, the importance of various types of interactions between infrastructures naturally differ depending on the type of perturbation to the system and the application for which model results are intended. Even at the level of complexity present within the CIPDSS model, the model architecture and processes which it can represent inevitably reflects the priorities and assumptions of its programmers, and processes important to a particular scenario may be left out. Such an observation can be made with regard to the implementation of the CIPDSS model. For example, changes in population caused by evacuation (as discussed in more detail later) or immigration propagate through only some infrastructures. Presumably this is the case because population movement was not envisioned during model development as a driving mechanism for a scenario.

Although CIPDSS incorporates considerable research to identify interdependencies between critical infrastructure and much progress has been made in modeling these interactions, there has been relatively limited validation of the model by comparison with real world data. Validation efforts by the developers of CIPDSS have consisted primarily of conceptual validation only for the more important descriptive variables for each infrastructure subsector to determine if the model produces a reasonable response to perturbations. This validation included sensitivity analysis, as well as review of model processes by subject matter experts. Of course, comparison with real-world data is only possible for scenarios which have a close corollary in historic events, limiting its application by CIPDSS developers.

Validation is also hampered by the difficulty in obtaining operational data for a wide variety of infrastructures and particularly data, which quantifies the interdependency between various infrastructures. This is further complicated by the fact that much of the critical infrastructure is in the private domain and descriptive information may be considered proprietary or of competitive value.

The range of temporal resolutions required of an all-purpose DSS presents additional challenges. Model systems may be required to represent behaviors which in reality take place on time scales from seconds to months or years (Pederson et al., 2006). For example, a time scale of minutes to days is necessary to represent short-term events such as blackouts or deliberate attacks on infrastructure while resolution on the time scale of weeks may be required to model the temporal development of an infectious disease outbreak and even longer periods might be necessary to resolve long term impacts of events such as major natural disasters. The difficulty of validation magnified by the challenge of data held in the private domain and wide range of temporal scales which a modeling system must handle are significant limitations on successful use of models to inform decisions about critical infrastructure. For any model system to meet the above challenges requires syntheses of input from a large number of potential users as well as flexibility of the modeling system to allow for future development.

Disruption Scenarios

The utility of CIPDSS and the challenges described earlier are illustrated by a series of scenarios, executed by the authors, which reflect disruptions to the road and telecom systems modeled. Simple examples were chosen which could be easily presented but which display CIPDSS capability of propagating disruptions across infrastructures. To begin the analysis, CIPDSS is run for a base case scenario representing a generic large city with a population of five million operating under normal circumstances. Then, two sets of scenarios are run on top of the base scenario: in the first case, various disruptions to the road system are simulated, and in the second case disruptions to the telecommunications system. The scenarios were run using CIPDSS and are illustrated here with results that show the first three days of output. The results describing the effects on infrastructure of the two disruption scenarios are discussed in the next section, and comparisons are made to the results of the base-case scenario run.

Disruptions to the Road System

Disruptions to the road system were modeled using three disruption scenarios. The first disruption scenario depicts a 25 percent loss in roadway capacity which begins at the start (time = 1) of the first day (Figure 2, run 2A). This represents loss to capacity which might result from damage to the entire road system as in the case of an earthquake. This damage might also represent the loss of a particular piece of infrastructure, such as a bridge, which, because of its central location, creates a bottleneck which impacts the operation of the entire road system. As CIPDSS considers roads in the aggregate, an estimate must be made by the user, from a transportation model or expert judgment, as to what extent damage to an indi-

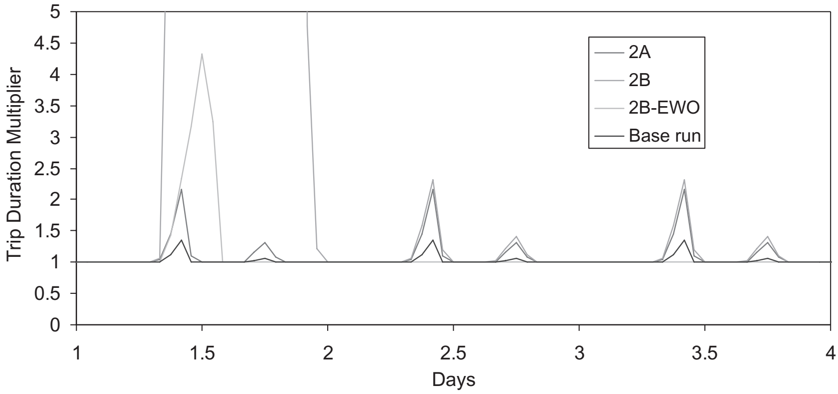

Figure 2. Modeled Trip Duration Multiplier for Road Damage (2A), Evacuation (2B), Evacuation with Restricted Travel (2B-EWO), and Normal Operation (base run)

vidual infrastructure element would affect the entire road system. Roads are assumed to remain at reduced capacity for the entire model run, unless additional input is included to describe repair of roads.

The second scenario includes the same loss of road capacity while at the same time initiating a massive evacuation where a quarter of the city's population attempts to leave the city over a period of five hours starting in the early morning (shown at time = 1.3 days) on the first day (Figure 2, run 2B). By default model assumptions, this evacuation is assumed to take place entirely by personal vehicle with a single passenger per vehicle. The third scenario is the same as run 2B, but a government alert is issued requesting that only essential workers report to job sites at the same time as the evacuation order (2B-EWO). This serves to eliminate most (90%) of normal daily travel, reducing competition with evacuees for road capacity. Note that during periods of low traffic density the trip duration multiplier remains at a value of one for all runs, so only the base run is visible.

Results of these three scenarios as well as the base run are illustrated in Figure 2 with the model variable *Trip Duration Multiplier* which represents the ratio of the current time required to complete a trip to the time taken to complete a trip when traveling at free-flow speed. The free flow speed of a road is defined as the speed of a vehicle under favorable weather conditions with minimal interaction with other vehicles, and is similar to the speed limit. *Trip Duration Multiplier* is an intuitive metric of quality of road service, as it represents the experience of road users and can be easily translated into delay time experience by commuters or other services dependent on roadways (e.g., emergency services, delivery of supplies). As is typical of traffic patterns within urban areas in the base run increases in travel time are observed during morning and evening rush hours. Default model parameters create higher traffic density during morning rush hour but these patterns can be adjusted to match behavior to actual traffic patterns observed in a given city.

In the scenario where operational capacity of the road system decreases (run 2A), there is an increase in travel times only during normal rush hour periods by a factor of 3. In the evacuation scenario (run 2B), the addition of evacuees to normal road traffic results in roads that quickly reach capacity, resulting in gridlock (indicated by a travel time multiplier which exceeds the scale of the graph). In this scenario, the model predicts that gridlock persists for approximately 14 hours until the work day ends and the evacuation is completed. In the same scenario, with an essential-workers-only alert ordered at the same time as the evacuation order (run 2B-EWO), the number of evacuating vehicles results in severely slowed traffic but the road system does not reach gridlock and the evacuation is completed within the desired five-hour period. In the analysis of an actual scenario these intuitive results would be validated and possibly refined by comparison with a detailed evacuation transport simulation, the value of CIPDSS lies in the estimation of cascading effects in other infrastructure sectors.

Disruptions to the Telecommunications System

Two scenarios were run for disruptions to the telecom system. The first (run 3A) specifies a 25 percent loss of trunk line (the high-speed connection between telephone central offices) capacity which occurs at the start of the first day (time = 1). Default calculations of repair time result in trunk line damage taking approximately one month to fully repair. Hence trunk capacity remains essentially unchanged during the three-day period examined here. Repair time could be modified by changing parameters (such as additional investment in labor or equipment for repair) within a telecom repair subsector of the model. The second scenario (run 3B) has the same loss of trunk capacity and also a sudden increase in call demand. This increase results in three times the normal call level but the normal calling pattern with time of day is retained. This increase in demand begins at the start of the first day (time = 1) then decreases and returns to normal by the end of the third day.

The output variable *Wire-line Availability* (shown in Figure 3) represents the predicted fraction of land line call attempts which connect successfully on the first try. Plots of availability of cellular service would appear similar. Under normal circumstances almost all calls connect on the first try. Loss of 25 percent of trunk-line capacity (run 3A) causes only a very small number of calls to fail during periods of high demand because there is still excess trunk capacity available. However, significant impacts on other critical infrastructure sectors result from loss of trunk capacity, as described further later. When call demand is higher than normal, as in scenario 3B, the number of calls which are dropped increases sharply. During

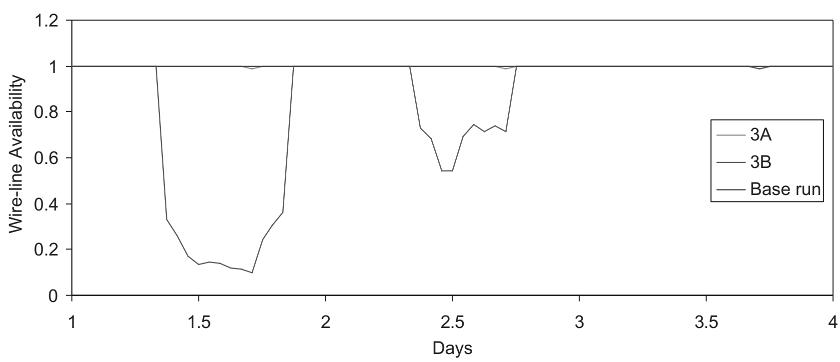

Figure 3. Modeled Availability of Wire-Line Telecom Service Under Conditions of Trunk Line Loss (3A), Trunk Line Loss with Increased Demand (3B), and Normal Operation (base run)

period of maximum demand (during business hours) on the first day of the simulation, less than 10 percent of calls are connected on the first try, with switch capacity to handle the number of calls being the limiting factor.

Effects of Disruptions on Other Infrastructure Systems

The strength of the CIPDSS model is in allowing investigation of how disruptions in one infrastructure propagate to other infrastructure systems. Examples of this type of propagation can be observed from the scenarios presented earlier for the road and telecommunications sectors. The causative link between the initial disruption and the current infrastructure can be readily identified and explored, potentially allowing for the evaluation of remedial measures. In the following we look at the behavior of a small selection of output variables from other infrastructure subsectors to illustrate the usefulness of this ability.

The first example of propagation of disruptions to other infrastructure systems is model predictions of Emergency Medical Services (EMS) Response, the number of calls that can be responded to (or that are demanded, whichever is smaller), measured in calls/hour. The base run shows a typical pattern of EMS response, reflecting greater frequency of calls for EMS service from midday through evening.

In the scenarios involving disruption to the road system, little change in EMS response is observed when rush-hour travel times increase by a factor of three (run 2A, Figure 4). The decrease in EMS response rate as a result of increased travel time is minimal because the model assumes that ambulances are given right of way, and so their performance is not significantly impacted until traffic density is quite high. When an evacuation is ordered (run 2B), the capacity of the road system is reached, causing gridlock, and significantly decreasing the rate at which EMS systems can respond to calls. EMS response is limited by traffic congestion until late at night, when the evacuation is completed and traffic abates at the end of the day. Under model assumptions, those calling for EMS service are assumed to remain in queue until they can be reached. Hence, late at night and into the morning of the second day, calls are answered at a much higher rate than normal, as EMS works through

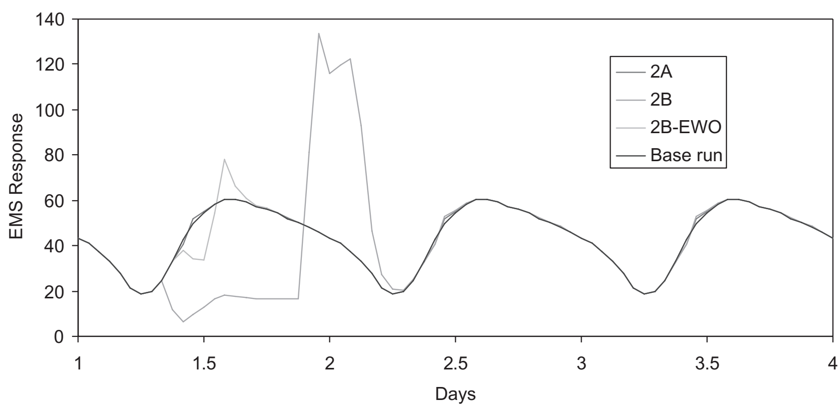

Figure 4. Modeled EMS Response Rate Under Conditions of Road Damage (2A), Evacuation (2B), Evacuation with Restricted Travel (2B-EWO), and Normal Operation (base run)

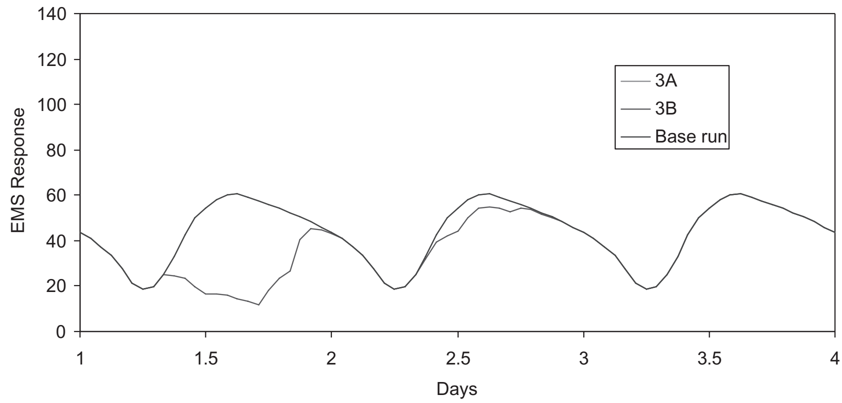

Figure 5. Modeled EMS Response Rate Under Conditions of Trunk line Loss (3A, which is identical to the base run), Trunk Line Loss with Increased Demand (3B), and Normal Operation (base run)

this backlog of calls. With an essential-workers-only alert in place (run 2B-EWO), the same effect is observed but to a much reduced extent.

In the first scenario (run 3A), where trunk capacity is lost, results are similar to the base run, as few wireline or wireless telephone calls fail to connect (Figure 5). When, in addition, the telephone systems become overloaded (scenario 3B), during the first day, EMS response decreases as both wireline and wireless calls fail to reach the emergency services operator. The possible response rate also decreases because loss of telecom services decreases the effectiveness of the EMS. Late that night when the overload of the phone system subsides, and more calls reach emergency services the volume of EMS response begins to increases back to normal levels (converging with the base run).

In the case of these telecom scenarios, two different assumptions come into play to describe the impacts of telecom on EMS. It is assumed that those who reach an emergency services dispatch but who do not receive a response for up to several hours because of road conditions will remain waiting for help, while those who fail to reach an emergency services dispatcher on the first try will abandon their attempts to contact help. Similar calculations are made by the model of the response of law enforcement and fire fighters, and similar perturbations in the response rate are seen in these services. This illustrates an opportunity for further model development. The simple but inconsistent assumptions about the behavior of those in need of EMS service who find their access to service blocked because of failures of the road and telecom systems could be easily improved for greater realism.

We can also investigate the effect of road and telecom disruptions on the hospital system. One summary metric for the hospital system is *Number Treated*, the number of patients being treated at any given time as inpatients within the hospital system. In the base run this variable has a daily periodicity resulting from typical patterns of higher discharge rates in the morning and higher admission rates in the afternoon. In the case of a 25-percent loss of road capacity (run 2A) there is no impact on the number of patients within the hospital system (the run overlaps with the base-run scenario). However, when traffic volume increases to the point of gridlock as observed in the evacuation scenario (run 2B), the number of those afflicted by illness who are able to reach the hospitals decreases sharply, resulting in a decrease

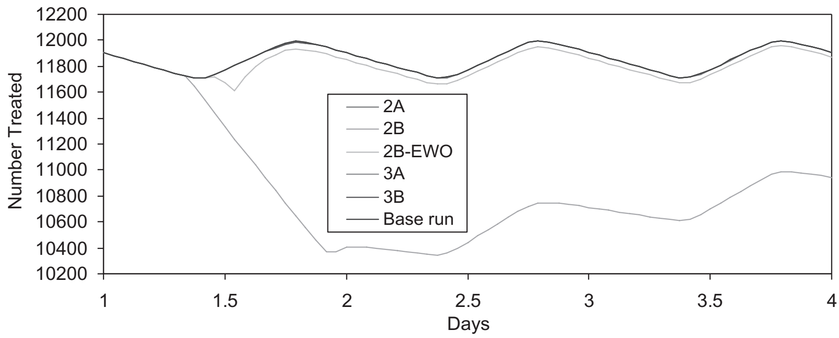

Figure 6. Modeled Number of People Treated Within the Hospital System Under Conditions of Road Damage (2A), Evacuation (2B), Evacuation with Restricted Travel (2B-EWO), Trunk Line Loss (3A), Trunk Line Loss with Increased Demand (3B), and Normal Operation (base run). With the exception of runs 2B and 2B-EWO all results are identical to the base run

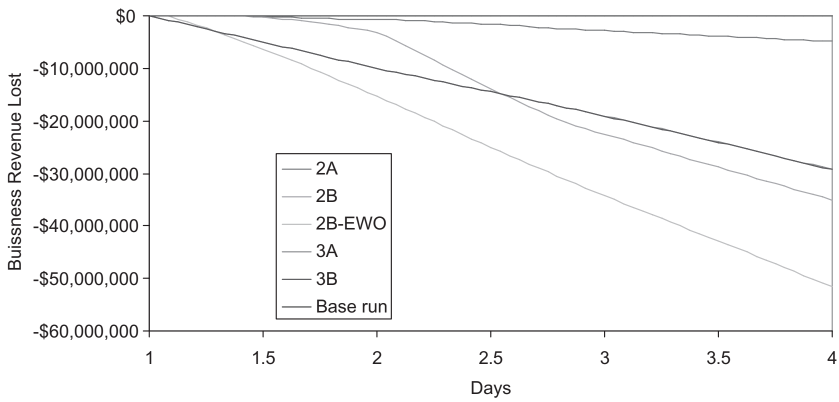

Figure 7. Modeled Lost Business Revenue Under Conditions of Road Damage (2A), Evacuation (2B), Evacuation with Restricted Travel (2B-EWO), Trunk Line Loss (3A), Trunk Line Loss with Increased Demand (3B), and Normal Operation (base run)

in the inpatient population. When traffic density decreases and gridlock ends, the number of patients treated slowly increases, converging back to a steady state value. A much smaller decrease in the number treated is observed for the evacuation scenario when an essential-worker-only alert (run 2B-EWO) is in place. As shown in Figure 6, no impact is observed on this value from the telecom scenarios (runs 3A, 3B overlap with the base run) as they are assumed to have no strong linkages, which might prevent patients from reaching the hospitals. This scenario indicates an area for further development of the model's treatment of interdependencies in that the variables describing the evacuation scenario are coupled to the hospital system through the traffic sector but not coupled directly to population. As a result, the expected 25-percent decrease in population as a result of the evacuation is not reflected in decreased demand for hospital or other services.

A final summary statistic, *total business revenue losses*, represents the cumulative loss from all lost consumer spending (Figure 7). For comparison, the base-run model calculation of total nominal spending over the same four-day period is $740 million. Calculation of nominal spending and lost spending is divided into sections based on transaction mode (cash, check, credit, and automatic payment spending). Division of spending between these modes is based on average data from the American Bankers Association. Spending is also divided into seven subcategories describing the items purchased (e.g., housing, food, transportation) based on averages of U.S. Department of Commerce data. Various disruptions will impact the spending modes differently; for example, only scenarios 3A and 3B impact cash spending because they decrease the number of operating ATMs (through loss of telecommunication trunk lines) while all scenarios impact check and credit transactions.

Increased travel times (run 2A) result in a $7 million decrease in spending through check and credit modes. Evacuation (run 2B) results in a larger $35 million loss of revenue also from the check and credit modes. The essential-workers-only alert (run 2B-EWO) results in the highest loss, $52 million from the same modes, because a large number of businesses are impacted by lack of workers. In the case of telecom disruptions, scenario 3A results in a loss of over $29 million, with losses from all modes. This is because operational capacity of trunk lines is linked to availability of business data networks and hence processing of these transactions within the model. Although in reality loss of normal telephone service would be expected to result in lost revenue, scenario 3B results in the same losses as 3A because phone availability and spending are not coupled within the model.

Estimates of lost business revenue resulting from various disruptions and proposed mitigations are highly useful. In many cases monetary losses resulting from the loss of critical infrastructure services can easily exceed the costs resulting from direct damage. However, the previous example illustrates the need for further development in that business losses are not sensitive to overloading of the telecom system as might be expected. These loss estimates are only useful if they can be relied on to capture all major interdependencies. This can only be achieved by coordinated model development between the sector teams, coupled with iterative model development through comparison with real-world data, but without these steps real-world applications are limited.

Conclusion

These scenarios help to illustrate some general observations about modeling of critical infrastructure for decision making. CIPDSS generally performs as intended, allowing for rapid production of scenarios that allow easy comparison of very different types of events and their impact across multiple infrastructures. Mitigation or response scenarios (such as the essential-workers-only alert or investment in telecom repair) can then readily be investigated through programming of additional scenarios. A single model, such as CIPDSS, which can be applied to a wide variety of disruptions and mitigations, is particularly helpful in that it allows for comparisons of very different types of events, including indirect effects, using a consistent set of metrics.

In these ways, a DSS can help to provide a quantitative framework for evaluation of various scenario consequence and mitigation strategies, particularly for events that cross infrastructure system boundaries because of widespread physical damage or cascading effects. This type of broad application differs significantly from other types of emergency planning models, for example, evacuation planning models, which are intended to address a single specific problem. This capability can assist government and infrastructure managers in making rational and defensible choices determining resource allocation and policy for hazard mitigation and in planning for emergency response.

Opportunities for further development were observed. One example is the propagation of changes in the population as a result of in-migration or evacuation, which is present in CIPDSS in only some of the infrastructure sectors. Thus, some obvious population effects are left out of the model, such as the exclusion of the effect of evacuation (i.e., a decrease of population) on the number of hospitalizations. CIPDSS also exhibits a problem often faced by developers of large-scale models spanning many interconnecting subroutines: a great deal of coordination between sector modeling teams is needed in order to insure consistency in process assumptions. The CIPDSS model formulation provides several illustrations of this modeling challenge, including conflicting assumptions about the behavior of persons denied timely emergency services because of loss of telephone service versus loss of transport capacity. Another example is the model's decoupling of overloads to the telephone system from monetary losses within the business sector.

Simulation models like CIPDSS characteristically undergo frequent revision as model developers refine their system understanding. Thus, while the late-2005 version of the model was deployed by DHS for a number of investigations, including the one reported on here, the model has since undergone several revisions. It now includes a number of improvements, which include enhanced evacuation modeling capabilities and more extensive infrastructure interconnectivity. In a sense, the use of CIPDSS while it simultaneously undergoes improvement is a reflection of the real-world tension between the necessity of deployment of a national security tool to meet pressing needs and the recognition that additional model development and refinement are ultimately needed to create a more useful tool.

One way that model refinements are identified is through validation exercises. As model results are only of use if they accurately represent real-world consequences, it is critical that model results be compared with observational data from real events. This is necessary perhaps not so much to evaluate computational methods or input data as to test the model's conceptual framework against real-world complexity. Modeling of relevant scenarios proposed by independent sources is another useful tool for model evaluation. As ongoing work on infrastructure modeling continues to deliver improvements, it is expected that CIPDSS and similar decision support models for infrastructure systems will become increasingly useful tools for evaluation of the risks associated with large-scale disruptions that transboundary crises are sure to cause.

About the Authors

Laura J. Steinberg is Dean of the LCS Smith College of Engineering and Computer Science at Syracuse University. Her research on the effects of extreme events on infrastructure and community resilience has been published in such journals as *Natural Hazards Review*, *Earthquake Spectra*, and *Urban Affairs Review*.

Nicholas Santella is a research associate in the Department of Environmental and Civil Engineering at Southern Methodist University. His research focuses on infrastructure modeling and environmental protection.

Kyle Parks is a graduate student in the Department of Environmental and Civil Engineering at Southern Methodist University. He is pursuing research on the protection of water distribution infrastructure.

References

Conrad, S. H., LeClaire, R. J., O'Reilly, G. P., & Uzunalioglu, H. (2006). Critical national infrastructure reliability modeling and analysis. *Bell Labs Technical Journal*, *11*(3), 57–71.

Fair, J. M., LeClaire, R. J., Wilson, M. L., Turk, A. L., DeLand, S. M., Powell, D. R., et al. (2007). An integrated simulation of pandemic influenza evolution, mitigation and infrastructure response. Technologies for Homeland Security, IEEE Conference (May 16–17).

Gray, B. H., & Hebert, K. (2007). Hospitals in hurricane Katrina: Challenges facing custodial institutions in a disaster. *Journal of Health Care for the Poor and Underserved*, *18*(2), 283–298.

LeClaire, R., Pasqualini, D., Bandlow, A., Ewers, M., Fair, J., & Hirsch, G. (2007). A prototype simulator for infrastructure protection: An application to decision support for controlling disease outbreaks. *Proceedings of the 25th International Conference of the System Dynamics Society*.

Little, R. G. (2004). Holistic strategy for urban security. *Journal of Infrastructure Systems*, *10*, 52.

Mendonca, D., & Wallace, W. A. (2006). Impacts of the 2001 World Trade Center attack on New York City critical infrastructures. *Journal of Infrastructure Systems*, *12*(4), 260–270.

Min, H. J., Beyeler, W., Brown, T., Son, Y. J., & Jones, A. T. (2007). Toward modeling and simulation of critical national infrastructure interdependencies. *IEE Transactions*, *39*, 57–71.

Moore, D. A., & Kellogg, D. A. (2007). Infrastructure impacts and facility sighting issues during hurricanes. *Process Safety Progress*, *26*(2), 108–113.

National Infrastructure Protection Plan (NIPP). (2006). Introduction. Retrieved September 15, 2008, from http://www.dhs.gov/xprevprot/programs/editorial_0827.shtm

O'Rourke, T. D. (2007). Critical infrastructure, interdependencies and resilience. *The Bridge*, *37*(1), 22–29.

O'Rourke, T. D., Lembo, A. J., & Nozick, L. K. (2003). Lessons learned from the World Trade Center disaster about critical utility systems. In *Beyond September 11th: An account of post-disaster research* (pp. 269–290) (Special Publication 39). Boulder, CO: Natural Hazards Research and Applications Information Center, University of Colorado.

Pederson, P., Dudenhoeffer, D., Hartley, S., & Permann, M. (2006). Critical infrastructure interdependency modeling: A survey of U.S. and international research INL/EXT-06-11464. Retrieved August 15, 2008, from http://www.inl.gov/technicalpublications/Documents/3489532.pdf

Power, D. J. (2002). *Decision support systems: Concepts and resources for managers*. Westport: Quorum Books.