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Using Dynamic Bayesian Networks for Investigating the Impacts of Extreme Events

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1. Introduction

Investigating resiliency and interdependency of critical urban infrastructure has been the topic of interest in recent years (see for example, Zhang and Peeta 2011; Oh 2010). This is because of a surge in natural and man-made disasters over the last decade and limited resources available to cope with the resulting infrastructure failure. With an increased level of interdependencies among infrastructures, the potential for cascading failures are of a great concern. A cascading failure is one in which a failure in one infrastructure system causes the failure in one or more components of a second infrastructure (Rinaldi et al., 2001). Much of today's emergency preparedness research is heavily focused on what is considered by many to be the eight "critical" infrastructures: (1) Telecommunications, (2) Electric Power Systems, (3) Natural Gas and Oil, (4) Banking and Finance, (5) Transportation, (6) Water Supply Systems, (7) Government Services and (8) Emergency Services. Within the United States' transportation infrastructure systems, there exists approximately 5,000 public airports; 590,000 highway bridges; 120,000 miles of major railroad tracks; 2,000,000 miles of pipelines; 300 inland/coastal ports; 80,000 dams and 500 major urban public transit agencies. A large majority of these transportation infrastructure systems are highly interdependent with one another. The failure/collapse of one will more than likely cause the failure/collapse of another.

Urban infrastructure systems are vulnerable to a wide range of hazards from nature, technological errors, and human activities. Resiliency is connected with the recovery capacity of the infrastructure. These systems' interdependence introduce the added layer of uncertainty. Measures of resiliency are robustness, redundancy, resourcefulness and rapidity. Various classifications are used to define infrastructure interdependencies; however, classifications suggested by Rinaldi et al. (2001) are physical, geographic, cyber, and logical.

In this chapter we apply Dynamic Bayesian Networks (DBNs) for investigating resiliency and interdependency of critical urban infrastructure during extreme events. We study the decision framework for defining resiliency. We review different categories of modeling and performance measures of serviceability of the infrastructure in the face of extreme events.

2. Literature review

The word "resilience" is used in a variety of contexts and has been debated significantly since 1970. However, in light of terrorism threats and some natural disasters in the recent past, it is being studied in terms of the urban infrastructure. Resilient has also been connected with recovery capacity; for example, Primm (1984) suggested that it can be measured at the speed at which a system returns to its original state following an interruption.

Many approaches have been used to model infrastructure interaction including for example, agent-based models (Dudenhoeffer 2006), input-output models (Setola 2009), neural networks (Min and Duenas-Osorio, 2009) and scalable multi-graph methods (Svendsen and Wolthusen, 2007). As well as differing in their general approach, these methods differ widely in the type, size and number of networks being considered. The approaches can be combined in a collective model where different infrastructure networks are encompassed in a single model structure or a distributed type where each network is modeled separately and the results are passed between the models according to some mediating mechanism.

Agent-based models are computer simulations of systems where entities called agents are used to represent the behavior of system components. One notable example of agent-based modeling applied to the area of interdependent infrastructure is the Critical Infrastructure Modeling Software (CIMS) developed by a group at the Idaho National Laboratory (Dudenhoeffer et al., 2006). Input-output inoperability models (IIM) are financial models that have been used for analyzing the cascading effects in critical infrastructure systems (Setola et al., 2009). IIM uses inoperability levels to describe the state of each infrastructure network. A neural network is a collection of densely interconnected simple computing units called artificial neurons loosely based on the architecture of the human brain. Neural networks have been used for reliability analyses on interdependent infrastructures (Min and Duenas-Osorio et al., 2009). Scalable multi-graph models (Svendsen and Wolthusen et al., 2007) have been proposed as a means of representing both services that are consumed instantly (e.g., electricity and telecommunications) and those that exhibit buffering (e.g., water and gas) in the same model structure. The research group at the Idaho National Laboratory (INL) undertook a review of the state of the art in modeling critical infrastructure interdependencies in 2006. The group identified 30 modeling systems that could be applied to the interdependencies of critical infrastructure (Pederson 2006).

The Bayesian Network (BN) has recently become a popular method for coding uncertainty (see for example, Jha 2009). The use of BNs was proposed as an alternative approach to modeling the interdependencies of critical infrastructure (Buxton et al., 2010). Because an important feature of a BN model is the bidirectional reasoning that is a natural function of this model, it appears that modeling interdependent infrastructures works well with this concept. An infrastructure interdependency is a bidirectional relationship between two or more infrastructures through which the state of infrastructure A influences or is correlated to the state of infrastructure B, and vice versa (Grubesic and Murray, 2006).

Dynamic Bayesian Networks (DBNs) are extensions of BNs that take the time varying natures of various events into consideration (Jha 2009); thereby, allowing the modeling of close to real-world scenarios more realistically. This paper explores the use of DBNs for modeling transportation infrastructure interdependencies while considering the resiliency of impacted infrastructure.

3. Resiliency and interdependency of critical urban infrastructure during extreme events

The resiliency and interdependency of critical urban transportation infrastructure needs to be carefully explored during extreme events. The impacts of a particular hazard may be indirect because of the weaknesses in infrastructure systems. For example, in the event of earthquake, few properties are destroyed by the actual shaking but many are destroyed by fire. This example illustrates how an independent system of linked relationships connects a hazard event with its ultimate outcome (Little 2002). When analyzed separately, the impact of one disrupted infrastructure system can be fairly estimated; however, interdependence introduces an added layer of uncertainty. The nature of interdependence can be a cascading failure, where a disruption of one infrastructure causes disruption of another; escalating failure, where a disrupted infrastructure prohibits the recovery of another infrastructure that failed earlier; and common cause failure, where a disrupted infrastructure system fails as a result of a common cause such as a natural disaster.

Power systems are perhaps the most important component of critical infrastructure because other systems require a continuous flow of energy to operate. Communications and information infrastructure includes linkages which move data from point to point. This also is critical during emergencies. Transportation is an important component of the urban infrastructure which facilitates the flow of goods in and out of an urban area. Water and Wastewater systems in the cities are old and their upgrades are essential.

Within the literature, there are several concepts for measuring resiliency. The resilience triangle quantifies the loss of functionality from damage and disruption emerges from disaster research (Tierney and Bruneau, 2007). The resilience triangle helps to visualize the magnitude of the impacts of a disruption on the infrastructure. The depth of the triangle shows the severity of damage and the length of the triangle shows the time to recovery.

Resiliency of transportation infrastructure needs to be carefully and precisely investigated during extreme events. Given the uncertainty surrounding the hazard variables such as location, frequency and magnitude, we cannot anticipate and prevent all disasters. However, the reliability in the continuity of infrastructure systems can be ensured by countermeasures.

The R4 framework of resiliency (Bruneau et al., 2003) defined four measures for resiliency:

- Robustness, which is the ability of systems, system elements and other units of analysis to withstand disaster forces without significant degradation or loss of performance;
- Redundancy, which defines the extent to which systems, system elements, or other units are substitutable if significant degradation or loss of functionality occurs;
- Resourcefulness, which is the ability to diagnose and prioritize problems and to initiate solutions by identifying and mobilizing material, monetary, informational, technological, and human resources; and
- Rapidity, which is the capacity to restore functionality in a timely manner, containing losses and avoiding disruptions.

For transportation infrastructure, resiliency measures the availability of alternate routes, the reduction in total delay, the adaptive use of high occupancy vehicle lanes, and the ability to transfer passenger travel to other non-single occupancy vehicle modes to free up highway and roadway capacity to maintain freight mobility (Giuliano and Golob, 1998).

4. Bayesian networks as a decision-making tool

One of the main reasons for lack of coordination and poor decision-making in the face of an extreme event is the inability of comprehending the multitude of information, to maximize the utility of the single decision that needs to be made. For example, a quantitative measure of the reduced Quality of Life (QOL) due to forced migration in the wake of hurricanes may be difficult to estimate. The timing of well thought out decisions also plays a critical role since delay in decision-making by a split second may have devastating consequences. This is true with any critical situation, such as during a war which can be won or lost with one right or wrong decision. Extensive research using game theory has been done in this area.

Bayesian Networks (BNs) have been extensively applied in problems where causality, uncertainty, and interdependence among variables plays a role (Jha 2006 & 2009). Using a BN offers many advantages over traditional methods of determining causal relationships. Using BN, independence among variables is easy to recognize and isolate while conditional relationships are clearly delimited by a directed graph edge: two variables are independent if all the paths between them are blocked (given the edges are directional). Not all the joint probabilities need to be calculated to make a decision; extraneous branches and relationships can be ignored. The BN algorithm can run in linear time (based on the number of edges) instead of exponential time (based on the number of parameters). The theory of BN is available in standard references and only presented here briefly (Gamez et al., 2004; Jasen 2001).

Consider a domain U of n variables, $x_1,....,x_n$. Each variable may be discrete having a finite or countable number of states, or continuous. Given a subset X of variables x_i where $x_i \in$ U, if one can observe the state of every variable in X, then this observation is called an instance of X and is denoted as $X = p(x_i \middle| x_1,...,x_{i-1},\xi)\vec{k}_X = p(x_i|\Pi_i,\xi)\vec{k}_X$ for the observations $x_i = k_i, x_i \in X$. The "joint space" of U is the set of all instances of U = $p(X = \vec{k}_X \middle| Y = \vec{k}_Y)$, which denotes the "generalized probability density" so that $X = p(x_i \middle| x_1,...,x_{i-1},\xi)\vec{k}_X = p(x_i|\Pi_i,\xi)\vec{k}_X$ given $Y = \vec{k}_Y$. For a person with current state information, $\xi\, p(X|Y,\xi)$ then denotes the "Generalized Probability Density Function" (gpdf) for X, given all possible observations of Y. The joint gpdf over U is the gpdf for U.

A Bayesian network for domain U represents a joint gpdf over U. This representation consists of a set of local conditional gpdfs combined with a set of conditional independence assertions that allow the construction of a global gpdf from the local gpdfs. One assumption imposed by Bayesian Network theory (and indirectly by the Product Rule of probability theory) is that each variable x_i, $\Pi_i \subseteq \{x_1,....,x_{i-1}\}$ must be a set of variables that renders x_i and $\{x_1,...x_{i-1}\}$ conditionally independent. In this way:

$$p(x_i \middle| x_1,...,x_{i-1},\xi) = p(x_i|\Pi_i,\xi) \tag{1}$$

A Bayesian Network Structure then encodes the assertions of conditional independence in Eq. (1) above. Essentially then, a Bayesian Network Structure, B_s, is a directed acyclic graph such that: (1) each variable in U corresponds to a node in B_s, and (2) the parents of the node corresponding to x_i are the nodes corresponding to the variables in $[Pi]_i$. A Bayesian-network gpdf set Bp is the collection of local gpdfs $p(x_i|\Pi_i,\xi)$ for each node in the domain.

4.1 Handling uncertainty

Uncertainty is an attribute of information. A review of literature (e.g., see Klir 2002; Higashi and Klir, 1983) dealing with uncertainty reveals that a highly original, unorthodox theory of human affairs involving uncertainty was conceived and developed by George Shackle, a British economist and philosopher in early 1900. Shackle introduced the possibility theory to handle uncertainty.

4.1.1 Possibility theory

While probability theory has traditionally been used to handle uncertainty, in recent works (Klir 2002; Kikuchi and Chakroborty, 2006) use of possibility theory has been advocated, a theory originally pioneered by George Shackle. Kikuchi and Chakroborty (2006) note that the distinction between the two theories (possibility and probability) is rooted in the type of information they handle, and how it is formalized in a functional form, the distribution. The probability distribution represents much more specific (rigid) information than the possibility distribution. It is characterized by the concept of propensity, or actual occurrence of events. The additive property of the probability distribution clearly suggests consistency in the evidential support.

The possibility distribution, on the other hand, is founded on the concept of disposition, which implies "judgment" in the feeling of "possibility," "achievability," "acceptability," and "capacity of the events to occur." The possibility distribution covers a set of "possible ranges," less precise information than the probability distribution. *Hence, it is natural that how to express ignorance and uncertainty is an important part of the possibility theory framework.*

The possibility and necessity measures of possibility theory constitute the upper and lower bounds of probability measure. Conceptually, this is because only the possible events can be probable (Smets 1998). With a better quality of information, the difference between possibility and necessity measures narrows and each converges to the probability measure (Kikuchi and Chakroborty, 2006).

The value of probability is interpreted as propensity of occurrence of an event in an objective sense; and hence, it clearly has application to risk and uncertainty associated with strategic decision-making to seek countermeasures in the face of a possible attack by an adversary or hostile country. The value of possibility and necessity, on the other hand, is associated with the sense of force or momentum to support a particular decision alternative. Its uses are suited to comparing (ordering) two situations, or understanding the degree of uncertainty or degree of support for an alternative.

Uncertainty plays a key role in understanding the resiliency and interdependency of urban infrastructure during extreme events. In order to handle uncertainty, an integrated framework can be proposed in which the probability distribution of the Dynamic Bayesian Network (DBN) can be represented by a possibility distribution. In seeking decisions to go from one stage to the next, randomized decision rules can be implemented, similar to that proposed by Berger (1980).

4.2 Early model development

A year before the 9/11 attack on the World Trade Center and the Pentagon, a simulation model, called Site Profiler, using Bayesian Networks, had predicted that the Pentagon was a likely terrorist target. On that occasion, no one took the mathematical prediction seriously enough to do anything about it. The rest, as you know it, is HIS-TO-RY! Site Profiler (Hudson, Ware, Blackmond-Laskey and Mahoney, 2000), was developed after the bombing of U.S. Air Force servicemen in Khobar Towers, Saudi Arabia, in June 1996, in which 20 persons were killed and 372 were wounded, and the August 1998 bombings of the U.S. embassies in Dar es Salaam, Tanzania, and Nairobi, Kenya, where a total of 257 people were killed and more than 4,000 wounded.

The user of this system would enter information concerning a military installation's assets through a question-and-answer interface very similar to that of a tax preparation software package (Site Profiler actually modeled its interface on the one used in Turbo Tax).

Site Profiler was distributed to all U.S. military installations around the globe to assist the site commanders by providing the necessary tools to assess terrorist risks, to manage those risks, and to develop antiterrorism plans.

This synopsis should tell us two (2) things. First, is that mathematics can be a very powerful tool for assessing terrorist risks. Second, is that we need to think very carefully before discounting the results that the math produces, no matter how far-fetched many of them may seem.

4.3 Software

Modeling BNs can be a very difficult task. A number of commercial software packages are available for developing BBN based models. The more popular ones are (1) Analytica (Lumina, 2004); (2) Netica (Norsys, 2005); (3) Hugin (Hugin Expert A/S, 2004) and GeNie (DSL, 2005). Each package has its own strengths and weaknesses.

The Netica software is used to model the real-life examples presented later. Before constructing the Bayesian Network, a conceptual model of the scenario should be developed. The conceptual model will allow for conditional relationships to be developed prior to entering this information into the Netica software. The concept of conditional probability is very useful because there are numerous "real-world" examples where the probability of one event is conditional on the probability of a previous event.

5. Characterization of an extreme event

In the financial world, extreme events are termed "extraordinary items" which are defined as unusual in nature **AND** infrequent in its occurrence (Kieso, Weygandt and Warfield, 2007). Using this information, let us define an extreme event as an incident, that is; (a) unusual in nature **AND/OR** (b) infrequent in its occurrence. In our definition, both (a) and (b) do not have to take place simultaneously for an event to be classified as "extreme." Let us explore this matter in more depth.

Unusual in nature can be characterized as an event that possesses a high degree of uncertainty, such as a large magnitude earthquake occurring in Washington, D.C.

Infrequency of its occurrence can be characterized as an event that does not reasonably expect to occur in the foreseeable future, using the example above, an earthquake of a magnitude of 6.0 or greater occurring in Washington, D.C.

While many extreme events have occurred here in the United States, no better incident meets this definition than the terrorist attack on the World Trade Center on September 11, 2001. Many citizens living on the East Coast of the United States view the occurrence of a major earthquake as something that is not of an immediate concern. Many do not worry about it because the long held belief was that it WILL NEVER happen here!

Well it did! This extreme event occurred on Tuesday afternoon, August 23, 2011. At approximately 1:53 p.m., the strongest earthquake to hit the state of Virginia since May 31, 1897 took place. With a magnitude of 5.9, this rare earthquake rattled almost the entire East Coast, turning a lovely and calm Tuesday afternoon into one of total chaos. Cellular phone service was jammed, area buildings were evacuated and police/fire emergency dispatchers could not keep up with all of the incoming calls!

Earthquakes on the East Coast are rare, but they do happen, and these earthquakes are often concentrated in certain areas. One such area is the Central Virginia Seismic Zone, where the August 23, 2011 earthquake occurred. Unlike the state of California or the continent of Japan, Virginia is not located near the edge of a tectonic plate. Although the bedrock in this zone has no major faults, it is loaded with smaller faults that occurred when the Appalachian Mountains were formed.

Although it has been 114 years since a major earthquake of this magnitude has occurred, the August 23rd quake was a stark reminder that we can no longer assume the Alfred E. Neuman attitude of “What, Me Worry?” So, what can we do? Is it possible to model such events and reduce the inadequacy of our preparations and the great losses associated with these extreme events?

6. Example studies

In this section, we present several examples to investigate the resiliency and interdependency of critical infrastructure in extreme events. The first is the Virginia earthquake example whose analysis is presented without examining resiliency and interdependency. In the second and third example, a Dynamic Bayesian Network is employed to perform the analysis. The second example is from a power failure in a subway system operated by the Washington Metropolitan Area Transit Authority (WMATA). The third example is related to hurricane planning and preparedness.

6.1 Virginia’s earthquake example

Can it happen again!? That was the question asked by many of the residents of the state of Virginia. Of course it can! But let us examine this in more depth. Since February 21, 1774, the state of Virginia has had only 20 (see Table 1) recorded earthquakes, ranging in magnitude from 1.9 (May 6, 2008) to 5.9 (May 31, 1897 & August 23, 2011).

Time	Number of Earthquakes
1700’s	1
1800’s	7
1900’s	6
2000’s	6

Table 1. Number of earthquakes in Virginia

Not shown in the above table is the fact that from 1774 to 1833 (59 years) there were no recorded earthquakes in the state of Virginia. Again, from 1975 to 2003 (28 years) there were no recorded earthquakes in the state of Virginia. This interval between earthquakes appears to have a rate of decay of 50 percent. It appears that the number of earthquakes in the state of Virginia is increasing. How!? Based on the table, it seems that the next earthquake will occur in the year of 2025. Using the year of 2011 as the benchmark and dividing 28 years by 2 and adding that number to the year 2011, we get the year 2025! But is that truly correct?

From 1774 to 2011 (237 years), there have only been 20 earthquakes in the state of Virginia. Given that information, there is an eight (8) percent [20/237] chance that the state of Virginia will experience an earthquake. That means there is a 92 percent chance that an earthquake will never occur. What about the earthquake's magnitude? Of the 20 earthquakes, only three (3) have had a magnitude greater than or equal to 5.0. That means there is only a 15 percent [3/20] chance of an earthquake having a magnitude of at least 5.0. There is an 85 percent chance that the earthquake will have a magnitude of less than 5.0.

Using the Bayesian method, let us try to answer the following question. What is the probability that the state of Virginia will have another earthquake with a magnitude of 5.0 or greater? Simple! Take the probability of Virginia experiencing an earthquake (0.08) multiplied by the probability of the earthquake having a magnitude of 5.0 or greater (0.15). To answer the question, there is a one (1) percent chance [0.08 x 0.15] that the state of Virginia will experience an earthquake having a magnitude of greater than or equal to 5.0. On the other hand, there is a 99 percent chance that the state of Virginia will experience an earthquake but with a magnitude of less than 5.0.

6.2 WMATA example

In order to illustrate this example, an artificial real-life scenario is constructed as follows: It is a clear and sunny Monday morning and you decide to take the WMATA metro subway system to work. You have an important 8:00 a.m. meeting and your boss is also attending. It is 7:10 a.m. and the train is moving from the Pentagon Station to Downtown Washington, D.C. via the "Yellow Line" (see Figure 1). In 10 minutes, you will be in the office. You will have enough time to get your coffee and to discuss the Washington Redskins victory over the Dallas Cowboys in yesterday's game.

Suddenly, the train abruptly stops! You hear the train operator say, "This train will be moving shortly!" Well, 15 minutes later, the train is still in the same position and the train operator again says, "This train will be moving shortly!" Suddenly, off go the lights! Everyone is in panic mode and you look at your cell phone and it is now 7:47 a.m.! You realize that you will not be making it to your meeting on time and you also notice that you have no cell phone service! You cannot even call the office and let them know where you are! An hour later you arrive in the office only to be met by the "steely" eyes of your boss and you decide it is not worth the trouble in trying to explain what in the heck happened.

The next morning you pick up the *Washington Post* and you read, "**Snake Cuts Power to Thousands of Pepco Customers**" (Hedgpeth, 2011). To your chagrin, the article states that five (5) circuit feeders were not working at a substation, leaving 6,800 customers without electricity and stranding several Metro trains. The article also quoted a Pepco spokesperson as saying, "The snake got stuck inside a breaker and was electrocuted!" Of course, your next reaction was, "How in the Sam Hill does something like this happen!?" "Aren't these people supposed to be prepared for anything!?"

Fig. 1. Map of the WMATA Rail System (courtsey of www.wmata.com)

Although the above story is fictional, the facts concerning the power failure are real. No Metro trains were stranded on that day. That information was only included to round out the story.

6.2.1 Constructing the Dynamic Bayesian network

A conceptual model of the above example is created as shown in Figure 2. Several extreme event scenarios are created using the WMATA example. First, if there is no power outage (see Figure 2), there is a 92.3% chance that the Metro trains and its passengers will **NOT** be stranded. But, a funny thing happened when the scenario was switched! If there is a power outage (see Figure 3), there is a 96% chance that the power outage is weather-related and there is a 92.3% chance that the Metro trains and its passengers will **BE** stranded.

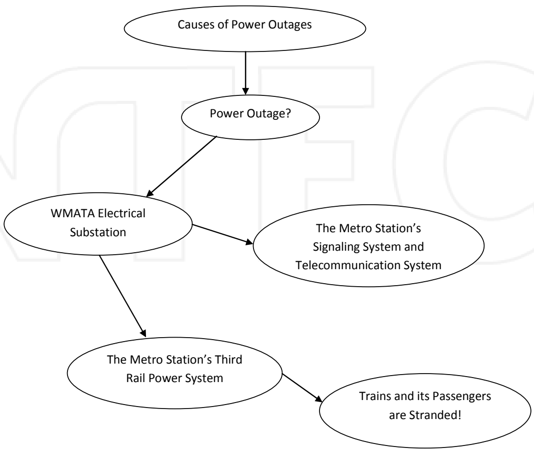

Fig. 2. A conceptual extreme event model for the WMATA example

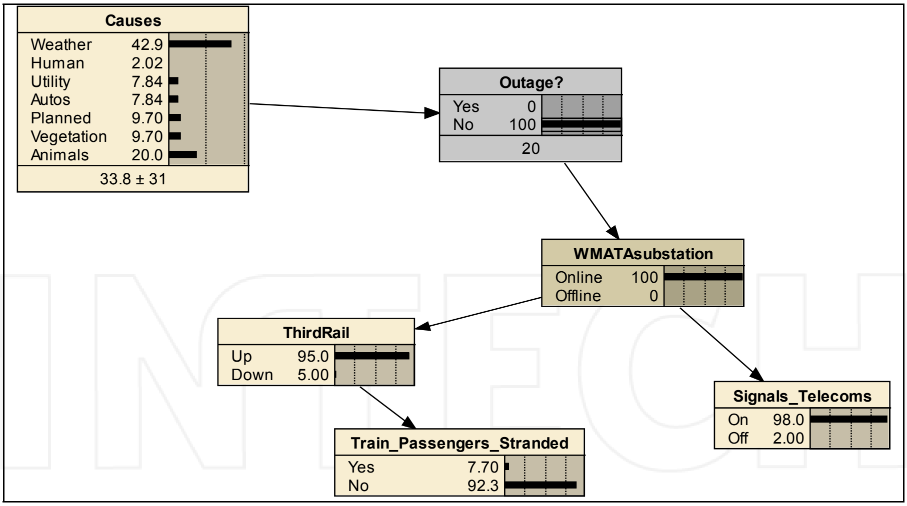

Fig. 3. A Dynamic Bayesian Network (DBN) with **NO** power outage

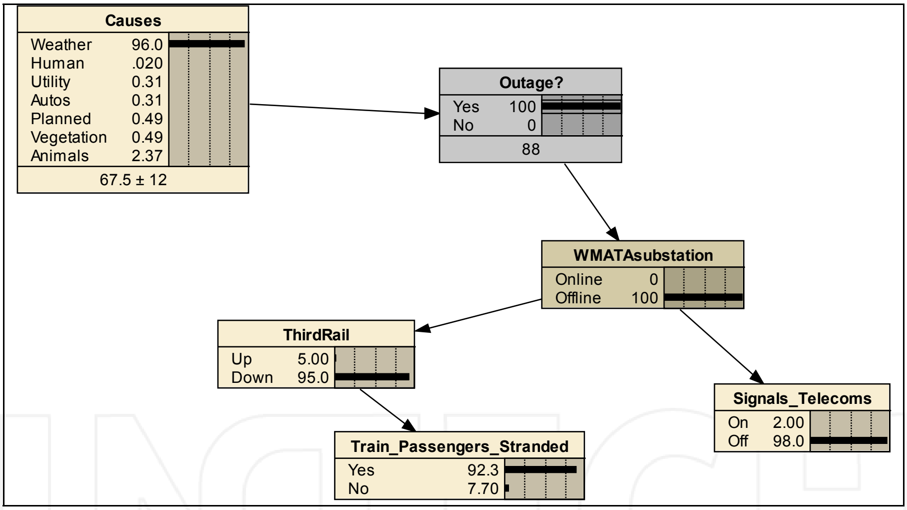

Fig. 4. A DBN with power outage

Although many approaches have been used to model infrastructure interdependencies, it was demonstrated, in principle, that DBNs can be used for modeling and evaluating interdependent infrastructures. In addition, the use of the Netica software allows for the modeling and evaluating of complex transportation infrastructure interdependencies. As we build newer systems, the complexity of these systems is steadily increasing and becoming more and more interdependent. Also, the operation of these systems is so complex that it defies the understanding of all but a few experts, and sometimes even they have incomplete information about the system's potential behavior. But, with the use of DBNs, modeling these complexities should become much easier in the future.

6.3 An example of hurricane planning and preparedness with a DBN

In the case of an impending hurricane a DBN can be used to plan for evacuation and displacements based on a threshold value of the probability of the extent of the disaster. Consider the case of hurricane Katrina which had multiple decision-makers with multiple perceptions of the impending disaster. Moreover, in the case of Katrina it was not clear who had the authority to order evacuations as necessary. Weather prediction centers, such as the hurricane center in Miami generally do a very good job in plotting the path of the impending hurricane and its severity. We can attach a probability of severity due to an impending hurricane using the weather predictions over a planning horizon.

An application of a Dynamic Bayesian Network for predicting the Quality-of-Life (QOL) of displaced citizens due to a hurricane, such as Katrina is shown in Figure 5. It represents a Directed Acyclic Graph (DAG). Figure 5 legends are shown in Table 2. If comprehensive

Legend	Explanation
Weather Forecast	Time-dependent weather forecast that predicts the category of a hurricane and its path
Contingency Measures	Contingency measures in place in the wake of an impending hurricane
Decision Maker's Action	Measure of coordinated response of decision-makers in the face of an impending hurricane
Damage Severity	Damage caused by a hurricane, measured in three categories: low, medium, high
Quality-of-Life Measure	Extent of degradation in the quality-of-life of displaced population

Table 2. Figure 5 Legend

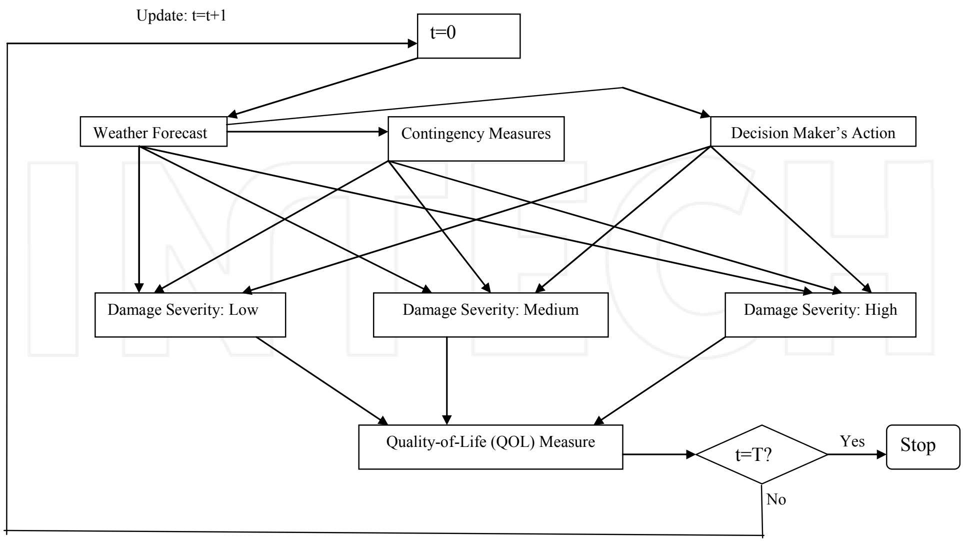

Fig. 5. A DBN Application for Hurricane Evacuation and Planning

data were available the DBN shown in Figure 5 is capable of estimating the QOL of the displaced population and also relative effectiveness of contingency measures and decision maker's actions. A sensitive analysis can also be conducted if additionl data were available. Having such a tool will allow decision-makers to take timely and coordinated measures in the wake of an impending hurricane to minimize the degradation of the QOL of displaced population.

7. Conclusions and future works

In this Chapter, we discussed the resiliency and interdependency of critical urban infrastructure systems in extreme events, and showed the applicability of Dynamic Bayesian Networks (DBNs) in examining resiliency and interdependency of such systems through a series of examples. The key contribution of our work lies in the critical analysis of extreme events and their impact on urban infrastructure systems and recognizing DBN as a valuable tool to model resiliency and interdependency.

In future works, a planning model can be developed using the DBN and a simulation tool, for a robust and sustainable community hard hit by catastrophic natural disasters. Such a model can:

- Measure the relative vulnerability of different geographic regions of the world to some key natural hazards, such as earthquakes, hurricanes, and floods.
- Identify development factors that contribute to risk, and show in quantitative terms, how the effects of disasters could be either reduced or exacerbated by policy choices.
- Demonstrate the ways in which development contributes to the configuration of risk and vulnerability.
- Provide quantitative evidence to advocate for the reorientation of development policy and planning in a way that contributes to the management and reduction of disaster risk.

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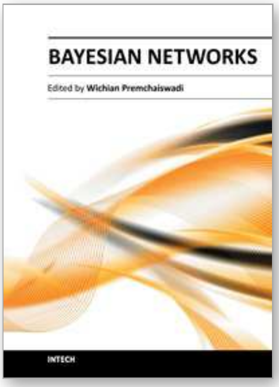

Bayesian Networks

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Bayesian Belief Networks are a powerful tool for combining different knowledge sources with various degrees of uncertainty in a mathematically sound and computationally efficient way. A Bayesian network is a graphical model that encodes probabilistic relationships among variables of interest. When used in conjunction with statistical techniques, the graphical model has several advantages for data modeling. First, because the model encodes dependencies among all variables, it readily handles situations where some data entries are missing. Second, a Bayesian network can be used to learn causal relationships, and hence can be used to gain an understanding about a problem domain and to predict the consequences of intervention. Third, because the model has both causal and probabilistic semantics, it is an ideal representation for combining prior knowledge (which often comes in a causal form) and data. Fourth, Bayesian statistical methods in conjunction with Bayesian networks offer an efficient and principled approach to avoid the over fitting of data.

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