FUZZY SIMULATION FOR INFRASTRUCTURE EFFECTS UNCERTAINTY ANALYSIS

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ABSTRACT
In this paper we propose a method for conducting infrastructure effects-based modeling in uncertain environments. Critical infrastructure is composed of intertwining physical and social networks. Events in one network often cascade to other networks creating a domino effect. This cascading effect is not always well understood due to uncertainties in the multiple levels of effect. To account for these uncertainties, we present a method using fuzzy finite state machines (FFSM).

Keywords: fuzzy simulation, critical infrastructure, decision support system, interdependency modeling

1. INTRODUCTION AND MOTIVATION

Critical infrastructure in the United States is defined as "systems and assets, whether physical or virtual, so vital to the United States that the incapacity or destruction of such systems and assets would have a debilitating impact on security, national economic security, national public health or safety, or any combination of those matters. " (U.S. Congress 2001) The categorization of such infrastructures varies slightly between countries, but is consistent in principle. The U.S. Government breaks the infrastructure into thirteen individual sectors:

- Agriculture;
- Food;
- Water;
- Public Health;
- Emergency Services;
- Government;
- Defense Industrial Base;
- Information and Telecommunications;
- Energy;
- Transportation;
- Banking and Finance;
- Chemical Industry; and
- Postal and Shipping. (Clinton 1996)

Sectors in turn contain individual infrastructures such as highways, rail systems, electric power generation and distribution, etc. Some of these systems are managed by government agencies, but the majority resides with industry. These infrastructures are characterized by a complexity of intertwined relationships that exist due to such factors as growing technological connectivity and economic requirements for distributed operations.

While this interconnectivity has increased information exchanged and improved efficiency of operations, it has also resulted in a potential chain of effect such that when a system is acted upon by an external force, it causes a domino effect or rippling of reaction not only within its own sector, but across multiple dimensions of infrastructure.

Effects Analysis, also referred to as effects-based and interdependency analysis, centers on gaining understanding on the resulting chain of effect that results when a system is perturbed by an event. While system dynamics may be well modeled and understood along individual infrastructures, such as in an electric power grid model or a water distribution model, how multiple infrastructures interact and affect each other, especially in light of upset conditions challenge current day understanding. Primary effects of an event are most often immediately observable and understandable; the subsequent chains of events that occur are less understood. The lack of appreciation for these second order, third order, n-order effects pose a serious problem for decision makers and responders in the event of global, national, and local event response.

A common method of representation for the systems of study in Effects Analysis is to use a directed graph or digraph and observe impact propagation. The system is decomposed into a set of key assets, and interdependent relationships, which in turn are modeled in a directed graph G(N,E) where N, the set of nodes, represents key assets, and E, the set of edges, represents the relationship between nodes. The system itself may represent functionally, physically, or behaviorally related group of regularly interacting or interdependent elements; that group of elements forming a unified whole.

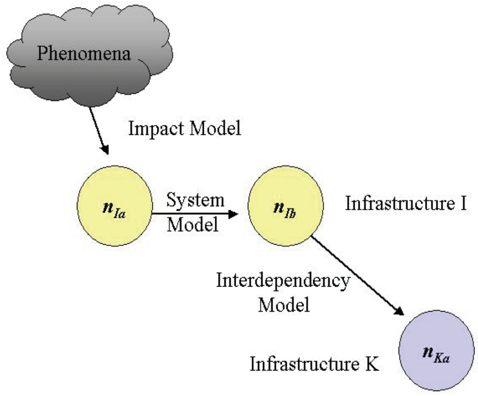

Figure 1: Chain of effects from phenomena to emergent impact

1.1. Uncertainty

To better understand these issues and representation, let n_{Ia} and n_{Ib} $\in$ N be interconnected system nodes from infrastructure I, and the supplier of some resource or influence. Further let n_{Ka} $\in$ N be a system node from infrastructure K and the consumer of that resource with edge $e(I_b,K_a)$, $\in$ E representing the resource flow between the two nodes. Interest therefore arises when a phenomena or event disrupts infrastructure I, causing a cascading effect into infrastructure K as illustrated in Figure 1.

Such analysis, however, is complicated by uncertainty. This is truly a system of systems model and may incorporate various sub-models to represent the nature of the phenomena, the impact that the phenomena has on an infrastructure system, the infrastructure system model itself, and finally an interdependency model that captures the relationship between different infrastructures.

At each of these system layers or models, uncertainty can exist. Further, this uncertainty may be very difficult to identify and thus quantify. As an example consider the attempt to model the impact of hurricane wind damage on housing structures and predict the subsequent impact on not only the individual structures, but on electrical power, and on population mobility trends during and immediately after the impact event.

Wind damage models may be employed to estimate the potential damage to physical structures. This information can be represented in the form of a damage matrix, Table 1, or a damage curve, Figure 3. This damage matrix developed by Filliben et. Alt. (2002) list the probability of damage to a residential structure broken down by loss or roof and by total

Table 1. Damage Matrix for Residential Housing

v mph		90	100	110	120	130	140
R	P(R/v)	0.03	0.2	0.5	0.8	1.0	1.0
C	P(C/v)	0	0	0.02	0.05	0.2	1.0

Several issues arise from using this information in an infrastructure effects model.

1. Damage predictions are usually based on models utilizing either generic specifications or on the actual infrastructure in a specific area. In the first case, damage predictions on basic structural requirements do not account for the specifics of geographical areas. Conversely, in the second case, modeling for specific geographical areas, does not necessarily capture features outside of that area.
2. While absolutes can be modeled with high confidence, intermediates states are more difficult to ascertain.

Additionally, the primary effect may not be the main issue of concern, but a subsequent emergent behavior might be the focus of analysis. Consider the case of wind damage in a residential community. A driving concern to emergency coordinators and responders, may not be the damage itself, but the mobility patterns of the residents and the effect that changes in infrastructure plays, i.e. when do residents vacate and return? In this case, wind damage may be only one consideration to residential mobility. Other factors may include electric power, proximity to the event, availability of transport, etc…

As such, one can see that effects analysis modeling is wrought with multiple levels of uncertainty. The goal of effects analyses should not be the determination of a precise outcome, but it should be to identify a set of possible outcomes to a given event or series of events. It is with this consideration that we introduce fuzzy set theory and fuzzy simulation as a means to model sets of possible emergent effects.

2. FUZZY SIMULATION

2.1. Uncertainty in Simulation Models

Computer simulation is the attempt to gain understanding of real work phenomena that are too complex for strictly analytical evaluation. A computer simulation uses a mathematical model to represent the object system, initial conditions (i.e. an initial data sets and assumptions on system state) are established, and one or more iterations of the simulation are run to gain understanding on system performance.

While the use of computer simulation continues to grow, it is important to understand the issues and limitations associated with its use. Specifically, some potential disadvantages include:

- A stochastic simulation only produces an estimate of a systems true characteristics based on a set of initial inputs (Law and Kelton 1982)

- It is possible to place too much confidence in the result of a simulation's outcome. If either the underlying model or the data is incorrect, then the results of the simulation will reflect a level of uncertainty. (Law and Kelton 1982)
- The demand for numerical precision and measurability may lead to over simplification and approximation also introducing uncertainty (Anglani 1998)

Aló et alt (2002) further emphasizes the above points in stating that in modeling decision making under uncertainty, it is often the case that the decision maker does not know or have full understanding of the true "state of the world" surrounding his/her decisions. Further, this lack of knowledge may also include the lack of probabilistic data associated with the potential states of the world. These limitations, however, do not diminish the value that computer simulation adds in system understanding. The key then is to both comprehend and mitigate these potential drawbacks. This paper focuses on a method to capture the multiple levels of uncertainties associated with infrastructure effects modeling.

Current simulation techniques to mitigate uncertainty in modeling and simulation results include the use of confidence bounds on simulation results. Multiple methods can be employed to establish and minimize these uncertainty bounds including conducting large numbers of stochastic simulation runs, analyzing input data precision, and incorporating model uncertainty into the final output. The method that we propose for infrastructure effects modeling is the use of fuzzy set theory not only to capture uncertainty, but to preserve the nature of the uncertainty throughout the simulation process.

2.2. Fuzzy Simulation Integration

The integration of fuzzy set theory into simulation has been proposed and demonstrated in earnest since the mid-1990's. Anglani et alt (1998) used fuzzy sets by to model the uncertainty of the time interval between events in a discrete simulation. He states that the integration of fuzzy sets into simulations allows the formulation and solution of problems whose complexity or simply the lack of state knowledge inhibits the use of traditional mathematical models in solution development.

Sevastjanov and Rog (2003) likewise used fuzzy sets to model the interval between events over the more traditional approach of a probabilistic distribution of times for events in a logistics simulation. Hullermeier (1996) citing that the knowledge of dynamical systems is often vague or ill defined, applied fuzzy set principles in developing a differential equation model for the prediction of object trajectory in spatiotemporal reasoning. Still, however, the application of fuzzy principles has not been readily adopted in all simulation application areas.

To support infrastructure effects analysis, we propose the application of fuzzy finite state machines (FFSM) to model asset state in infrastructure modeling. At the simplest level a finite state machine can be described as "a collection of inputs, a collection of outputs, and a finite collection of states, which describe the effect of the various inputs signals." (Wilson and Watkins 1990). More precisely given the current state and a set of inputs, the finite state machine, based upon a defined rule set, determines the next state, and maps input signals to output signals. A FFSM is the implementation of the principles of a finite state machine, but allows the system to deal with the reality of non-precise or non-crisp sets of state, inputs, and outputs. One of the first descriptions of FFSM's implementation was by Grantner and Patyra (1993) which described the used of fuzzy logic state machines in VLSI implementation. A more recent work by Grantner et alt (2000) described the use of FFSM in addressing ontological control problems and recovery actions in large PC-based systems.

3. MODEL DEVELOPMENT

As discussed in Section 1, one issue in modeling phenomena impact and the subsequent effects is that the impact that a trigger event imparts on an infrastructure item may not be precisely known in terms of both immediate and lasting influence. Multiple methods exist to capture this uncertainty. One method may be to use a probabilistic distribution function model using the expected (i.e. average) effect or the worst-case scenario in modeling. The method that we propose, however, is the incorporation of fuzzy sets to capture the uncertainty of effect for individual events and further, to utilize this concept to carry forward uncertainty as effects cascade forward in time.

In addition to uncertainty associated with the effect of the trigger event, uncertainty may also exist as to the exact state of the entity or node in questions. Due to incomplete knowledge or immeasurable status, some states may not be fully understood prior to the need to model them. Examples include the physical status of a piece of equipment or facility that is neither under the direct control nor immediately observable by the modeler. Also consider the example of more subjective nodes such as public confidence or public opinion concerning particular topics. Aló et alt. (2002) discuss similar issues in while applying fuzzy functions to derive optimal decisions in uncertain environments.

The approach that we have taken is to define a node as the tuple: N(I, E, Sp , Sn, O, Fe, Fp) where

I = a nonempty finite set of input entities required for node operation
E = a nonempty finite set of trigger events
S_p = a nonempty finite set of present states
S_n = a nonempty finite set of next states
O = a nonempty finite set of output entities resulting from node operation (F_p)

F_e = the mapping of effect of a trigger event on the current node state S_p

F_p = is the node process associated with the transformation of input (I) to output (O) (i.e. State transition function).

Figure 2 illustrates this concept.

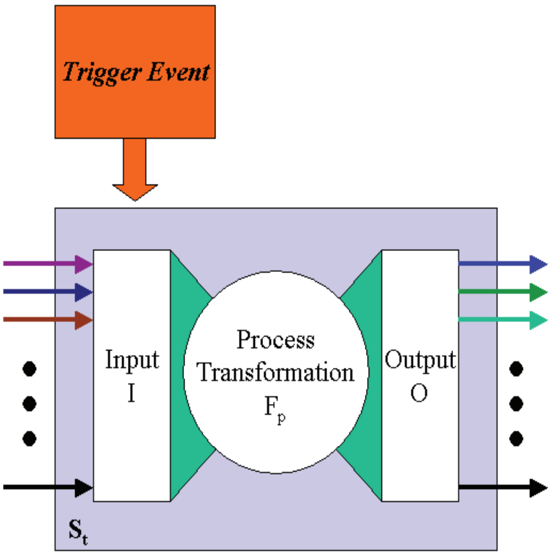

Figure 2. Node functional representation.

Consider the case where the effect of an event is not precisely known. We will model this uncertainty in the form of a fuzzy set and fuzzy mapping of consequence.

Let $S = \{s_1, s_2, s_3, \ldots s_n\}$ be the possible state of node N with $Sp \in S$ and $S_n \in S$. Let $E = \{e_1, e_2, e_3, \ldots e_m\}$ represent possible trigger events. High-level examples of trigger events may include fire, flooding, a tornado, component failure, human error, and malicious attack.

As defined earlier, F_e is the impact relation that a trigger event will have on the present state, S_p. Thus F_e: $S \times E \rightarrow S$. Note that the impact of an event depends not only on the nature of the event, but may also depend on the current state of the system. Under perfect conditions, this relationship would be precisely defined. In reality however, uncertainty often exists as the to exact nature of the effect. To account for uncertainty, define Ω_e as the set of fuzzy of potential outcomes (i.e. new states) that could result from an effect e. Further define μ as the membership function of S in Ω_e,

s.t. $\mu(s) =$ for s Ω (1)

$\mu(s) \in [0,1]$ for s Ω (2)

$$\text{So } \Omega = \{s_1/\mu(s_1), s_2/\mu(s_2), \ldots\ldots s_n/\mu(s_n)\}. \quad (3)$$

Membership values of μ(si) = 0 are not included in the set for brevity. Now the F_e function becomes a fuzzy mapping, F_e: $S \times E \rightarrow \Omega_e$ where Ω_e represents the uncertainty of effect for event e. Consider the following example. The node (i.e. asset of interest) is an electrical substation described by the following tuple: N(I, E, Sp , Sn, O, Fe, Fp) with

I = {0 (no electricity), 1(electricity)};
S = {0 (shutdown, requiring repairs),
1 (shutdown, no Input power),
2 (operational)};
O = {0 (no electricity), 1 (electricity)};
E = {0 (flooding to a level > 3 feet),
1 (fire in the substation),
2 (equipment failure),
3 (malicious attack),
4 (system repair)}

Fp is given in Table 1.

Table 2. State Transition Matrix

S_p	Input	S_n	Output
0	0	0	0
0	1	0	0
1	0	1	0
1	1	2	1
2	0	1	0
2	1	2	1

Consider a flooding event occurs that results in localized flooding to a depth of 3 feet at the substation of concern. Based upon damage analysis, the following impact matrix represents the state transitions that could occur over all possible initial states.

Table 3. Impact Matrix

Ω_e =

	$S_n = 0$	$S_n = 1$	$S_n = 2$
$s_p = 0$	1	0	0
$s_p = 1$	.8	.5	0
$s_p = 2$	.7	.5	.3

The rows represent the node's initial state and the columns represent the end state as a result of the event. The cells represent the membership value μ(s) for the combination (s_i, s_j). Further let the initial state be denoted by the following state matrix $S_p = [0\ 1\ 0]$ to represents the level of membership in the current state. The end state membership of the event then is denoted by $S_n = S_p \times \Omega_e = [.8\ .5\ 0]$.

While the end state of the substation is important, it is also important to examine this impact on other nodes within the interdependent network. Another aspect to evaluate is the effect on node output. Consider the mapping from S_n to O as described by O(s) = $[0\ 0\ 1]^T$. Then the uncertainty of output can be described by the following fuzzy set Ωo. Here Ωo =

[0/.7 0/.5 1/.3] which can be reduced to Ωo = [0/.7 1/.3].

The values of Ωo subsequently provide input to another node along the network and hence uncertainty is propagated down the system path.

4. PRELIMINARY RESULTS

As a proof of concept for the integration of fuzzy simulation into effects analysis, we constructed an infrastructure simulation utilizing fuzzy finite state machines. The framework we used for integrating the FSSM was CIMS© (Dudenhoeffer et alt 2006).

CIMS©, the Critical Infrastructure Modeling System, was developed at the Idaho National Laboratory to examine the interrelationships between infrastructure networks and more specifically, the emergent systems behaviors that develop when one or more nodes within the system are perturbed. A discrete event simulation, CIMS© uses an agent-based approach (ABM) (Rocha 1999) to model infrastructure elements, the relations between elements, and individual component behavior. The key characteristic of the agent and the simulations is that each agent exists as an individual entity which maintains a state, senses input, and possesses rules of behavior that act upon the inputs and either modify the state or produce an output. Each network within the simulation is modeled as a connected graph, G = (N, E), where N represents the nodes within the network and E represents the edges between the nodes. Edges also represent the relationship, i.e. interdependencies, between infrastructures.

The modification to CIMS© involved replacing deterministic process functions with a fuzzy transition table and a fuzzy state matrix. Additionally, where as before, input and output flow were crisp quantities, now they support passing fuzzy sets between nodes as input and output. Finally, CIMS© supports the insertion of events and the creation of event driven scenarios. This was modified to account for fuzzy effects from events. A nice feature of the FFSM integration with the CIMS© software package is that it allows the simultaneous modeling of both crisp and fuzzy relations.

The state transition algorithm used the Max-Min Composition relation (Tsoukalas and Uhrig 1997) to calculate the next state, as illustrated

$$R_1 \circ R_2 \equiv \int_{X\,x\,Z} \bigvee_{y} \left[\mu_{R_1}(x,y) \wedge \mu_{R_2}(x,z)\right] / (x,z) \qquad (4)$$

where R_1 is the initial system state including the current input matrix and R_2 is the state transition matrix. The resulting matrix is the next state matrix, which is then used to calculate the node's output.

Building States	Current			Next State					
	State	Power	Roads	0	1	2	3	4	5
0. Destroyed/Vacant	0	0	0	1					
	0	1	0	1					
	0	0	1	0.8	0.1				
	0	1	1	0.8	0.2				
1. Destroyed/Occupied	1	0	0	0.2	0.9				
	1	1	0	0.3	0.8				
	1	0	1	0.9	0.2				
	1	1	1	0.8	0.2				
2. Severely Damaged/Vacant	2	0	0			1			
	2	1	0			1			
	2	0	1			0.2	0.4		
	2	1	1			0.2	0.7		
3. Severely Damaged/Occupied	3	0	0			0.3	0.8		
	3	1	0			0.3	0.8		
	3	0	1			0.8	0.3		
	3	1	1			0.3	0.7		
4. Little to No Damage/Vacant	4	0	0					1	
	4	1	0					1	
	4	0	1					0.9	0.2
	4	1	1					0.2	0.8
5. Little to No Damage/Occupied	5	0	0					0.7	0.2
	5	1	0					0.3	0.6
	5	0	1					0.5	0.5
	5	1	1					0.2	0.9

Figure 3: Building/Facility Fuzzy State Transition Table

	Current		Next State			
Electric Power Distribution States	State	Power	0	1	2	Output
Component Damaged	0	0	1			0
	0	1	1			0
Component Operable, but no power	1	0		1		0
	1	1			1	1
Component Operable, with power	2	0		1		0
	2	1			1	1

Figure 4: Power Distribution Substation Fuzzy State Transition Table

The preliminary model developed to demonstrate the application of FFSM's in the simulation involves an evaluation of resident mobility given in a storm damage situation. Specifically we wish to evaluate the behavior of residents on evacuating their primarily residence. The work presented here does not reflect actual data to this point, but reflects a potential framework for evaluating this situation.

Given the area or interest, the first step was to model resident behavior in the form of discrete states. Here five states were identified for purposes of the simulation. Potential factors contributing to the decisions on occupancy that we incorporated into the model included electrical power and accessibility (i.e. roadway passage) to and from the residences. Figure 3 provides the transition matrix (R_2) used to determine the next state. The next states are represented in the table by their membership values. For example the transition from state 5 (Little or No Damage to residence, occupancy is maintained) given that Power is available and Roads are available $S_p \rightarrow S_n = \{4/0.2, 5/0.9\}$. Figure 4 represents the fuzzy state transition table for the electric substations.

4.1. Test Case

The simulation scenario centers on the impact of hurricane like winds in an urban setting. Figure 5 displays the subset of interest, which has been modeled using FFSM's in CIMS©.

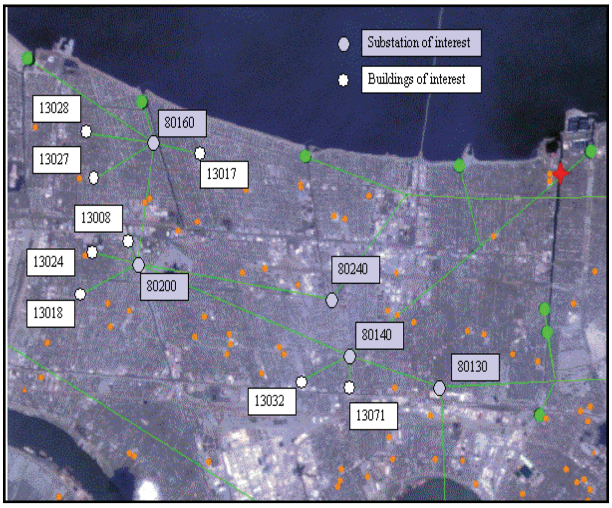

Figure 5: CIMS© network of fuzzy nodes and edges.

The primary nodes of interest are identified by their ID numbers in the figure and represent key facilities and electrical power substations. The green edges between then nodes represent the electric power supply to the facilities. The CIMS© framework with the fuzzy nodes and relationships allows the user to examine the propagation of uncertainty along system dependent relationships. Prior to this added feature, results were presented as crisp state output with no uncertainty representation.

Table 4. Run A – Base Case

80140 Substation Labarre	
state: 0 value:	0
state: 1 value:	0
state: 2 value:	1
Input power off:	0
Input power on:	1
NEXT STATE	
state: 0 value:	0
state: 1 value:	0
state: 2 value:	1
OUTPUT	
Power Off:	0
Power On :	1
13071 Saint Christopher School	
state: 0 value:	0
state: 1 value:	0
state: 2 value:	0
state: 3 value:	0
state: 4 value:	0.2
state: 5 value:	0.8
Input power off:	0
Input power on:	1
NEXT STATE	
state: 0 value:	0
state: 1 value:	0
state: 2 value:	0
state: 3 value:	0
state: 4 value:	0.2
state: 5 value:	0.8

Table 5. Run B – Fuzzy Impact Event

80140 Substation Labarre	
state: 0 value:	0.7
state: 1 value:	0
state: 2 value:	0.4
Input power off:	0
Input power on:	1
NEXT STATE	
state: 0 value:	0.7
state: 1 value:	0
state: 2 value:	0.4
OUTPUT	
Power Off:	0.7
Power On :	0.4
13071 Saint Christopher School	
state: 0 value:	0
state: 1 value:	0
state: 2 value:	0
state: 3 value:	0
state: 4 value:	0.5
state: 5 value:	0.5
Input power off:	0.7
Input power on:	0.4
NEXT STATE	
state: 0 value:	0
state: 1 value:	0
state: 2 value:	0
state: 3 value:	0
state: 4 value:	0.5
state: 5 value:	0.5

The first simulation run, Run A, is the base case, which shows all substations operating without event or disturbance. The purpose of this run was just to show the program consistency. Here Table 4 shows the results for two nodes, substation 80140 and building 13071.

The next run, Run B, illustrates the insertion of a fuzzy event at Substation 80140 which alters its state to $S_n = \{0/0.7, 1/0.4, 2/0.2\}$ and examines the propagation of the uncertainty of effect forward. The resulting impact on the substation and the cascading impact on Node 13071 is shown in Table 5.

5. CONCLUSION

In this paper we have discussed the research area of effects analysis and the challenges in modeling the uncertainty associated with unknown or imprecise cause-effect relationships. As one possible modeling tool, we demonstrated the application of fuzzy finite state machines to capture and propagate uncertainty across multiple effects. This principle was demonstrated in a simulation package called CIMS©. Preliminary results show that this has potential in providing decision makers with a means for better understanding the uncertainty and possible cause-effect paths resulting from infrastructure events.

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