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IMPROVING HOSPITAL EVACUATION PLANNING USING SIMULATION

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ABSTRACT

Hospital evacuation in the event of a hurricane is a complex and unpredictable process. Recent natural disasters have called attention to the importance of a timely evacuation plan. The success of an evacuation greatly depends on developing and evaluating alternative plans. However, there is no standard approach to address the issues of a hospital evacuation. This research describes the development of a simulation model and initial analysis to assess the effectiveness of an evacuation plan given different scenarios and resources.

1 INTRODUCTION

Hospitals are usually considered a safe haven and support system for the people involved in an emergency situation. As the foundation for many emergency response plans, hospitals are rarely considered subjects for evacuation. This research focuses on the event of a hurricane in which a hospital must decide to evacuate and relocate its patients and staff to nearby shelters.

The objective of our research is to propose simulation modeling as a tool to understand, analyze, and improve hospital evacuation plans. This research evaluates the effects of varying transportation, sheltering, and staffing plans for hospitals, while observing the effects on evacuation time and number of patients evacuated.

In surveying South Carolina and Florida hospitals, data were collected on the present state of evacuation plans. As of 2004, the Department of Health and Environmental Control in South Carolina requires all hospitals to develop and/or update their evacuation plans (DHEC 2004). However, risk managers have limited actual evacuations to aid them in refining and updating their hospital's plans. Some hospitals actually are forced to perform costly mock evacuations to evaluate many of the responses our research is modeling. We feel this research will benefit hospitals because simulation provides a method of testing many different scenarios over many replications to observe the outcomes that are critical to a successful evacuation.

Hospital evacuation planning involves several complex, interrelated steps. The evacuation process can be thought of as a set of activities, some of which are constrained by resources, but all of which must be completed for success. Taaffe and Tayfur (2006) propose optimization-based models that measure the ability to effectively evacuate patients from a hospital based on evacuation cost, clearance time and patient risk. Yet, with cost, time and risk as competing objectives, there is not one clear recommendation. Moreover, their work assumes all events and tasks during the evacuation are deterministic in nature. In addition to the uncertainties surrounding a hurricane event, the available resources for accomplishing an evacuation plan will be unique at any given time. While a mathematical programming approach may be applicable at a tactical level, there is a need for conducting simulation analysis to understand the interdependencies of operational-level decisions (Law and Kelton 2000). In this paper, we provide insight into these interdependencies through the use of simulation.

2 RELATED LITERATURE

Researchers have typically focused on general population evacuations as they pertain to the use of roadway infrastructure to move people away from a hazard (see, e.g., Sheffi et al. 1982, Pidd et al. 1996, Hobeika and Kim 1998, Franzese and Joshi 2002, Chang 2003, and Cova and Johnson 2003). Some researchers have addressed aspects of the evacuation problem such as decision making procedures (see, e.g., Tufekci 1995, Gladwin 2001, and Sorensen et al. 2004) and emergency preparedness training (Pollak et al. 2004), and Frantzich (1997) considers risk evaluation where hospitals serve as support for first responders. Vogt (1991), McGlown (1999), and McGlown (2001) even consider the decision-making process regarding evacuation of health care facilities and special needs populations. However, the problem of developing robust hospital evacuation plans using quantitative techniques is still largely unresearched. Taaffe et al. (2005) discuss the many issues and complexities inherent in not only hospital evacuation planning but also plan execution. Recently, the United States Government Accountability Office released a report that summarized preliminary observations of the issues surrounding health care facility evacuation due to hurricanes (GAO 2006). However, the report does not address how to improve, suggest, or implement more robust evacuation plans.

Consideration of hospital evacuation occurs when a threat to the population grows to include the hospital itself. However, the hospital under consideration is usually an integral part of a broader emergency response plan to deal with those injured or exposed to the threat, which could result in a decision not to evacuate despite the threat to the hospital. While hurricanes and floods were the primary concern for mass evacuation planning for many years, a more concentrated effort is now being given to hazardous material spills and terrorist incidents (see, e.g., Rogers 1994 and Lindell 2004). Broadening the number of possible threats expands both the scope of the problem and the number of hospitals which may be at risk.

One of the more difficult problems with transportation and sheltering plans is when the threat grows to include the "safe" facilities or hospitals. The U.S. hurricane season of 2004, for example, severely taxed resources both by direct impact and by the extent and frequency of the storms. It was not unusual for evacuees to find themselves the target of a storm after evacuation (Hoffman 2005). Given that hurricane-force winds can occur over a wide swath, there is a strong likelihood that multiple hospitals will undergo evacuation procedures (and each of these hospitals will be subject to potential critical systems failures). To date, there has been no documented research to address the logistics of such an evacuation.

3 MODELING HOSPITAL EVACUATIONS

As previously stated, Taaffe and Tayfur (2006) compare various resource and vehicle transport allocations for a hospital evacuation based on a deterministic optimization model. Due to the level of detail included in the model representing the evacuation decision-making process, it may become prohibitively difficult to formulate each decision mathematically. Even assuming that we can adequately represent each task or operation, we must also consider the variability in the duration of each of these sequential events that the hospital must complete during an evacuation. As a next step, this analysis could be extended to account for stochastic elements directly into the optimization model. However, this will not be a straightforward extension, and additional research will be required in this area. Instead, we incorporate the uncertainty of task duration and timing through the development of a simulation model. The next section presents the assumptions that were used in the analysis.

Based on data inputs and evacuation guidelines from several coastal hospitals in South Carolina and Florida, a model has been developed that determines the average evacuation time and the overall clearance (or evacuation completion) time, based on the parameters of a proposed evacuation plan. In this analysis, we only test a subset of possible representations, and alternative evacuation planning models are currently being investigated with input from the operators and risk managers at the hospitals. We selected our scenarios based on the operating conditions at Cape Canaveral Hospital (Florida) and Beaufort Memorial Hospital (South Carolina), both mid-sized facilities with 150-200 beds. It is assumed that there is one hospital for which we are evaluating its evacuation plan options. This hospital can send its patients, medical staff, and basic supporting equipment (e.g., IV hookups) to various sheltering facilities in the region. The logistics of transporting advanced medical equipment and supplies is omitted. Moreover, the sheltering facilities are assumed to be hospitals, and they will typically have most of the patients' medical equipment needs.

In this model, those patients who will be part of the evacuation plan are addressed. Also, all tasks related to preparing the patient for evacuation staging have been aggregated into a single stochastic delay. This could include preparing the patient for moving from the patient room, processing any/all paperwork regarding the move to a sheltering facility, moving to a first-floor staging area, etc. The evacuating hospital faces limited resources in terms of the number and size of transporting vehicles, staging area for transport, support staff to accompany transferred patients, and bed capacities at the sheltering facilities.

3.1 Model Structure

Using discrete-event simulation modeling, we can measure the effectiveness of evacuation policies by modeling human behavior and other stochastic decisions that may not be handled adequately in the optimization model. The goal is to design a set of experiments that systematically test alternate flows, staging, and scheduling of events during an evacuation. While there may be a universal set of experiments of interest regardless of the specific hospital being evacuated, there will still exist a need to study unique hospital characteristics to be able to accurately assess a plan's performance.

There are several approaches for model development, and we describe one potential methodology for incorporating the administrator/staff/patient decisions into the simulation. In Figure 1, we assume that there are three main areas of control within the evacuation process: storm control, patient / medical staff control, and administrator / risk manager control.

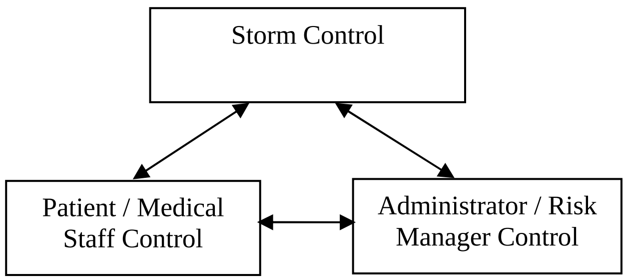

Figure 1: Simulation Model Structure

Using simulation, not only can we more accurately account for the stochastic nature of human decisions, but we can also characterize the uncertainty in the timing, severity and duration of the hurricane event, and provide 3- or 6-hour storm-track updates. It would likely have an effect on the speed at which an evacuation can be implemented, the time at which an evacuation is initiated, and the number of patients that can be safely evacuated. This functionality would be provided within the storm control function area.

Within the patient / medical staff function area, we will have the ability to monitor individual patient rooms and obtain evacuation status on each room (e.g., room occupied or not, patient type, evacuation decision (release, transfer, stay), and expected release or transfer time, if applicable). If there is additional patient/medical staff interaction that affects release or “ready for release” time, this information can be included in the model.

The third function area is administrator / risk manager control. This is a very important piece in the modeling process in that we can allow for *policy changes* in the midst of a hurricane event. This will provide hospital management with the ability to make decisions that change the responsibilities of doctors, nurses, and staff in how they are currently handling patients and the overall evacuation.

Ultimately, we would like to include appropriate detail in all of the control areas listed in Figure 1. In fact, most of the body of code has been included in the base simulation model. However, we have chosen to focus on the patient / medical staff control function for this first research paper on hospital evacuation.

We have developed the simulation model using the commercially-available simulation software package Arena, which is especially suited to representing process flows. We recognize that hospital evacuations can be influenced by the interactions of different persons (patients, nurses/staff, risk managers, and local emergency management personnel). As an area of future research, we plan to test the use of agent-based modeling as a means of more accurately representing these human behavioral decisions (see, e.g., Deadman 1999, Bonabeau 2002a, and Chen 2003). We may also be able to incorporate optimization within the simulation models that we develop. Highly detailed, discrete-event simulation models can run extremely slow, rendering near-term planning exercises fruitless. Through our extensive testing, we will incorporate the results and learning experiences into a more robust evacuation planning procedure.

3.2 Model Assumptions

We assume that there are three acuity levels. An acuity level 1 patient is denoted as any patient who is a candidate for early release, and these patients can expect to be released 24 hours earlier than normal to reduce the number that need to be transported to another facility. However, not all acuity level 1 patients will be released, based on any number of reasons where care cannot be provided away from the hospital. An acuity level 3 patient represents a critical care patient, such as those either waiting for or in recovery from a serious operation, or those that have an extreme ailment. All other patients would fall into the larger, middle group, which we denote as acuity level 2. There are no priorities placed on the order in which patients are evacuated (i.e., all three patient groups will be evacuated simultaneously based on the availability of the appropriate transport vehicles). In future research, we will recognize that certain acuity level 3 patients may require immediate evacuation to obtain the care that they need, possibly preempting a planned transfer of acuity level 1/2 patients.

Once a nurse is assigned to assist in transporting a group of patients, he or she will remain with the patients until the end of the evacuation to provide necessary care. Based on feedback from hospitals participating in the data collection effort, it is assumed that one nurse is required for every 5/5/2 patients of acuity level 1/2/3 for transporting patients.

In this model, there are three sheltering facilities, each of which can accommodate any of the patient types. We also include an overflow shelter to accommodate additional evacuated patients, when originally-anticipated shelter capacity is not provided for any number of reasons. The evacuating hospital can have up to 50 patients of each patient type, and the sheltering facilities are also assumed to have up to 50 beds available. Vans and ambulances are available for transport, and we will vary the number available across different experiments. Each vehicle can travel at speeds between 30 and 45 miles per hour, and all facilities are assumed to be 100 miles away from the evacuating hospital. We do not consider any costs in this model.

3.3 Model Detail

In this research, we are proposing simulation modeling as a tool to understand, analyze, and improve hospital evacuation plans. The model allows for adjusting any of the assumptions listed in Section 3.2 that provide input data or define a particular test scenario, including initial patient count prior to storm creation, nursing staff levels and allocation, evacuation transportation capabilities, and number of available shelters. The analysis provided in this paper will concentrate on evacuation times, both for individual patients and the overall evacuation completion time.

In modeling the hospital evacuation, we created five submodels that capture data input, patient control, evacuation, storm updates, and risk manager control. Within the data input submodel, the system creates patients and attaches each an array of assignments. Two important patient attributes are acuity level and expected release time. Based on either of these attributes, a patient may leave the hospital before evacuation begins. Also, according to acuity level, patients require a certain amount of time and staff members in order to evacuate the hospital.

Currently the number of staff members is pre-defined within the resource configuration. Each group represents a floor of the hospital and the corresponding patients by acuity level. For example, nurses assigned to floor 1 are responsible for acuity level 1 patients.

Patients continue to the patient control submodel which monitors room occupancy and patient evacuation status. After being assigned a bed, the patients wait for storm updates. If the patient's expected release time occurs before evacuation begins or within six hours of evacuation, then that patient prepares for release and exits the hospital system. Otherwise, patients will take part in the hospital evacuation. Additional patients can also arrive to the hospital prior to the evacuation, creating the ability to have an unpredictable number of patients at the beginning of an evacuation.

Our efforts have been focused on the evacuation process itself. First, each patient requires a nurse to move from a hospital room to the staging area, and the time to relocate the patients is a function of the patient's acuity level. Then, patients are divided into groups ready for transporting to shelters. Each group requires a nurse/staff member before proceeding to the loading area.

Depending on the patient's or group's condition, the amount of time and resources required to move the patient to the staging area and then load each patient onto a transport vehicle may range from a few minutes to nearly an hour.

As patients arrive to the staging area, they are assigned to travel to specific sheltering facilities. The current model utilizes two types of transport vehicles: vans for acuity levels 1 and 2 and ambulances for acuity level 3. Both types of vehicle types have the capacity to hold one batch or group of patients. If capacity is no longer available at the assigned shelter when the vehicle is ready to depart, the remaining patients travel to an overflow shelter with unlimited capacity. Once a van or ambulance arrives and unloads at a sheltering facility, it returns to the evacuation facility with similar transport delay times.

Once all patients are evacuated, the evacuation is declared complete, and an overall evacuation completion time is recorded. While this section does not present an exhaustive list of issues in this area, these are certainly among the most important. It is doubtful that any planning process will truly address all issues. However, the robustness of the plan will depend on solid coverage of the most essential issues.

4 EVACUATION MODEL RESULTS

In this section, we present the findings from the base model described in Section 3. We consider the following resource assignments in the base model:

10/10/25 nurses for acuity level 1/2/3 patients
3 shelters each with a capacity of 50 patients
1 overflow shelter with unlimited capacity
3 vans and 3 ambulances

For every test conducted, 20 simulation replications were run, all producing fairly low variation (reported half-width values in Arena were consistently less than one hour). This is due in large part to some simplifying assumptions that were made in the base model. Further model development will remove such assumptions, resulting in an even more stochastic environment to consider.

First, we tested several initial patient counts when using the resources defined for the base model, and the average evacuation times per patient and average completion times are reported in Table 4.1.

Table 4.1: Base Model

Patient Count	Avg. Evacuation Time (hrs)	Avg Completion Time (hrs)
50/50/50	40.4	65.1
40/40/40	31.1	47.6
30/30/30	24.0	36.5
50/40/30	31.5	46.5
30/40/50	36.2	65.3

The correlation between patient counts and evacuation times is not a major finding. Instead, the purpose of running each test was to observe the magnitude of the change in evacuation time across each test. Note that these patient counts represent hospitals similar in size to Cape Canaveral Hospital and Beaufort Memorial Hospital (input data sources from Section 2). Also note that these patient counts do not include the patients that could be released early (and, thus, did not require evacuation). For a hospital with 90 patients to evacuate, evenly split across all three acuity levels, the average evacuation time per patient is 24 hours, with an overall completion time of 36.5 hours. However, when increased to 150 patients (50/50/50 for acuity levels 1/2/3), the completion time approached three full days. The travel time assumptions are still quite liberal, which means that any additional delays on the roadways would only further exacerbate the delay in finishing the evacuation.

From the input data gathered, the critical task is transportation and not building evacuation. In other words, even if the hospital is evacuated more quickly, it would not change the patient evacuation times or evacuation completion time since transportation is the bottleneck. If, however, the transportation element can be reduced to requiring only a few hours, then the ability to efficiently prepare patients for evacuation would become increasingly important.

Note that the base model assumes only three ambulances and three vans. Based on the results, the bottleneck operation is the evacuation of acuity level 3 (critical care) patients. In order to gauge the effect of adding transport vehicles, we perform additional tests on each patient count. The new tests, shown in Tables A-1 – A-5 in the Appendix, report 12 combinations of initial vehicle requirements (including the base model). Increasing the number of ambulances has a greater positive impact than increasing the number of vans. Also, with fewer acuity 3 patients, the system approaches its optimal (minimum) evacuation time with a fewer number of vehicles. These results support the idea that acuity 3 patients create the bottleneck in the system and have the greatest effect on the results.

This simulation model has the potential to test other changes in resources. For instance, vehicle capacities may be varied to allow more or less patients per vehicle. Distance and travel times between the hospital and shelters can also be changed to demonstrate the impact of travel obstacles and shelter location relative to the hospital. Another variable to consider is the number of nurses for each type of patient. Holding the patient count constant, we can test the effect of the number of nurses assigned to each acuity level. In addition, we may vary the distribution of time required to prepare the patient for evacuation. The purpose of these additional tests would be to determine the resources with the greatest impact on the success of the evacuation, and these resources will be the focus for improving the system.

5 CONCLUSIONS AND FUTURE RESEARCH

In this paper, we proposed a simulation model as a method of understanding, analyzing, and improving hospital evacuation plans. The model utilizes resource requirement information to provide evacuation time data that can aid risk managers in making decisions regarding their hospital's plans for evacuation.

The base model has great potential to simulate the evacuation processes in an increasing amount of detail in future research. For example, new patients may not arrive to the hospital after the simulation run begins. However, the model has the potential to check in new patients, as long as the evacuation has not begun. New patients are assigned information regarding acuity and expected release time. If a bed is available, the patient enters the hospital; otherwise, the patient leaves the system.

In addition, a more advanced and accurate representation of staffing levels is under development at this time. This alternative process allows staff members to enter the system according to a hospital's current staffing schedule. The staff members are separated into different shifts and specific floor assignments.

While this research focuses on hospital evacuation due to hurricanes (where the evacuation can be planned), no-notice evacuation of hospitals would be an extension with great importance. Research on building evacuations in non-hospital settings would likely be included in such an extension.

APPENDIX: ADDITIONAL MODEL RESULTS

Table A-1: Alternative Test Set 1

TEST SET 1: Patient Count 50/50/50			
Num. of Vans	**Num. of Ambulances**	**Evacuation Time (hrs)**	
		Average per Patient	**Average Completion Time (hrs)**
3	3	40.4	65.1
3	6	37.6	56.4
3	9	36.8	56.2
3	12	36.4	56.0
	Average	**37.8**	**58.4**
5	3	38.8	65.4
5	6	35.8	49.7
5	9	35.0	49.6
5	12	34.7	49.6
	Average	**36.1**	**53.6**
8	3	38.1	65.3
8	6	35.2	48.3
8	9	34.3	48.0
8	12	34.0	48.0
	Average	**35.4**	**52.4**

Table A-2: Alternative Test Set 2

TEST SET 2: Patient Count 40/40/40			
Num. of Vans	**Num. of Ambulances**	**Evacuation Time (hrs)**	
		Average per Patient	**Average Completion Time (hrs)**
3	3	31.1	47.6
3	6	29.4	45.3
3	9	29.2	45.3
3	12	29.1	45.2
	Average	**29.7**	**45.9**
5	3	29.7	47.1
5	6	28.1	41.6
5	9	27.9	41.1
5	12	27.8	41.1
	Average	**28.4**	**42.6**
8	3	29.2	47.1
8	6	27.5	39.8
8	9	27.3	39.9
8	12	27.2	39.6
	Average	**27.8**	**41.6**

Table A-3: Alternative Test Set 3

TEST SET 3: Patient Count 30/30/30			
Num. of Vans	**Num. of Ambulances**	**Evacuation Time (hrs)**	
		Average per Patient	**Average Completion Time (hrs)**
3	3	24	36.5
3	6	22.6	35.3
3	9	22.5	35.3
3	12	22.3	35.3
	Average	**22.9**	**35.6**
5	3	23.1	36.4
5	6	21.8	35.3
5	9	21.6	35.4
5	12	21.4	35.4
	Average	**22.0**	**35.6**
8	3	22.7	36.3
8	6	21.4	35.3
8	9	21.2	35.4
8	12	21.0	35.4
	Average	**21.6**	**35.6**

Table A-4: Alternative Test Set 4

TEST SET 4: Patient Count 50/40/30			
Num. of Vans	**Num. of Ambulances**	**Evacuation Time (hrs)**	
		Average per Patient	**Average Completion Time (hrs)**
3	3	31.5	46.5
3	6	30.5	46.1
3	9	30.3	46.1
3	12	30.2	46.3
	Average	**30.6**	**46.3**
5	3	29.2	41.1
5	6	28.1	40.9
5	9	28.0	41.1
5	12	27.9	41.1
	Average	**28.3**	**41.1**
8	3	28.5	39.5
8	6	27.5	39.5
8	9	27.3	39.6
8	12	27.3	39.5
	Average	**27.7**	**39.5**

Table A-5: Alternative Test Set 5

TEST SET 5: Patient Count 30/40/50			
Num. of Vans	**Num. of Ambulances**	**Evacuation Time (hrs)**	
		Average per Patient	**Average Completion Time (hrs)**
3	3	36.2	65.3
3	6	32.5	47.1
3	9	31.6	45.1
3	12	31.3	45.0
	Average	**32.9**	**50.6**
5	3	35.3	65.1
5	6	31.6	46.9
5	9	30.7	41.7
5	12	30.3	41.4
	Average	**32.0**	**48.8**
8	3	34.8	65.1
8	6	31.1	47.0
8	9	30.2	41.5
8	12	29.9	41.3
	Average	**31.5**	**48.7**

REFERENCES

Chang, E. C. 2003. Traffic Simulation for Effective Emergency Evacuation [online]. March, 2003. <http://www.ictpaweb.org/publication/NCA/conferean03/Proceeding/074.pdf> [accessed July 6, 2006].

Cova, T.J. and J.P. Johnson. 2003. A network flow model for lane-based evacuation routing. *Transportation Research Part A* 37(7): 579–604.

Department of Health and Environmental Control (DHEC). 2004. Emergency Order – Evacuation Plans. State of South Carolina, August 30, 2004. <http://www.scdhec.net/hr/pdfs/licen/licgen/hleo.pdf> [accessed July 6, 2006].

Frantzich, H. 1997. Fire Safety Risk Analysis of a Health Care Facility. Department of Fire Safety Engineering, Lund University, October 11, 1997. <http://www.brand.lth.se/bibl/3085.pdf> [accessed July 6, 2006]

Franzese, O. and S. Joshi. 2002. Traffic Simulation Application to Plan Real-Time Distribution Routes. *Proceedings of the 2002 Winter Simulation Conference*. San Diego, CA.

Gladwin, C.H., H. Gladwin, and W.G. Peacock. 2001. Modeling Hurricane Evacuation Decisions with Ethnographic Methods. *International Journal of Mass Emergencies and Disasters* 19(2): 117–143.

U.S. Government Accountability Office (GAO). 2006. GAO-06-443R: Preliminary observations on the evacuation of hospitals and nursing homes due to hurricanes. February 16, 2006.

Hobeika, A.G. and C. Kim. 1998. Comparison of traffic assignments in evacuation modeling. *IEEE Transactions on Engineering Management* 45(2): 192–198.

Hoffman, M. A. 2005. Unusual hurricane season drives record tornado activity. *Business Insurance* 39: 4.

Law, A. and W. D. Kelton. 2000. *Simulation Modeling and Analysis*. 3rd Ed. New York: McGraw-Hill.

Lindell, M.K. 2004. Hazardous Materials. American Planning Association, Planning and Urban Design Standards, New York: John Wiley and Sons.

McGlown, K.J. 1999. Determinants of the evacuation of health care facilities. PhD Dissertation, University of Alabama at Birmingham.

McGlown, K.J. 2001. Evacuation of Health Care Facilities: A New Twist to a Classic Model. *Natural Hazards Review* 2(2): 90–99.

Pidd, M., F.N. de Silva, and R.W. Eglese. 1996. A simulation model for emergency evacuation. *European Journal of Operational Research* 90(3): 413–419.

Pollak, E., M. Falash, L. Ingraham, and V. Gottesman. 2004. Operational Analysis Framework for Emergency Operations Center Preparedness Training. In *Proceedings of the 2004 Winter Simulation* Conference, ed. R. G. Ingalls, M. D. Rosetti, J. S. Smith, and B. A. Peters, 839–848.

Rogers, G.O. 1994. The timing of emergency decisions: Modelling decisions by community officials during chemical accidents. *Journal of Hazardous Materials* 37: 353–373.

Sheffi, Y., H. Mahmassani, and W.B. Powell. 1982. A transportation network evacuation model. *Transportation Research Part A* 16(3): 209–218.

Sorensen, J. H., B. L. Shumpert, and B. M. Vogt. 2004. Planning for protective action decision making: evacuate or shelter-in-place. *Journal of Hazardous Materials* 109: 1–11.

Taaffe, K., R. Kohl, and D. Kimbler. 2005. Hospital Evacuation: Issues and Complexities. In *Proceedings of the 2005 Winter Simulation Conference*, ed. M. E. Kuhl, N. M. Steiger, F. B. Armstrong, and J. A. Joines, 943–950.

Taaffe, K., and E. Tayfur. 2006. Evaluating the Robustness of Hospital Evacuation Plans. Forthcoming in *Proceedings of the 2006 Industrial Engineering Research Conference.* Orlando, FL.

Tufekci, S. 1995. An integrated emergency management decision support system for hurricane emergencies. *Safety Science* 20(1): 39–48.

Vogt, B.M. 1991. Issues in Nursing Home Evacuations. *International Journal of Mass Emergencies and Disasters* 9(2): 247–265.

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