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Discrete-Event-Based Simulation Model for Performance Evaluation of Post-Earthquake Restoration in a Smart City

Abhijit Gosavi, Giacomo Fraioli, Lesley H. Sneed, and Nathaniel Tasker

Abstract—**Emergency responders are typically notified immediately after a major earthquake strikes. However, a time delay, called the travel time, is usually experienced between the notification and the arrival of the responders on the scene. The reparative work necessary after the responders arrive takes an additional amount of time, called the response time, depending on the nature of the damage and the volume of resources available. In a smart city, the restoration time, which is the sum of the travel and response times, should be minimized. A new discrete-event-based simulation (DEBS) model is presented in this paper to estimate the restoration time needed to bring the situation under control after notifying the response center. The DEBS model not only relaxes restrictive assumptions on travel time made by the Markov chain models from the existing literature, but it can also quantify the impact of resource volumes on restoration times. Additionally, the DEBS model is very useful for training purposes. The DEBS model was employed on a case study from the state of Missouri (U.S.). The experiments demonstrate that numerical results with the model take a short amount of computational time and that it can be implemented on a real-time basis in a smart-city infrastructure.**

Index Terms—**Earthquake, emergency management, smart city, training.**

I. Introduction

NATURAL hazards such as tornados, hurricanes, earthquakes, and volcanic eruptions are unavoidable and can become disasters causing extensive property damage and deaths of thousands of people, especially in densely inhabited areas. While each natural hazard tends to have its own unique characteristics, an earthquake generally triggers with a high probability a cascade of events from a gas leakage to a fire to a building/structural collapse. The final outcome may also involve flooding, especially if the affected area is near a sea or a major waterbody and if a tsunami is triggered or a dam or levee failure occurs. In this century itself, several major earthquakes have occurred, including the 2008 earthquake in Wenchuan, China, the 2009 L'Aquila earthquake in Italy, the 2010 earthquake in Chile, the earthquake in Haiti in 2010, the earthquake-tsunami in Japan in 2011, the 2011 earthquake in Christchurch, New Zealand, and the earthquake in Nepal in 2015.

The severity of these recent earthquakes indicates that there is a substantial need for developing a systematic disaster response and restoration plan for them.

When a major earthquake occurs, disaster management authorities dispatch resources, such as medical and rescue teams, firefighters, ambulances, medicines, water, and tents, to the affected area. Once the responders arrive on the scene, reparative efforts are directed toward evacuating the population affected and securing the area—thereby preventing further damage and avoiding secondary disasters that may follow the earthquake. Since resources are limited and must be deployed urgently, disaster managers need analytical tools that can help them formulate the best strategy for allocating resources to the affected area. Such analytical tools are especially useful for training purposes in which the analyst can change the volume of resources available to test its impact on the nature of the restoration plan [1].

The events that follow an earthquake are significantly different in terms of the time needed to address them. For instance, the four major events/incidents that are typical characteristics of an earthquake, namely gas leakages, fires, building/structural collapses, and flooding [2], have differences in *response times*, i.e., the time it takes the responders to conduct the reparative work described above, due to differences in the nature of the incidents.

A gas leakage can often be contained in a shorter time interval than a fire, while the response to a building collapse is likely to be more time-consuming. Flooding (e.g., due to tsunami waves or bursting of river banks) is the worst scenario in terms of the danger it poses to human lives and usually takes the greatest amount of time for response. Therefore, it is essential to account for each of these four incidents in a comprehensive model.

The cascade of the associated events in a major earthquake can be captured in stochastic models, such as the Markov chains, Brownian motion, renewal processes, or discrete-event-based simulation [3]. These models can help improve the understanding of the magnitude of damage that can occur and determine the volume of resources needed to bring the *situation under control*, i.e., to an acceptable state in which the injured have

Manuscript received December 20, 2018; revised March 20, 2019 and May 24, 2019; accepted June 27, 2019. This work was supported by the Intelligent Systems Cluster (ISC) at Missouri University of Science and Technology, Rolla, MO, USA. Review of this manuscript was arranged by Department Editor A. Solis. *(Corresponding author: Abhijit Gosavi.)*

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Digital Object Identifier 10.1109/TEM.2019.2927318

been taken to hospitals, and the roads necessary for emergency transportation have been cleared of debris. In the literature, work of this nature is often called *restoration*, which can take a few days, while reconstructing all the damaged buildings and structures is usually called *recovery* [4], which can take several years. The ability of stochastic models to accurately predict the *restoration time*, i.e., the time it takes from when the response center is notified until the situation is under control, depends on the input parameters considered as well as the quality of data available.

Recent advances in information and communication technologies have enabled the development of so-called *smart and connected cities*, or simply smart cities, in which information from sensors can be gathered and shared on a real-time basis to improve the quality of services. Smart cities are now a reality [5], and a study of the recent literature indicates that data gathered from sensors placed in strategic areas within smart cities help make them more livable and sustainable [6], [7], as well as reduce risk within the associated population [8]. Daniel and Doran [9] proposed the development of computer-based tools for the successful integration of real-time data from sensors into decision-making protocols for smart cities in order to enhance the coordination that must occur in between the different decision-makers and thereby improve the quality of life. For example, after an earthquake occurs in a smart city, gas lines and nuclear reactors could be automatically shut down, and readiness levels of fire/ambulance services could also be immediately raised. This requires a coordinated plan from emergency management personnel and city administration that necessitates using a broad announcement to the affected population (e.g., via cell phone text messages and radio announcements) for avoidance of hazardous roadways, as well as redirecting traffic through safer areas [10]. Sensors for detecting smoke, fire, and vibrations that are placed strategically in smart cities can ideally provide statistical data related to the dynamics of events that occur after an earthquake. This smart city data can then be employed to simulate the events that unfold via a simulation model capable of utilizing the data generated by smart cities.

This paper presents a new discrete-event-based simulation (DEBS) model that estimates the time needed to bring the situation under control (restoration time) for a given volume of resources under a variety of scenarios that can occur after an earthquake. The DEBS model 1) explicitly takes into account the time it takes to reach the affected area and the volumes of resources; and 2) accounts for all four major earthquake incidents enumerated above (gas leakages, fires, building collapsing, and floods). In addition, the DEBS model allows for exploring the relationship between the volume of resources and the expected restoration times, which can be used to optimize the volume of resources and study the differences that would result in the response from different emergency management centers. Finally, the simulation nature of the DEBS model makes it more easily implementable within a real-time smart city system in comparison to the computationally unwieldy Markov chain models of the past, discussed in the next section, which also do not consider the volumes of resources.

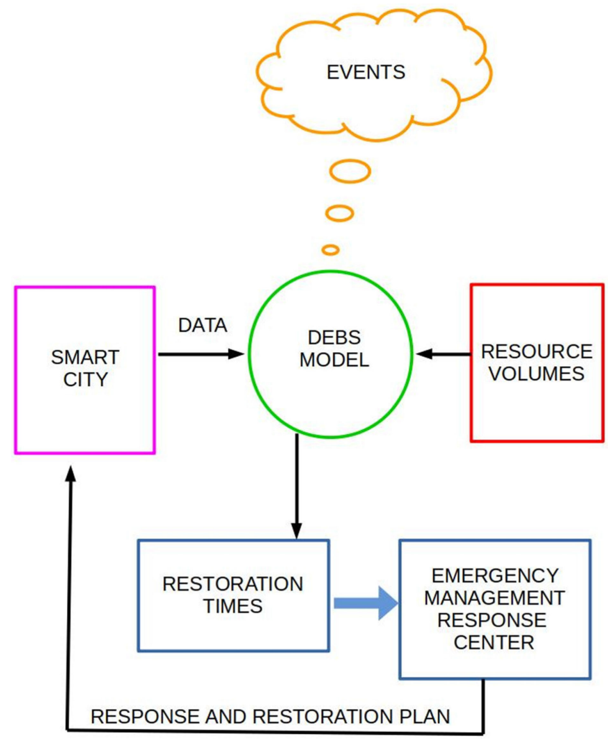

Fig. 1. Scheme for how the DEBS model would be utilized by the emergency management response center in a real-time basis in a smart city setting.

Fig. 1 is a schematic that demonstrates the DEBS model and how it can be employed in a real-time basis in a smart city setting. The sensors placed in strategic areas in smart city would feed data into the DEBS model, which could then be used to optimize the volume of resources needed and deliver a response and restoration plan that would enable the emergency management center to dispatch resources in appropriate volumes to the affected area.

The rest of this paper is organized as follows. Section II provides a background for this work, including a literature review. Section III formulates the problem. The numerical model and the experimental results are discussed in Section IV. Section V concludes this paper.

II. Background

One of the first models in the literature for emergency resources deployment via Markov chains was presented by Swersey [11], who applied a Markovian decision model to determine the number of units to dispatch after a fire. Study of the relationships between incidents such as fire, explosions, and toxic release as domino-effects, whose connecting probabilities can also be explicitly modeled, was presented by Delvosalle [12] and Khan and Abbasi [13] in the context of chemical processes. *Domino effects* are those phenomena that lead a system from a primary incident to a secondary incident, which has a magnitude that is the same as or higher (i.e., worse in terms of the danger it poses to the population affected) than the primary incident. Clini *et al*. [14] proposed mechanisms to model domino effects in industrial accidents. The study by Sekizawa *et al.* [15] is one of the first works to apply this concept for estimating the probability of fire after an earthquake. More recent models, such as those by Wei *et al.* [16] and Ghosh and Gosavi [10], have sought to build on these past works in terms of 1) using Markov chains as the underlying model and 2) employing probabilities for the domino effects (domino probabilities) that occur in the aftermath of an earthquake. Kammouh *et al.* [17] collected data regarding the damage, measured as downtime, caused by 32 different earthquakes to different infrastructures such as power plants, water systems, gas stations, and telecommunication systems with the purpose of developing restoration curves. The magnitude of the earthquake, as well as the level of development of the affected countries (considered as either developed or developing), was taken into account. Chang [18] studied an urban transportation-planning problem and developed a performance metric for the accessibility of an area in a post-earthquake scenario, but the work is not focused on measuring the restoration time or the domino effects. Nonetheless, these studies [17], [18] are useful references for future integration of urban data into simulation models for smart cities.

Past work closest to this research includes the studies by Fiedrich *et al.* [19], Wei *et al.* [16], and Ghosh and Gosavi [10]. Fiedrich *et al.* [19] used a combinatorial optimization model for resource allocation, but the focus of their work was on estimating the number of casualties, rather than on estimating the expected restoration time. Wei *et al.* [16] modeled a two-state Markov chain for the 2008 Wenchuan earthquake, but their model did not account for building collapse or flooding. Ghosh and Gosavi [10] used a model based on Markov chains for all four incidents, but because of the underlying semi-Markov process employed, some restrictive assumptions about the system were needed in terms of how its states evolve while the responders travel to the affected location. Those assumptions may introduce an inaccuracy in the estimation of the restoration times. In contrast, discrete-event simulation [20] is more flexible than Markov chains, which require the memoryless (Markovian) property to hold between state transitions; a property that is not always guaranteed in real-world settings and is an assumption often made to generate tractable mathematical models for estimating the response and restoration times.

Henson *et al.* [21] presented an activity-based model that is similar to a DEBS model but at a higher level from the modeling perspective and less detailed. Mishra *et al.* [22] presented a recent survey of simulation-based models like the DEBS model for disaster management. Mueller *et al.* [23] and Shi *et al.* [24] presented case studies of simulation-based modeling of disaster scenarios from India and China, respectively. However, these models did not study the restoration times needed for the analysis in this paper. The study by Alem *et al.* [25] was one of the first to measure restoration times, referred to as "lead times" in that work. Erdelj *et al.* [26] studied restoration times in the context of search and rescue, while Aros and Gibbons [27] made direct reference to disaster "response times," consistent with the study in this paper.

In summary, a study of the literature indicates a clear need for simulation-based models that can make realistic assumptions about travel times and resource volumes and deliver results that can be integrated online in a real-world, smart-city setting. This paper seeks to fill this gap via the DEBS model, which is explained in the next section.

TABLE I
DEFINITION OF EACH STATE MODELED IN THE SYSTEM

State (S)	Set of incidents contained in the state ($U(S)$)
1	{Stable}
2	{G}
3	{F}
4	{G , F}
5	{BC}
6	{G, BC}
7	{F, BC}
8	{G, F, BC}
9	{G, FL}
10	{F, FL}
11	{G , F, FL}
12	{BC, FL}
13	{G, BC, FL}
14	{F, BC, FL}
15	{G, F, BC, FL}

G = Gas Leakage; F = Fire; BC = Building Collapse; FL = Flooding

Note: States numbered 2 through 8 are the primary states, while states numbered 9 through 15 are the secondary states.

III. Problem Formulation

In this section, the underlying problem is formulated via the DEBS model. First, Section III-A presents the mechanism for state transitions that are experienced in the post-earthquake scenario. Then, Section III-B presents the DEBS model, which implements the state-transition mechanism.

A. State Transitions

The four basic incidents that the model will track are: Fire (F), Gas Leakage (G), Building Collapse (BC), and Flooding (FL). The so-called *state* is a combination of one or more of these incidents. The different states that the system can visit are defined in Table I. It should be noted that although the basic incidents considered in this work are the major incidents that are expected during an earthquake [2], other incidents (such as mudslides) are also possible depending on the area considered. The DEBS model presented in this work can be modified to incorporate additional incidents as applicable.

The system initiates in the stable state, where the system is assumed to be fully functional. When an earthquake occurs, the system evolves immediately in a probabilistic manner to any of the states numbered from 2 through 8 (see Table I). These states are herein referred to as the primary states. Then, after the system enters a primary state, the emergency management response center is contacted, and a decision is made regarding the volume of resources to dispatch to the affected area. Thereafter, the response center sends resources to the affected area. The

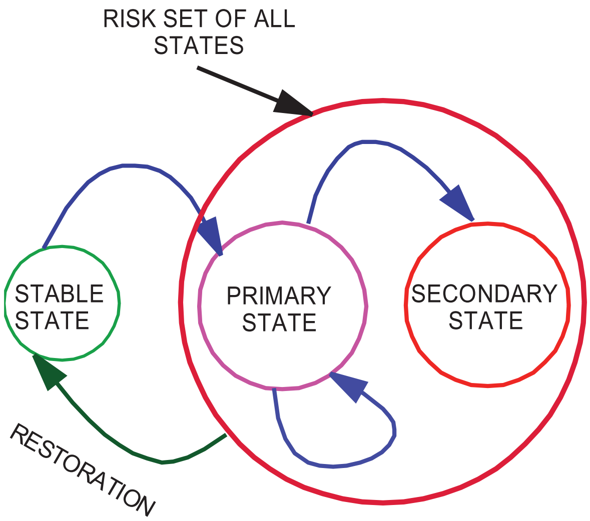

Fig. 2. Depiction of the different states visited by the system in the DEBS model. Note that the risk set is a union of the set of primary and secondary states, i.e., {2, 3, …, 15} in Table I.

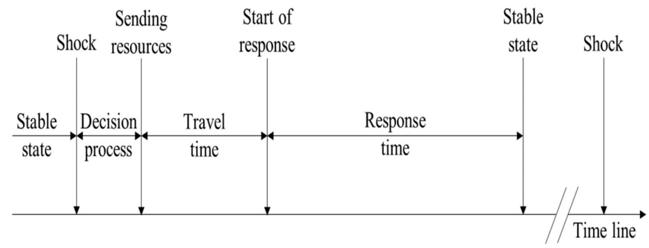

Fig. 3. Computerized timeline within the DEBS model, where one cycle is triggered by the earthquake shock and ends when the situation is brought under control (stable state).

resources arrive at the affected area after an amount of time called the travel time. By the time the resources arrive at the affected area, the system either remains in its own state (which is a primary state), or it transitions to one of the other primary states, or it advances to a worse condition (state). In the DEBS model, the worse conditions will be referred to as secondary states and will be represented by states numbered from 9 through 15 in Table I. The union of the set of primary states and the set of secondary states is called the risk set. Hence, the risk set is a finite set consisting of states numbered 2 through 15, and it contains all the states that pose danger to the population concerned. After the responders arrive, they bring the situation under control, i.e., the system returns from one of the states in the risk set to the stable state, after an amount of time called the response time, *RT*, which depends on the state in which the responders find the system when they arrive at the scene and on the volume of resources available.

It is worth noting that each of the states defined can be considered as either primary or secondary depending on the nature of the incidents contained in it. As an example, in Table I, states containing one or more of the three basic incidents, fire, gas leakage, and building collapse, are considered to be primary states, whereas states containing the flooding incident are considered to be secondary states. In general, a given state could be defined as a secondary state instead of a primary state if it results from a sequence of events (in the case of flooding, for example, a gradual levee failure followed by the progressively increasing flow of water to the area under study), which requires that a certain amount of time has elapsed before all the incidents in that secondary state appear. Determination of whether each state is primary or secondary should be made considering the characteristics of the area under study [28]. The DEBS model and the associated states can be easily altered accordingly.

Fig. 2 depicts the probabilistic transitions between the different types of states (stable, primary, and secondary) that can occur in the DEBS model as well as the risk set. It is important to note that, like the Markov chain models, the DEBS model involves state transitions, however these transitions do not need to satisfy the rigid Markovian property, providing significantly higher flexibility to the analyst in the process.

B. DEBS Model

The DEBS model is formulated to estimate the time needed to bring the situation under control under 1) a given set of resources and 2) the knowledge of the travel and response times when the response center is notified. Fig. 3 illustrates the DEBS model in which the different events associated to the earthquake, e.g., the earthquake shock, arrival of the emergency management personnel, etc., are tracked on a computerized timeline utilizing discrete-event simulation modeling [20].

Fig. 3 (DEBS model) can be explained as follows. The system starts in a stable state. When the earthquake shock occurs, a decision is made regarding the volume of resources to dispatch from the response center. The decision-making process takes a finite amount of time, which is due to the time spent in communication between the different authorities at the affected site and the response center; in a real-time implementation, this time would also include the time needed to run the simulation model and obtain the optimized outputs. Then, a finite amount of time elapses during which the responders travel to the affected site (corresponding to the travel time). After the responders reach the affected site, reparative work begins and ends with the restoration of the site to a working condition (stable state). Thus, this stage corresponds to the response time. The cycle ends here, and a new earthquake is simulated. The restoration time, which is the sum of the travel time and the response time, is computed for each earthquake. The DEBS model seeks to estimate the mean of the restoration time.

The notation used in the DEBS model is described as follows.

1) F: the basic incident of Fire.
2) G: the basic incident of Gas Leakage.
3) BC: the basic incident of Building Collapse.
4) FL: the basic incident of Flooding.
5) Stable state: the state where the system is yet to experience the shock, and also the state to which the system returns after the restoration is complete.

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6) Primary states: states to which the system transitions from the stable state; primary states considered in the model are numbered 1 through 8 and defined in Table I.
7) Secondary states: states to which the system transitions from the primary state that are worse than primary state; secondary states considered in the model are numbered 9 through 15 and defined in Table I.
8) Risk set: union of the sets of primary states and secondary states.
9) *S*: state.
10) *U(S)*: the set of incidents contained in state *S*.
11) *i*: index for a primary state in the system.
12) *j:* index for a state in the risk set in the system.
13) *PR(i)*: probability of transitioning from the stable state to the *i*th state in the system; note that *PR* denotes the vector that contains these probabilities.
14) *DP(i, j):* probability of transitioning from primary state *i* to a state in the risk state *j*; note that *DP* denotes the matrix that contains these probabilities, which are also called domino probabilities.
15) $TT(\omega(m))$: travel time associated to the *m*th sample earthquake.
16) *d*: incident, which could be either a fire, gas leakage, building collapse, or flooding.
17) *RT(d):* response time for incident *d.*
18) $RT_c(S)$*:* response time for state *S*.
19) *ReT*: restoration time, which is a random variable whose mean value is computed via the DEBS model.
20) *X*: volume of resources.
21) *Y*: travel-time scenario.

The DEBS model can be formally described as follows. The input variables to the DEBS model are as follows:

1) the probabilities of transitions of states, i.e., the vector PR and the matrix DP;
2) the (statistical) distribution of the travel times, TTs;
3) the response times, RTs, for each incident;
4) the volume of resources, X;
5) the travel time scenario Y.

The output from the DEBS model is the mean value of the restoration time (*ReT*). This computation requires (1)–(3) that are defined below. As a roadmap for the calculations in the rest of this section, note that the mean value of *ReT* will be estimated within the simulator using (3), which in turn will require, inside the simulator, the computation of RT*(d)* and $\mathrm{RT}_c(S)$ that are defined in (1) and (2), respectively.

RT*(d):* The response times for each incident are detailed in Table II. For the *d*th incident, the response time, RT*(d)*, represents the time in hours needed to bring the situation related to the *d*th incident under control when that incident is present in the system. The response time for any state is hence a function of all the incidents that occur in the affected area, i.e., associated to the current state of the system. Furthermore, the response time should also be a function of the volume of resources sent to bring the situation under control. Hence, the following model, inspired by a similar model by Shabtay and Steiner [32], was used to determine the response time for the *d*th incident:

TABLE II
RESPONSE TIMES (*RT(d)*) ASSOCIATED WITH EACH BASIC INCIDENT, *d*

Incident	Response Time Model (hours)	Worst Case Response Time (hours)
G	$7 + \frac{5}{X}$	12
F	$21 + \frac{15}{X}$	36
BC	$35 + \frac{25}{X}$	60
FL	$120 + \frac{80}{X}$	200

G = Gas leakage; F = Fire; BC = Building Collapse; FL = Flooding

Note: *X* denotes the level of resources.

$$\mathrm{RT}\,(d) = A + \frac{B}{X} \tag{1}$$

where $A > 0$ is a fixed minimum part of the response time, and B/X denotes the variable part of the response time in which *X* is the level of resources taking values from a set of positive integers; $B > 0$. This model was validated via a personal interview with a Fire Marshal [33]. The interview revealed that emergency responders use multiple layers, called "alarms." The least volume of resources, corresponding to $X = 1$, is allocated to the so-called "first" alarm. The response time associated to the first alarm would equal the maximum response time, $\mathrm{RT}_{\max}$. When the situation escalates, the second alarm is placed, and if it escalates further, the third alarm is placed. In this way, the marshal in charge can request an increasing volume of resources. When an earthquake occurs, it was learned [33] that the maximum possible volume of resources at disposal would be used to save lives. As the volume of resources *X* approaches infinity, the response time reaches the minimum response time, $\mathrm{RT}_{\min}$. This value would be nonzero since beyond a certain point, increasing the volume of resources does not improve the response due to redundancy of resources and other factors. For example, the interview [33] revealed that no more than two firetrucks can be useful for one building in *many* areas of inner cities, where population density is high, because the design of the buildings restricts entry to more than two firetruck-water systems.

The maximum and minimum response times can be obtained as follows: $\mathrm{RT}_{\max} = A + B$; and $\mathrm{RT}_{\min} = A$. Thus, $B = \mathrm{RT}_{\max} - \mathrm{RT}_{\min}$. In practice, these equations could be modified to improve the estimates if more data are available.

A key aspect to such models in the literature is that the response time should be a decreasing function of the volume of resources. This is a property that can easily be verified for the model above by taking the first derivative of the response time with respect to X, which yields $-\frac{B}{X^2}$ that can easily be shown to be strictly less than zero. It should also be noted that Monma *et al*. [34] employed the same properties in constructing the function in their study of government tasks, although the value of A is usually set to 0 in that case. Since the DEBS model involves tasks related to emergency management, regardless of how large the volume of available resources is assumed to be, the *RT(.)* will never equal zero, and so a positive term A was added to right-hand side of (1) above; this was confirmed via the personal interview [33]. This implies that there is a finite lower limit on the response time of each incident and hence naturally on the restoration time as well.

$RT_c(S)$*:* The combined response time associated to a state S will be defined as follows:

$$\mathrm{RT}_c\left(S\right) = \sum_{d \in U(S)} \mathrm{RT}\left(d\right)\phi \tag{2}$$

where ϕ denotes a correction factor such that $\phi \geq 1$ and *U(S)* denotes the set of basic incidents associated to state *S*. The correction factor accounts for the fact that the combined response time for a given state may exceed the sum of the individual response times of each incident contained in the state.

ReT: In the discussion that follows, the expression underlying the DEBS model used to determine the restoration time is presented. It should be noted that since the state transitions are probabilistic, each earthquake simulated will also display randomness in terms of the states it visits. A probability triple $(\Omega, \mathcal{F}, P)$ is considered, where Ω denotes the universal set of all possible earthquakes, $\mathcal{F}$ denotes the sigma field of subsets of Ω, and P is a probability space on $(\Omega, \mathcal{F})$. Using the DEBS model, random samples $\omega(1), \omega(2), \ldots$, of earthquakes are generated from the measurable space. Then, from the strong law of large numbers, with probability 1, the mean restoration time, *ReT*, can be estimated as follows:

$$E\left[ReT\right] = \lim_{k \to \infty} \frac{1}{k} \sum_{m=1}^{k} \left[\mathrm{TT}\left(\omega\left(m\right)\right) + \mathrm{RT}_c\left(\omega\left(m\right)\right)\right] \tag{3}$$

where E[.] denotes the expectation operator, k denotes the number of earthquakes simulated, $\mathrm{TT}(\omega(m))$ denotes the travel time in the mth sample earthquake, and $\mathrm{RT}_c(\omega(m))$ denotes the response time associated to the state in which the responders find the system upon arrival in the mth sample earthquake. In practice, to use a formulation such as the one shown in (3), a large value for the sample size k is needed.

IV. Model Setup and Experimental Results

In this section, numerical experimentation is conducted using the DEBS model considering a case study and two different scenarios. Section IV-A presents the numerical data used for the inputs of the model, and Section IV-B discusses the outputs.

A. Model Setup

This section provides details on the numerical values of the input variables needed in the DEBS model for the case study. In particular, the inputs for the DEBS model are: the transition probability vector (PR), the travel times (TTs), the domino probabilities (DPs), and the response times (RT). Estimation of the PR vector and the DP matrix require consultations with subject matter experts and data collected from the area under study.

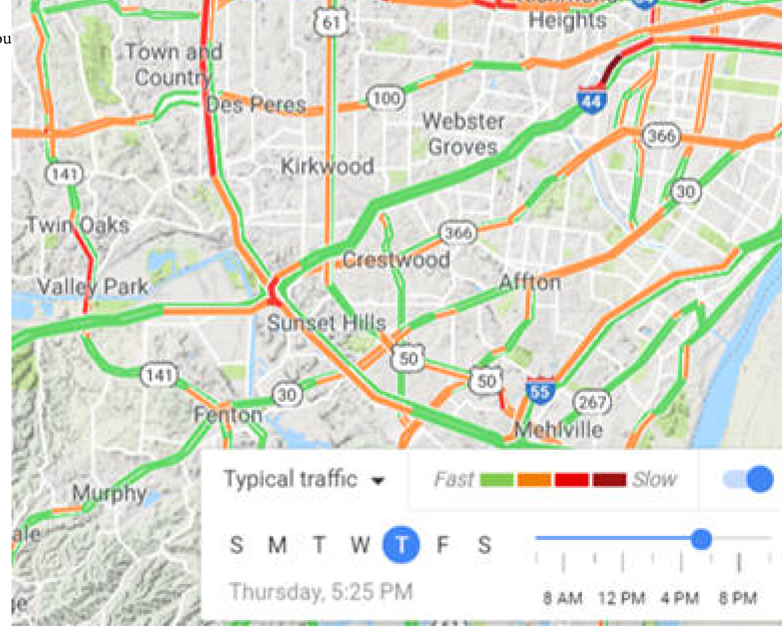

Fig. 4. Map of the most congested roads in inner St. Louis, Missouri, U.S. metropolitan area [29].

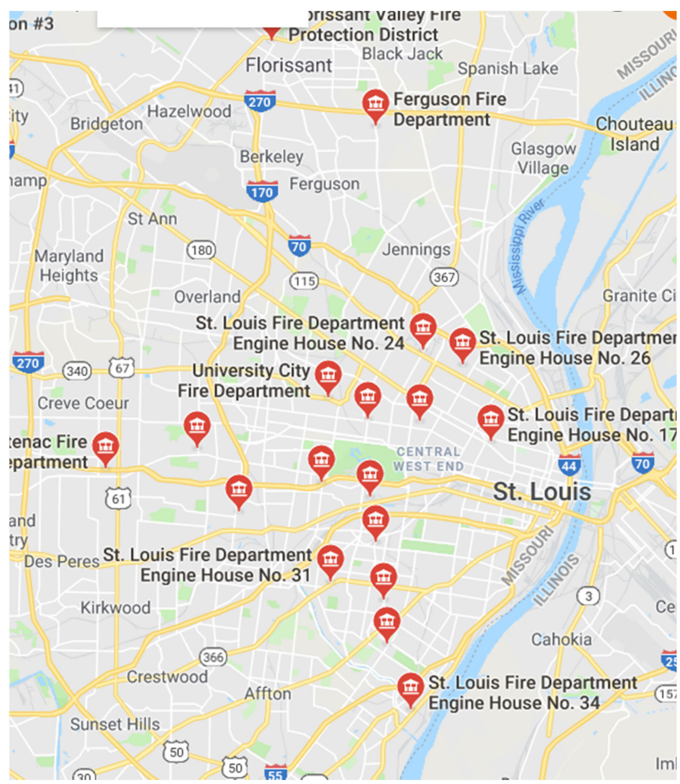

Fig. 5. Locations of the fire departments in the inner St. Louis, Missouri, U.S. metropolitan area [30].

The case study considered in this paper is based on data from the St. Louis, Missouri, U.S. region, where the probability of flooding due to an earthquake is rather low. Therefore, first, a low-probability flooding scenario is presented along with input data relevant for this region. Then, to illustrate the flexibility of the model, a second scenario is presented in which a higher probability of flooding is considered.

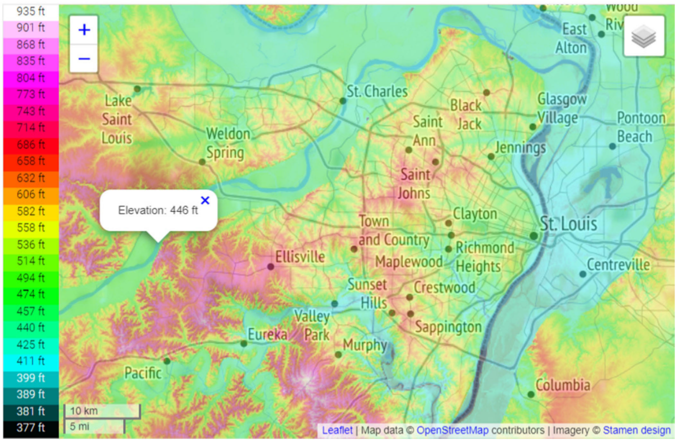

Fig. 6. Map of the St. Louis metropolitan area showing that one of the areas most susceptible to flooding is the area near the bridge that connects St. Louis to Centreville in Illinois [31].

As an example, Figs. 4–6 show the nature of data that would need to be gathered to estimate the travel times in the metropolitan area of St. Louis, Missouri, U.S., which is in close proximity (approximately 240 km) to the New Madrid Seismic Zone (NMSZ). In particular, Fig. 4 shows the busiest roads linking to the bridges over the Mississippi River that connect St. Louis to the neighboring state of Illinois. These bridges would be critical locations for smart city sensors since a significant amount of traffic flows through these bridges. Fig. 5 shows the locations of the local fire departments in the St. Louis metropolitan area. Finally, Fig. 6 shows the flood zones in the same area. Identifying flood zones would be imperative in developing a smart response to a disaster, which relies on data gathered from strategically placed sensors. An interesting feature of the area shown in Figs. 4–6 is that it is in close proximity to the NMSZ, certain roads and bridges are critical in terms of traffic flow, and the areas surrounding these roads and bridges are susceptible to flooding.

1) Low Flooding-Probability Scenario: The following inputs are from low flooding-probability conditions, typical of many cities in the U.S., and apply to the case study from the St. Louis region. The following values were used for the PR vector and the DP matrix.

PR*(i)* denotes the probability of going from the stable state to the primary state *i*. The following values were used for the elements of the PR vector:

$$\mathrm{PR} = \left[\frac{1}{4}, \frac{1}{4}, \frac{1}{16}, \frac{1}{4}, \frac{1}{16}, \frac{1}{16}, \frac{1}{16}\right]. \quad (4)$$

The values above are representative of a generic scenario in which each of the three primary incidents, F, G, and BC, occur with a probability of 1/4. For the probability of states with combinations, a lower probability of 1/16 was used. These probabilities can be easily changed in the DEBS model based on past experience within an area and/or on the basis of data provided by subject matter experts.

$\mathrm{DP}(i,\ j)$ in the model denotes the probability of transitioning from primary state *i* to a state *j* in the risk set. In other words, *i* denotes a state to which the system transitions when the response center is notified (i.e., a primary state), which indicates that *i* belongs to the set, $\{2,\ldots,8\}$, and *j* belongs to the risk set, $\{2,\ldots,15\}$. All states are numbered and defined in Table I.

To construct the DP matrix in this numerical experimentation, a generic scenario was used in which the probability of remaining in the same state was assumed to be 10%, i.e., $\mathrm{DP}(i,i) = 0.1$ for all *i*. The transitions to other states were assumed to follow a pattern in which the transitions of higher likelihood were assigned higher probabilities. Thus, for instance, from State 3 (F), the transition probability to State 4 (F and G) and to State 7 (F and BC) were assigned equal values of 0.35, but the transition probability to State 8 (F, G, and BC) was assigned a lower value of 0.1. Also, any transitions to states involving FL were assigned lower values, since flooding was considered the least likely event. But as in the case of the PR vector, it should be noted that these values would depend on the area under study and can easily be changed in the DEBS model. Furthermore, it is very beneficial for training purposes to have emergency response models where input data can be changed at will to conduct what-if-analyses [1].

In what follows, all values of DP*(.,.)* not specified below were set equal to zero. Also, naturally, the sum of the values from any given state should equal 1, i.e., $\sum_j \mathrm{DP}(i,j) = 1$ for every *i*.

1) From State 2: $\mathrm{DP}(2,2) = 0.1; \mathrm{DP}(2,4) = 0.9$.
2) From State 3: $\mathrm{DP}(3,3) = 0.1; \mathrm{DP}(3,4) = 0.35; \mathrm{DP}(3,7) = 0.35; \mathrm{DP}(3,8) = 0.1; \mathrm{DP}(3,10) = 0.1$.
3) From State 4: $\mathrm{DP}(4,4) = 0.1; \mathrm{DP}(4,8) = 0.5; \mathrm{DP}(4,11) = 0.2; \mathrm{DP}(4,15) = 0.2$.
4) From State 5: $\mathrm{DP}(5,5) = 0.1; \mathrm{DP}(5,6) = 0.1; \mathrm{DP}(5,7) = 0.3; \mathrm{DP}(5,8) = 0.1; \mathrm{DP}(5,12) = 0.1; \mathrm{DP}(5,13) = 0.1; \mathrm{DP}(5,14) = 0.1; \mathrm{DP}(5,15) = 0.1$.
5) From State 6: $\mathrm{DP}(6,6) = 0.1; \mathrm{DP}(6,8) = 0.5; \mathrm{DP}(6,14) = 0.2; \mathrm{DP}(6,15) = 0.2$.
6) From State 7: $\mathrm{DP}(7,7) = 0.1; \mathrm{DP}(7,8) = 0.5; \mathrm{DP}(7,14) = 0.2; \mathrm{DP}(7,15) = 0.2$.
7) From State 8: $\mathrm{DP}(8,8) = 0.1; \mathrm{DP}(8,15) = 0.9$.

Based on the personal interview [28], it was learned that each additional incident in a given state can lead to an approximately 10% increase in the combined response time. Thus, the correction factor was taken as $\phi = 1.2$ for two incidents, $\phi = 1.3$ for three incidents, and $\phi = 1.4$ for all four incidents in the state.

The response time, RT, associated with each basic incident is a function of the level of resources, *X,* as shown in Table II. For the purpose of the numerical experimentation in this study, the values shown in Table II were based on the data by Ghosh and Gosavi [10] and validated through a personal interview [33]. However, it should be noted that these values can be changed in the DEBS model considering the area under study. The response time for each state in Table I can be calculated by adding the numbers of hours needed for responding to each incident after the earthquake and then applying the appropriate correction factor. For example, in State 15, which involves Gas Leakage (G), Fire (F), Building Collapse (BC), and Flooding (FL), the response time for $X = 2$ is $(7 + 21 + 35 + 120 + \frac{5+15+25+80}{2})(1.4) = 343.7$ h, where $\phi = 1.4$. In this way, the response time for each state in Table I is computed for any level of resources. Five levels of resources were used in the experiments performed

TABLE III
TRAVEL TIMES, *TTs*, ASSOCIATED TO DIFFERENT TRAVEL-TIME SCENARIOS, *Y*

Travel-Time Scenario Indicator (*Y*)	Travel Time Distribution (in hours)
1	*UNIF(1, 2)*
2	*UNIF(2, 4)*
3	*UNIF(4, 8)*
4	*UNIF(8, 16)*
5	*UNIF(12, 24)*

with the DEBS model, where *X* takes values from the set {1, 2, 3, 4, 5}. As a first attempt, it is assumed herein that the resources deployed are appropriate to address the incidents encountered when the responders arrive on the scene (i.e., even if the system transitions to a different state), which may not be the case. In addition, certain states (with certain combinations of incidents) may require a response that is sequential rather than simultaneous. Future work could consider these issues to further improve the model capabilities.

The travel time, TT, is a function of the distance from the responding center to the affected area and also of the traffic and infrastructure situation after the shock. According to Anastassiadis and Argyroudis [35], the roadway system is sensitive to direct damage, such as roadway and bridge failure, and to indirect damage due to debris of collapsed buildings. As a result, the travel times are likely to be random variables. In this case, a random travel time, whose distribution function is assumed to be known from past observations of traffic, was employed. In this study, a uniform distribution for the travel time was assumed, where the lower limit would represent the lowest value, *a*, under the best traffic conditions, and the upper limit would represent the highest value, *b*, under the worst traffic conditions. The associated uniform distribution is commonly represented as UNIF*(a, b)* in the simulation literature [20]. It is worth noting that since the DEBS model is founded in discrete-event simulation, changing these distributions to other distributions is a trivial task. This is not the case with the Markov chain models, as a different distribution can mean a difference in the associated state transitions.

In this paper, five different values for the travel time were considered, associated to five different travel-time scenarios *Y*, which are shown in Table III. The first scenario, corresponding to $Y = 1$, is the best case scenario in which the time taken by the responders to arrive at the affected site is a uniformly distributed random duration between 1 and 2 h. The remaining four scenarios involve durations of increasing magnitude, where the scenario in which $Y = 5$ is the worst-case scenario where the time duration is uniformly distributed between 12 and 24 h. The best-case scenario corresponds to a situation where the affected site is closest and the only one that has to be visited. The worst-case scenario involves a situation where the response center is far from the affected site and is not the only affected site. These values were chosen to test whether the model can work robustly under a variety of travel-time scenarios. Clearly, these values would need to be chosen depending on the local conditions, e.g., the nature of the roads available and the nature of the vehicles used.

2) High Flooding-Probability Scenario: In the second scenario, a higher probability of flooding was considered. For these experiments, the DP matrix was changed to account for the higher flooding-probability, while none of the other inputs were changed. In other words, the input vector PR(.) was chosen as described in (4), and the input variable TT was chosen as described in Table III.

As in the previous scenario, DP*(.,.)* values not defined below were set equal to zero. The states numbered 9 through 15 involve flooding (see Table I), and hence here, the transition probabilities to many of these states were set to higher values than in the low flooding-probability scenario. These higher probabilities are indicated in bold below.

1) From State 2: $\mathrm{DP}(2,2) = 0.1; \mathrm{DP}(2,4) = 0.7; \mathrm{DP}(2,9) = \mathbf{0.2}$.
2) From State 3: $\mathrm{DP}(3,3) = 0.1; \mathrm{DP}(3,4) = 0.15; \mathrm{DP}(3,7) = 0.15; \mathrm{DP}(3,8) = 0.1; \mathrm{DP}(3,10) = \mathbf{0.5}$.
3) From State 4: $\mathrm{DP}(4,4) = 0.1; \mathrm{DP}(4,8) = 0.3; \mathrm{DP}(4,11) = \mathbf{0.4}; \mathrm{DP}(4,15) = 0.2$.
4) From State 5: $\mathrm{DP}(5,5) = 0.1; \mathrm{DP}(5,6) = 0.1; \mathrm{DP}(5,7) = 0.1; \mathrm{DP}(5,8) = 0.1; \mathrm{DP}(5,12) = 0.3; \mathrm{DP}(5,13) = 0.1; \mathrm{DP}(5,14) = 0.1; \mathrm{DP}(5,15) = 0.1$.
5) From State 6: $\mathrm{DP}(6,6) = 0.1; \mathrm{DP}(6,8) = 0.25; \mathrm{DP}(6,13) = 0.25; \mathrm{DP}(6,14) = 0.2; \mathrm{DP}(6,15) = 0.2$.
6) From State 7: $\mathrm{DP}(7,7) = 0.1; \mathrm{DP}(7,8) = 0.3; \mathrm{DP}(7,14) = 0.4; \mathrm{DP}(7,15) = 0.2$.
7) From State 8: $\mathrm{DP}(8,8) = 0.1; \mathrm{DP}(8,15) = 0.9$.

B. Output Data

A computer program was written in the software program MATLAB to generate a discrete-event simulator of the system. The software was run on a personal computer with an Intel Pentium Processor with a speed of 2.66 GHz on a 64-bit operating system. The program takes approximately 25 s to run. Ten replications were used to estimate the restoration time. Each replication was run for 1 000 000 h of simulated time with an overall average of 4400 earthquakes in each replication. Equation (5) below shows the standard approach used for computing statistical confidence intervals from the means

$$\bar{x} \pm t_{\frac{\alpha}{2},\, n-1},\ \frac{s}{\sqrt{n}} \tag{5}$$

where $\bar{x}$ denotes the sample mean of the restoration time (*ReT*), *s* denotes the standard deviation of the samples, and *n* denotes the sample size, which equals the number of replications; for experiments performed in this study, $n = 10$ was used. In (5), the component following $\pm$ denotes the half-width. As is standard, α was assumed to equal 0.05 (i.e., a 95% confidence level was used) [20].

1) Low Flooding-Probability Scenario: The results of the experimentation for the low flooding-probability conditions, typical of the St. Louis region, are presented in Table IV. The results show that for a given volume of resources, *X,* the restoration time increases as the travel time between the response center and the affected site increases (i.e., increasing value of *Y*).

TABLE IV
RESULTS FROM LOW FLOODING-PROBABILITY: MEAN RESTORATION TIMES ALONG WITH THE HALF-WIDTH OBTAINED AT 95% CONFIDENCE LEVEL

Restoration Times (in hours) For Different Levels Of Resources And Travel Time Scenarios					
Y	*X*=1	*X*=2	*X*=3	*X*=4	*X*=5
1	361.238 ± 1.56	288.283 ± 0.91	263.859 ± 0.89	251.693 ± 0.86	244.373 ± 0.87
2	362.666 ± 1.53	289.836 ± 0.91	265.383 ± 0.87	253.213 ± 0.87	245.905 ± 0.86
3	365.681 ± 1.56	292.831 ± 0.91	268.370 ± 0.87	256.157 ± 0.87	248.830 ± 0.86
4	371.574 ± 1.60	298.881 ± 0.96	274.437 ± 0.92	262.182 ± 0.88	254.850 ± 0.85
5	377.504 ± 1.63	304.944 ± 0.97	280.419 ± 0.93	268.197 ± 0.82	260.879 ± 0.85

Note: The values in the table should be read as follows: $\overline{\mathrm{Re}T} \pm h$, where $\overline{\mathrm{Re}T}$ denotes the sample mean of *ReT*, and *h* denotes the half-width of the confidence interval on the mean.

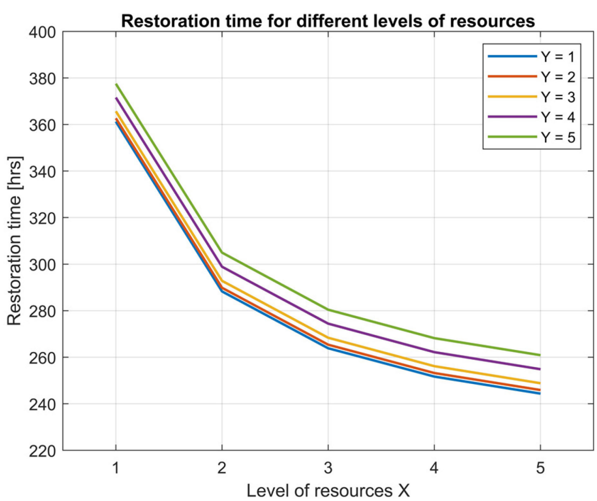

Fig. 7. Low flooding-probability: Restoration time versus level (volume) of resources (*X*) for a given travel time scenario (*Y*).

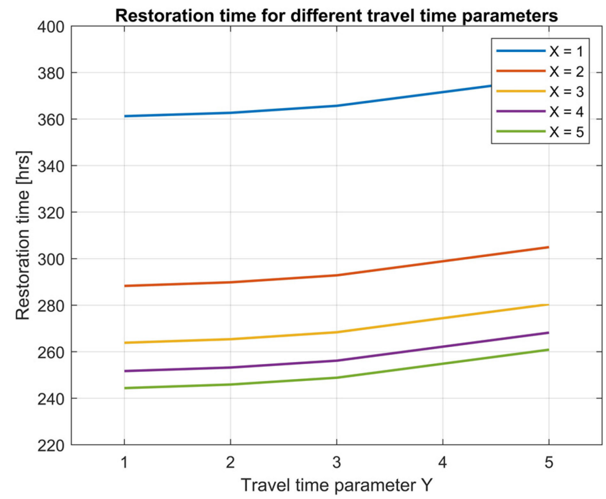

Fig. 8. Low flooding-probability: Restoration time versus travel time of the affected site from the response center (*Y*) for a given volume of resources (*X*).

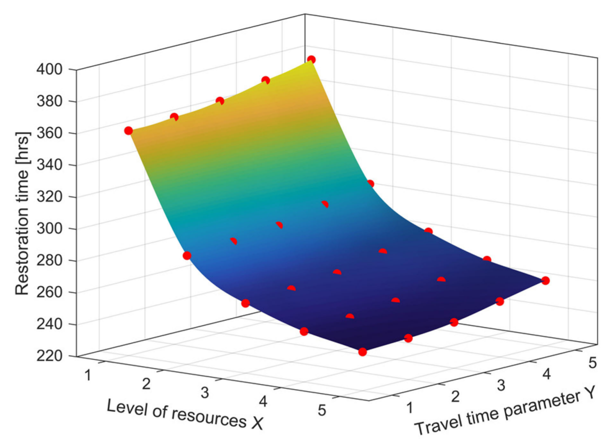

Fig. 9. Low flooding-probability: Relationship between the restoration time and the independent variables *X* and *Y*.

Similarly, for a given value of the travel-time function, *Y*, the restoration time decreases as the volume of resources, *X*, increases. Figs. 7 and 8 are constructed to show this relationship in a graphical format.

Fig. 7 clearly shows a nonlinear relationship between the level of resources and the restoration time. Furthermore, it shows that selecting the appropriate level of resources is a nontrivial task that would require simulation-based analysis of the nature performed here.

Fig. 8 shows a less nonlinear relationship between travel time and the resulting restoration time. The figure also suggests that selection of the appropriate response agency when multiple agencies are available would require careful study of the associated restoration times.

While the overall trends in restoration time with volume of resources and travel time are intuitive, the graphs clearly demonstrate a nonlinear relationship that cannot be predicted quantitatively without a simulation model of the nature proposed here. Hence, the proposed DEBS model would be useful for performing what-if analyses for training purposes that can go a long way in improving the quality of preparedness efforts of emergency managers [1].

Fig. 9 shows a three-dimensional plot of the relationship between *X*, *Y*, and the restoration time. Fig. 9 indicates that the two parameters, *X* and *Y*, produce a nonlinear/nonplanar surface for the restoration time. This result is reasonable, given that each of the two parameters has a nonlinear relationship with the restoration time. The interplay of these parameters and the nonlinear/nonplanar nature of the resulting surface graph again support the need for a simulation model of the nature proposed here to provide quantitative predictions for the restoration time. This relationship between *X*, *Y*, and the restoration time is particularly important in determining which response center(s) to select. For example, a certain response center could arrive more quickly but with lower volumes of resources, whereas a different response center could have a longer arrival time but with a larger volume of resources. In this case, the results could

TABLE V
RESULTS FROM HIGH FLOODING-PROBABILITY: MEAN RESTORATION TIMES ALONG WITH THE HALF-WIDTH OBTAINED AT 95% CONFIDENCE LEVEL

Restoration Times (in hours) For Different Levels Of Resources And Travel Time Scenarios					
Y	*X*=1	*X*=2	*X*=3	*X*=4	*X*=5
1	374.682 ± 2.02	299.013 ± 1.23	273.625 ± 1.10	260.976 ± 1.05	253.413 ± 0.99
2	376.119 ± 2.03	300.533 ± 1.24	275.136 ± 1.08	262.482 ± 1.02	254.855 ± 0.99
3	379.107 ± 1.94	303.585 ± 1.27	278.091 ± 1.05	265.511 ± 0.99	257.873 ± 1.02
4	384.107 ± 1.98	309.590 ± 1.33	284.142 ± 1.06	271.486 ± 0.99	263.916 ± 0.96
5	390.829 ± 1.84	315.600 ± 1.28	290.148 ± 1.01	277.483 ± 1.02	269.898 ± 0.95

Note: The values in the table should be read as follows: $\overline{\mathrm{Re}T} \pm h$, where $\overline{\mathrm{Re}T}$. denotes the sample mean of *ReT*, and *h* denotes the half-width of the confidence interval on the mean.

be used to determine which response center would minimize the restoration time.

2) High Flooding-Probability Scenario: The results obtained from the high flooding-probability scenario are presented in Table V. These results show that the restoration time increases in a statistically significant manner due to the higher flooding probability. In the worst case, where the resource volumes are the lowest, $X = 1$, and the travel times are the longest, $Y = 5$, the mean restoration time increases by 13.325 h relative to the low flooding-probability scenario. These experiments also demonstrate the flexibility of the DEBS model, as well as its usefulness for training purposes, in predicting the restoration times under scenarios where the inputs are different due to different local conditions.

V. CONCLUSION

Reaching a superior coordination of the activities that involve the restoration needed immediately after an earthquake is a key area of research in emergency management. However, there is little in the literature on simulation modeling of the dynamics of the events that occur immediately after a critical disaster such as an earthquake. This paper sought to fill this gap in the literature by developing a simulation model capable of estimating the time needed to restore the area affected by an earthquake and thereby evaluate the performance of the restoration. Furthermore, while smart and connected cities are increasingly attracting attention in the U.S., not only from city planners but also from an academic perspective, the literature on developing a smart response to a disaster is sparse. This paper attempted to make a joint contribution from both the smart-living and disaster-management aspects. The DEBS model, which can be tied to communication technologies employed within smart city architectures, helps pave the way for future integration of these two fields, which is increasingly being envisaged in a nationwide attempt to make cities smarter [36].

The numerical results presented in this paper demonstrated the importance of the interplay of the two input parameters in our study, i.e., the level of resources and the travel time. This interplay is likely to be critical for future studies, especially in the emerging domain of smart cities, where mass communication strategies and GPS systems are expected to work in tandem with disaster-management strategies. The DEBS model could also be used to compare the efficacy of two or more different locations for storing emergency resources, which is a problem that has been studied in general in the literature [37]. Finally, future research involving multiple centers could consider insights from game-theoretic models [38].

ACKNOWLEDGMENT

The authors would like to thank the Department Editor, the Special Issue Editors, and the three anonymous reviewers for their careful reading of the manuscript and for providing valuable feedback that has significantly improved this paper.

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