17th World Conference on Earthquake Engineering, 17WCEE

Sendai, Japan - September 13th to 18th 2020

MODELING CASUALTY ARRIVAL RATES AT HOSPITALS AFTER EARTHQUAKES

K. Eid[(1)], P. Gardoni[(2)]

[(1)] *Research Assistant, University of Illinois at Urbana-Champaign, karleid2@illinois.edu*
[(2)] *Professor, University of Illinois at Urbana-Champaign, gardoni@illinois.edu*
Director, MAE Center: Creating a Multi-hazard Approach to Engineering

Abstract

The healthcare system is the organization of people, institutions and resources that deliver healthcare services to a target community. In this system, hospitals are the pillars and main providers of acute care, and their emergency departments (EDs) are the points of entry for all patients with emergencies. Over the past decades, EDs have been suffering from a frequent crowding crisis under normal conditions whereby the Institute of Medicine has described the problem as being "at the breaking point." More critically, extreme natural and anthropogenic events (like earthquakes, hurricanes, tornadoes, fires and explosions) can significantly exacerbate the situation through an extraordinary surge in casualties. While ED performance has been studied in normal conditions, there is limited research on ED performance following extreme events. Particularly, there has been limited research on ED arrival rates following such events. Current arrival rate models have four main limitations. Firstly, they do not accurately capture the time dimension of arrivals at EDs which is essential in determining arrival rates. Secondly, they do not capture the inherent aleatory variability and epistemic uncertainty since they determine a single estimate of arrivals. Thirdly, they do not capture the physical damage to infrastructure. Fourthly, the current approaches are limited to earthquakes and are not easily transportable to other natural and anthropogenic hazards. To address these limitations, we develop a general mathematical formulation that transforms spatially distributed random quantities known as random fields into temporally distributed random quantities known as stochastic processes at destinations. We then use this mathematical formulation for earthquake casualties, transforming the random field of the earthquake intensity measure into a stochastic process of casualty arrivals at the ED. Lastly, we apply the proposed formulation on an example community. The resulting stochastic casualty arrival rate (i.e., demand) can considerably assist hospitals in their disaster planning and preparedness and can be coupled with ED service rate (i.e., capacity) models to predict ED reliability (i.e., their ability to avoid excessive wait time).

Keywords: Casualty Arrivals; Emergency Department; Regional Disaster; Random Fields; Stochastic Processes.

1 Introduction

The healthcare system is the organization of people, institutions and resources that deliver healthcare services to a target community. In this system, hospitals (permanent or temporary) are the pillars and main providers of acute care, and their Emergency Departments (EDs) are the points of entry for all patients with emergencies. Over the past decades, EDs have been suffering from a frequent crowding crisis under normal conditions, with the term crowding referring to the state where there are insufficient resources to meet patient demands on a timely basis. The problem has been so pronounced that the Institute of Medicine has described the problem as being "at the breaking point" [1].

Consequently, there has been an extensive amount of research on ED crowding under normal conditions [2]. Many studies have focused on predicting patient arrival rates over time (i.e., ED demand), especially since arrival rates have proven to be a controlling factor in ED crowding [3]. Several researchers have applied time-series based approaches to predict hourly, daily and monthly arrival rates at EDs [4], while other researchers have used linear and Poisson regression [5]. More recently, researchers have also leveraged artificial neural networks to predict arrival rates [6].

However, extreme natural and anthropogenic events (like earthquakes, hurricanes, tornadoes, fires and explosions) can exacerbate ED crowding through a significant surge in ED demand. The increase in the ED demand might also be coupled with a drop in the ED patient service rate (i.e., ED capacity) due to direct and/or indirect damage to facilities and supporting infrastructures, and due to the shortage of ED staff and medical supplies. Consequently, the healthcare system risks catastrophic failure when it is most needed.

Joshi and Rys [12] show that ED performance is strongly affected by the arrival pattern as well as the time duration over which victims arrive at the ED, emphasizing the need for accurate arrival rates over time. However, so far, there has been limited research on ED performance under disaster conditions, with particularly limited research on ED demand following disasters due to the complexity of the problem and the scarcity of data [7]. Therefore, when studying ED performance under disaster conditions, most papers currently use arbitrary arrival rate models; like step functions of arbitrary values for earthquake scenarios [8], or a simple Poisson process to model arrivals for a terrorist attack scenario [9]. Other studies use an empirical arrival rate curve that they transport from an entirely different community/disaster and scale it linearly [10, 11].

The few attempts that specifically focus on modeling post-disaster arrivals at EDs have four main limitations. Firstly, they do not accurately capture the time dimension of arrivals at EDs which is essential in determining arrival rates. Secondly, they do not capture the inherent aleatory variability and epistemic uncertainty since they determine a single estimate of arrivals. Thirdly, they do not capture the physical damage to infrastructure. Fourthly, the current approaches are limited to earthquakes and are not easily transportable to other natural and anthropogenic hazards [13, 14, 15].

Therefore, there is a need for a new formulation that better quantifies the uncertain patient arrival rates at EDs under general disaster conditions. We develop a general mathematical formulation that transforms spatially distributed random quantities known as random fields into temporally distributed random quantities known as stochastic processes at destinations. We then use this mathematical formulation for earthquake casualties, transforming the random field of the earthquake intensity measure into a stochastic process of casualty arrivals at the ED. The formulation presents many advantages. Firstly, it captures the time dimension of arrivals via space-to-time conversion. Secondly, it incorporates aleatory variability and allows uncertainty quantification throughout the transformation steps. Thirdly, the formulation captures the damage to infrastructure and its effects on patient arrival times. Fourthly, the formulation is general and can be applied to a wide range of problems where spatially distributed random quantities are collected at destinations.

This paper is organized into four sections. After this introduction, Section 2 describes the general formulation developed to transform a random field into a stochastic process. Section 3 discusses the problem-specific formulation in the case of casualty arrivals after earthquakes. Section 4 illustrates the formulation by applying it to the case of the Centreville virtual community. Lastly, Section 5 presents some conclusions.

2 General Formulation

To develop a methodology that applies to a wide range of problems and disasters, we develop a novel and general formulation that transforms spatially distributed random quantities into temporally distributed random quantities at destinations. We seek to achieve this mathematically by transforming random fields that model spatial variability into stochastic processes that model temporal variability. This section presents a high-level description of the transformation. Table 1 introduces the variables and parameters for the random field and stochastic process.

Table 1: Random Field and Stochastic Process Notations

Random Field	Stochastic Process
$V(\boldsymbol{s})$: Spatial random field at $\boldsymbol{s}$ $\boldsymbol{s}$: Spatial location s.t. $\boldsymbol{s} \in D$ $\boldsymbol{s}_0$: Location of destination s.t. $\boldsymbol{s}_0 \in D$ D: Spatial domain	$\{Y(t)\}$: Stochastic process at time t, at destination $\boldsymbol{s}_0$ t: Time s.t. $t \in T$ T: Temporal domain

2.1. Quantity Derivation

The random field $V(\boldsymbol{s})$ can be an intensity measure from which we derive the quantity of interest $Q(\boldsymbol{s})$ at $\boldsymbol{s}$ (e.g., the number of casualties) that will be collected at destination $\boldsymbol{s}_0$. This could be expressed as

$$V(\boldsymbol{s}) \rightarrow Q(\boldsymbol{s}) \tag{1}$$

As a special case, $V(\boldsymbol{s})$ could directly be the quantity that will be collected at destination $\boldsymbol{s}_0$, in which case $Q(\boldsymbol{s}) = V(\boldsymbol{s})$.

2.2 Space-to-Time Conversion

We then project the spatial location $\boldsymbol{s}$ of $Q(\boldsymbol{s})$ into an arrival time $\tau(\boldsymbol{s})$ at the destination $\boldsymbol{s}_0$ per the following mapping:

$$\tau(\boldsymbol{s}): D \mapsto T \tag{2}$$

where $\tau(\boldsymbol{s})$ is the arrival time of quantity $Q(\boldsymbol{s})$ to its destination $\boldsymbol{s}_0$. Specifically, $\tau(\boldsymbol{s})$ is a mapping from the spatial domain into the temporal domain, and the conversion is done depending on the specific problem (e.g., based on travel time in the case of casualties at location $\boldsymbol{s}$ going to an ED at location $\boldsymbol{s}_0$).

2.3 Domain Collection

We then collect the isochron set $\Omega(t) \subseteq D$ of locations $\boldsymbol{s}$ at which the derived quantity $Q(\boldsymbol{s})$ has the same arrival time $\tau(\boldsymbol{s}) = t$ for $\forall t \in T$

$$\Omega(t) = \{\boldsymbol{s} | \tau(\boldsymbol{s}) = t\} \tag{3}$$

As long as the space-to-time conversion is deterministic, the isochron set $\Omega(t)$ is deterministic. If $\tau(\boldsymbol{s})$ is stochastic, $\Omega(t)$ becomes a random set of points. In this case, simulations can be used to generate realizations of the random isochron set $\Omega(t)$, and the analyses are repeated for each realization.

2.4 Process Assembly

Subsequently, for $\forall t \in T$ we sum the $Q(\boldsymbol{s})$ at locations $\Omega(t)$ to assemble the stochastic process $Y(t)$.

If $\boldsymbol{s}$ is continuous, for $\forall t \in T$ we can write

$$Y(t) = \int_{\Omega(t)} Q(\boldsymbol{s}) d\boldsymbol{s} \tag{4}$$

If $\boldsymbol{s}$ is discrete (i.e. lattice), for $\forall t \in T$ we can write

$$Y(t) = \sum_{\boldsymbol{s} \in \Omega(t)} Q(\boldsymbol{s}) \tag{5}$$

2.5 Process Probability Distribution $f_Y(t)$

Lastly, we derive the probability distribution $f_Y(t)$ for process $Y(t)$. When $\Omega(t)$ is deterministic, we use convolution operations at each $t \in T$ to derive $f_Y(t)$. If $\Omega(t)$ is probabilistic, we can use repeated realizations of the random sets of points $\Omega(t)$ and analyze them to find the probability distribution $f_Y(t)$ of $Y(t)$.

This formulation focuses on a single destination point but could easily be extended to consider multiple destinations $\{\boldsymbol{s}_{0k}: k = 1, \cdots, K\}$ and multiple batches $\{Q_j(\boldsymbol{s}): j = 1, \cdots, J\}$ from each origin point.

3 Problem-specific Formulation

The formulation presented in Section 2 is general and can be used in a wide range of problems. Yet, it also has the flexibility needed to be tailored to specific applications.

Considering a region and a scenario earthquake, this section uses the proposed formulation to transform the random field of the earthquake intensity measure into a stochastic process of casualty arrivals at the ED.

3.1 Quantity Derivation

3.1.1 Earthquake Random Field $\boldsymbol{V}(\boldsymbol{s})$

The earthquake intensity measure constitutes the random field $V(\boldsymbol{s})$. The spatial distribution of casualties $Q(\boldsymbol{s})$ is derived from it. Here, we use the peak ground acceleration, $PGA(\boldsymbol{s})$, as the earthquake intensity measure. We consider $ln[PGA(\boldsymbol{s})]$ as our random field to benefit from the properties of Normally distributed quantities [16]. Hence, we model the random field as

$$V(\boldsymbol{s}) = ln[PGA(\boldsymbol{s})] \tag{6}$$

$$V(\boldsymbol{s}) = ln[PGA(\boldsymbol{s})] = M(\boldsymbol{s}) + Z(\boldsymbol{s}) + \varepsilon(\boldsymbol{s}) \tag{7}$$

where $M(\boldsymbol{s})$ is the mean-field at $\boldsymbol{s}$, $Z(\boldsymbol{s})$ is the normal zero-mean spatially correlated intra-event field at $\boldsymbol{s}$, and $\varepsilon(\boldsymbol{s})$ is the normal inter-event residual which is constant for all $\boldsymbol{s}$ for any given realization of the earthquake [17,18].

3.1.2 Building and Infrastructure Damage

Having the earthquake random field $V(\boldsymbol{s})$, and data on the building inventory and transportation infrastructure in the affected region, the amount of damage to buildings and infrastructure can be computed using appropriate fragility functions and repair rates [19,20,21]. Fragility curves are the conditional probability of attaining or exceeding a prescribed performance level for a given $V(\boldsymbol{s})$ at the site [22]. Repair rate curves provide the number of expected repairs per unit length of the linear element as a function of $V(\boldsymbol{s})$.

3.1.3 Casualties $\boldsymbol{Q}(\boldsymbol{s})$

Given the population's spatial distribution at the time of the earthquake and the amount of damage to the built environment (determined in the previous subsection), statistical/empirical models can be used to predict the number and severity of casualties at each location. The approach allows us to determine the number of casualties of a single severity level $Q(\boldsymbol{s})$ at $\boldsymbol{s}$, or the number of casualties of any m severity levels $\boldsymbol{Q}(\boldsymbol{s}) = [Q_1(\boldsymbol{s}), Q_2(\boldsymbol{s}) \ldots Q_m(\boldsymbol{s})]$ at $\boldsymbol{s}$. Figure 1 illustrates the derivation of the spatial distribution of multi-severity casualties $\boldsymbol{Q}(\boldsymbol{s})$ from random field $ln[PGA(\boldsymbol{s})]$.

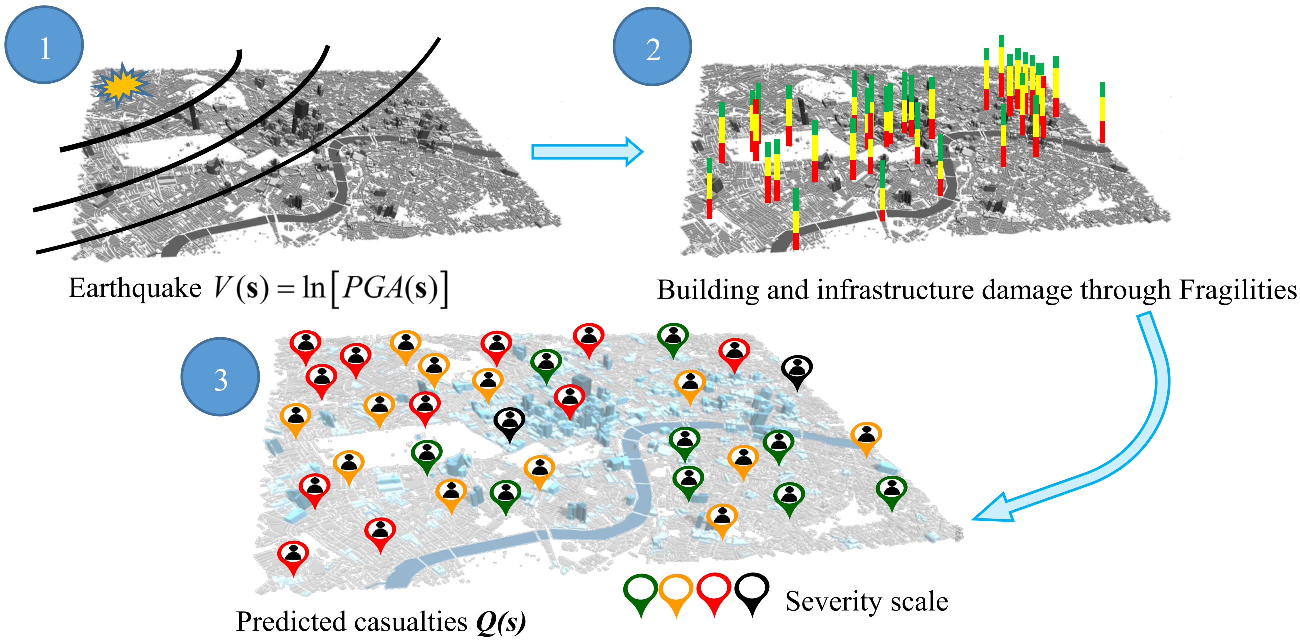

*Figure 1: Illustration of the Derivation of Casualty Estimates **Q(s)** from Intensity Measure PGA(s)*

For simplicity in the presentation, in the remainder of this derivation, we focus on a single severity level and use notation $Q(\boldsymbol{s})$.

3.2 Space-to-Time Conversion

The space-to-time conversion $\tau(\boldsymbol{s})$ can include several dimensions aside from direct transport. For the case of casualty arrivals to EDs after earthquakes, $Q(\boldsymbol{s})$ is a discrete variable (i.e., the number of casualties) at discrete locations $\boldsymbol{s}$ (e.g., buildings, sidewalks, bridges). Before arriving to the ED, casualties $Q(\boldsymbol{s})$ might need time to be searched for and rescued. We denote this processing time as $\tau_P(\boldsymbol{s})$. Also, they might need to wait before they can be transported. We denote this queuing time as $\tau_q(\boldsymbol{s})$. Lastly, they need time to travel along the damaged network and reach the ED. We denote this transportation time as $\tau_{TR}(\boldsymbol{s})$. As a result, the space-to-time conversion can be written as

$$\tau(\boldsymbol{s}) = \tau_P(\boldsymbol{s}) + \tau_q(\boldsymbol{s}) + \tau_{TR}(\boldsymbol{s}) \tag{8}$$

Since the quantity of interest is the arrival rate at the ED, and not the rate at which definitive care is administered, $\tau(\boldsymbol{s})$ is defined as the time at which the casualty physically reaches the ED. Hence, queuing for care at the ED at $\boldsymbol{s}_0$ is not included in $\tau_q(\boldsymbol{s})$, and is subsequently not included in our arrival time $\tau(\boldsymbol{s})$.

Figure 2 illustrates this space-to-time conversion for earthquake casualty arrivals.

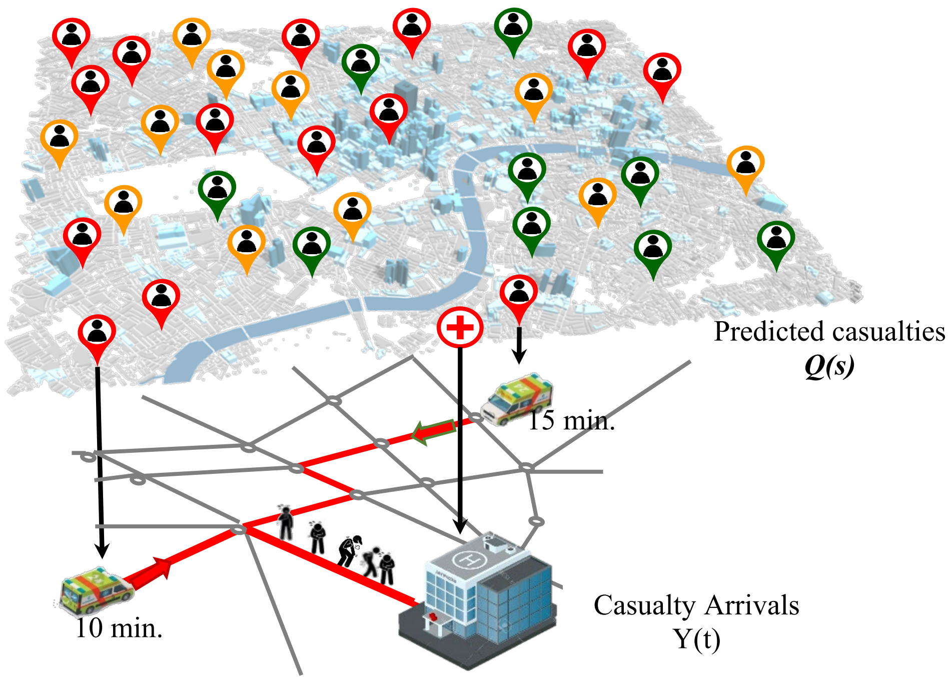

Figure 2: Illustration of the Space-to-Time Conversion for Earthquake Casualty Arrivals to EDs

3.3 Domain Collection

We apply Eq. (3) to collect the domain. As long as the arrival time of casualties $\tau(\boldsymbol{s})$ is deterministic, the isochron set $\Omega(t)$ is deterministic. If $\tau(\boldsymbol{s})$ is stochastic, $\Omega(t)$ becomes a random set of points and needs simulations.

3.4 Process Assembly

Afterward, since the casualties are distributed at discrete locations $\boldsymbol{s}$, the stochastic process of casualty arrivals $Y(t)$ is assembled per Eq. (5).

3.5 Process Probability Distribution $f_Y(t)$

Lastly, we find the probability distribution $f_Y(t)$ of casualty arrivals $Y(t)$ at time t by either convolutions or simulations.

Having the probability distribution $f_Y(t)$, any property relating to the stochastic process $Y(t)$ can be determined via mathematical manipulation.

Of particular interest to our problem is the rate of casualty arrivals $\tilde{Y}(t)$ that can be expressed as

$$\tilde{Y}(t) = h[t, Y(t)] \quad (9)$$

4 Application

This section uses the proposed methodology considering the virtual community of Centerville [23] subject to an earthquake scenario [24].

4.1 Community Description

The Centerville community considered in this application is a virtual yet realistic testbed community. It is a small-scale city with a population of 50,000. Its building stock consists of mostly low-rises, with some medium-rise structures. It also has one hospital (i.e. ED) as can be seen in Figure 3. The community is assumed here to be located on the United States' west coast.

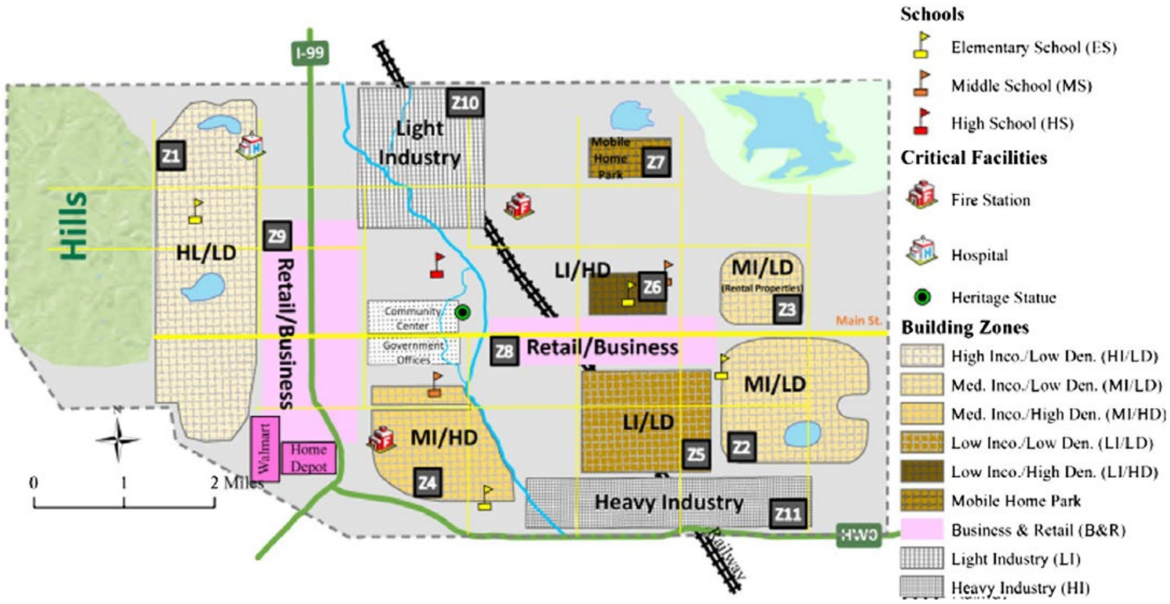

Figure 3: Centerville Plan [23]

The transportation infrastructure is modeled as a network of roads and bridges as shown in Figure 4 [23].

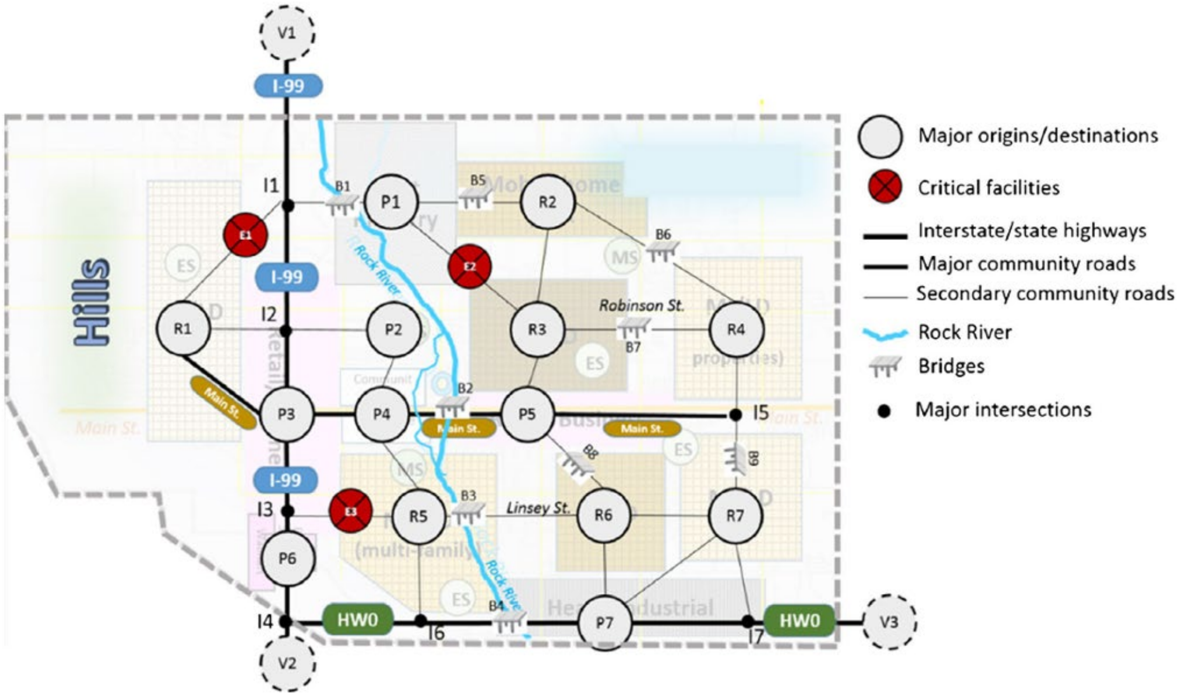

Figure 4: Centerville Transportation Network [23]

4.2 Quantity Derivation

The random field considered $V(s) = ln[PGA(s)]$ is for a scenario earthquake of magnitude 7 at a distance of 5 km. The ASK 14 GMPE [16] along with Jayaram and Baker's correlation model [25] are used to model the random field at each node. The building and bridge damage states are modeled using fragilities to capture five damage states (DS): none, slight, moderate, extensive, complete; with the complete damage state in turn divided into complete with collapse and complete without collapse. For the sake of explaining the proposed formulation, the fragilities are taken from FEMA's Hazus-MH Technical Manual [26].

Lastly, given the spatial distribution of the population as well as damage, and using values per FEMA's Hazus-MH Technical Manual [26], multi-severity casualty estimates are derived at each node using multinomial distributions. The casualty breakdown is defined by a four-level injury severity scale (shown in Table 2), where Severity 1 is the lowest form of injury, and Severity 4 means instantaneous death.

Table 2: Injury Severity Levels

Injury Severity Level	Injury Description
Severity 1	Injuries requiring basic medical aid that could be administered by paraprofessionals. These types of injuries would require bandages or observation.
Severity 2	Injuries requiring a greater degree of medical care and use of medical technology such as x-rays or surgery, but not expected to progress to a life-threatening status.
Severity 3	Injuries that pose an immediate life-threatening condition if not treated adequately and expeditiously. Some examples are uncontrolled bleeding and punctured organ.
Severity 4	Instantaneously killed or mortally injured

Under crisis conditions, the Emergency Medical Services (EMS) as well as Emergency Departments at hospitals focus primarily on patients with immediate life-threatening conditions and either decline or divert patients of lesser severity [27]. So, while the approach applies to multi-severity casualties, for the remainder of this application we focus only on casualties with immediate life-threatening injuries (i.e. Severity 3) and define $Q(\boldsymbol{s})$ as such.

4.3 Space-to-Time Conversion

Eq. (8) identifies three components to the space-to-time conversion for earthquake casualty arrivals. For the search-and-rescue time $\tau_P(\boldsymbol{s})$, studies have shown that a substantial portion, if not most, search-and-rescue is carried out by untrained survivors, especially during the first hours of a disaster [28]. In the case of Centerville's micropolitan community, we assume that the search-and-rescue process (done mostly by untrained survivors alongside experts) will be underway in parallel across the community, and at a relatively quick pace (since the building inventory is largely characterized by low to mid-rise construction). Hence, the casualties at each building are assumed to undergo search-and-rescue concurrently. Therefore, we assign to $\tau_P(\boldsymbol{s})$ a uniform distribution with minimum and maximum values of 0 and 120 min, respectively.

$$\tau_P(\boldsymbol{s}) \sim \text{Uniform}(0,120) \qquad [\text{min.}] \tag{10}$$

Nonetheless, if desired, $\tau_P(\boldsymbol{s})$ could be site-specific and could be replaced by physical models that are dependent on building material, geometry and structural demand as well as survivor and expert labor.

For the transportation time $\tau_{TR}(\boldsymbol{s})$, studies have also shown that most casualties are not transported by ambulance. Indeed, if ambulances are not promptly available, survivors do not tend to wait for them but will use the most expedient means to transport neighboring casualties [28]. Hence, casualty transportation can be assumed to be concurrent as well. Furthermore, since Centerville is not densely populated, we assume no congestion on the roads. Hence, we calculate $\tau_{TR}(\boldsymbol{s})$ as follows:

$$\tau_{TR}(\boldsymbol{s}) = \frac{d(\boldsymbol{s},\boldsymbol{s}_0)}{v} \tag{11}$$

where v is the speed that is assumed to be constant at 50 km/h, and $d(\boldsymbol{s},\boldsymbol{s}_0)$ is the shortest distance in the damaged network between the casualty at $\boldsymbol{s}$ and the ED at $\boldsymbol{s}_0$.

Lastly, accounting for survivor transport of casualties, we assume casualties are not queued at $\boldsymbol{s}$. Therefore, the time $\tau_q(\boldsymbol{s})$ is 0 for $\forall \boldsymbol{s} \in D$.

4.4 Domain Collection

Due to the uncertainties in $\tau_P(\boldsymbol{s})$ and $\tau_{TR}(\boldsymbol{s})$, $\tau(\boldsymbol{s})$ is uncertain. As a result, to define the domain $\Omega(t)$ $\forall t \in T$ we use simulations.

4.5 Process Assembly

Lastly, since the closed-form distribution of the casualties $Q(\boldsymbol{s})$ in this application is analytically intractable, we assemble the stochastic process $Y(t)$ of casualty arrivals per Eq. (5) and generate its distribution via simulations. With the rate of casualty arrivals $\tilde{Y}(t)$ being of particular interest, we estimate its time-varying mean $\mu(t)$ and standard deviation $\sigma(t)$.

The arrival rate curves for 2,000 realizations are generated using Monte Carlo simulations and are smoothed with a gaussian kernel of bandwidth 15 min [29]. They are shown in Figure 5. The curves $\mu(t)$, $\mu(t) + \sigma(t)$ and $\mu(t) + 2\sigma(t)$ are also plotted for reference.

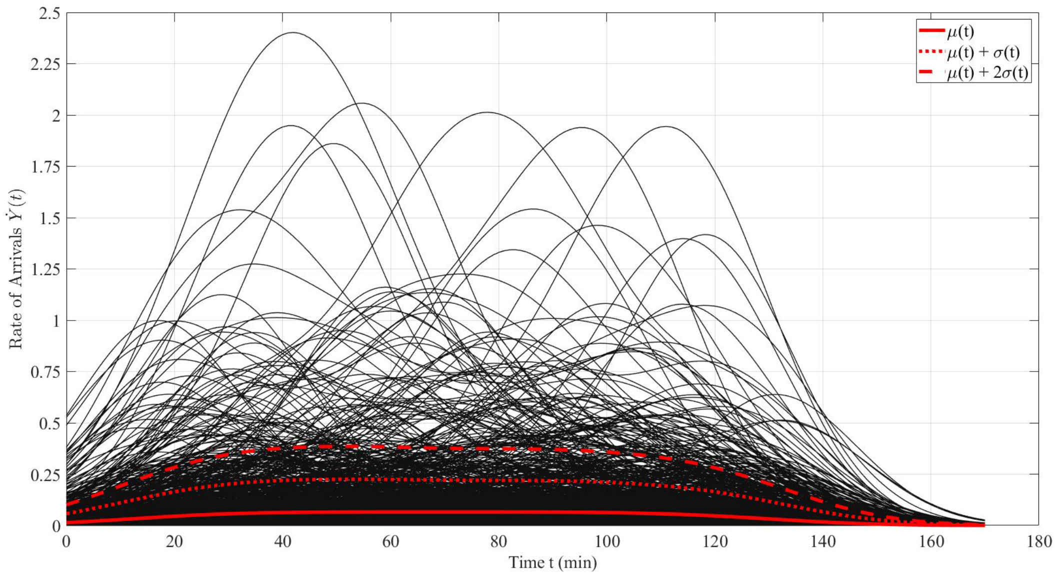

Figure 5: Casualty Arrival Rate Curves

The results show a relatively low average arrival rate $\mu(t)$, which is expected due to the small population size of Centerville and a building inventory of mostly low-rises. The mean arrival rate would likely be higher in more densely populated urban communities. Also, there is significant variability expressed in relatively high values of $\sigma(t)$ and in numerous casualty arrival rate curves with values neighboring two to three immediate life-threatening injury arrivals every 15 min.

Furthermore, the capacity of EDs in many micropolitan hospitals is modest to start with. In fact, in many cases providing the necessary resources to stabilize an immediate life-threatening injury might temporarily suspend the ED's ability to care for other casualties. Additionally, in case of an earthquake the ED's capacity is likely to decrease due to either direct damage to the hospital facilities (i.e. structural and non-structural damage), reduction or loss of functionality of supporting critical infrastructure (e.g. power and water), or reduction of medical resources (e.g. personnel and supplies). In this context, the above casualty arrival rate curves are essential to provide hospital administrators and clinicians a quantitative basis for disaster planning and preparedness. If coupled with ED capacity models, the above casualty arrival rates can quantitatively predict ED reliability and ability to serve a community.

5 Conclusion

To quantify casualty arrival rates after disasters, we developed a general mathematical formulation that transforms spatially distributed random quantities known as random fields into temporally distributed random quantities known as stochastic processes at destinations. The formulation presents many advantages. It captures the time dimension of arrivals via the space-to-time conversion, it incorporates aleatory variability and allows uncertainty quantification in every step of the transformation, it captures the damage to infrastructure and its effects on patient arrival times, and it is general in that it can be applied to a wide range of problems. We used the proposed formulation to quantify earthquake casualty arrivals, transforming the random field of the earthquake intensity measure into a stochastic process of casualty arrivals at an emergency department. We illustrate the proposed formulation considering an example community. The estimated stochastic demand at emergency departments can considerably assist hospitals in their disaster planning and preparedness and can be coupled with emergency department capacity models to predict emergency department reliability.

6 Acknowledgments

This work was supported in part by the Center for Risk-Based Community Resilience Planning, a NIST-funded Center of Excellence [Grant Number 70NANB15H044]. Opinions and findings presented are those of the writers and do not necessarily reflect the views of the sponsor.

7 References

[1] Institute of Medicine (2007) Hospital-Based Emergency Care: At the Breaking Point. Washington, DC: The National Academies Press. https://doi.org/10.17226/11621

[2] Hoot, N. R., & Aronsky, D. (2008). Systematic review of emergency department crowding: causes, effects, and solutions. *Annals of emergency medicine*, *52*(2), 126-136.

[3] Wiler, J. L., Griffey, R. T., & Olsen, T. (2011). Review of modeling approaches for emergency department patient flow and crowding research. *Academic Emergency Medicine*, *18*(12), 1371-1379.

[4] Schweigler, L. M., Desmond, J. S., McCarthy, M. L., Bukowski, K. J., Ionides, E. L., & Younger, J. G. (2009). Forecasting models of emergency department crowding. *Academic Emergency Medicine*, *16*(4), 301-308.

[5] McCarthy, M. L., Zeger, S. L., Ding, R., Aronsky, D., Hoot, N. R., & Kelen, G. D. (2008). The challenge of predicting demand for emergency department services. *Academic Emergency Medicine*, *15*(4), 337-346.

[6] Gul, M., & Guneri, A. F. (2016). Planning the future of emergency departments: forecasting ed patient arrivals by using regression and neural network models. *International Journal of Industrial Engineering*, *23*(2).

[7] Gul, M., & Guneri, A. F. (2015). A comprehensive review of emergency department simulation applications for normal and disaster conditions. *Computers & Industrial Engineering*, *83*, 327-344.

[8] Paul, J. A., George, S. K., Yi, P., & Lin, L. (2006). Transient modeling in simulation of hospital operations for emergency response. *Prehospital and disaster medicine*, *21*(4), 223-236.

[9] Hirshberg, A., Stein, M., & Walden, R. (1999). Surgical resource utilization in urban terrorist bombing: a computer simulation. *Journal of Trauma and Acute Care Surgery*, *47*(3), 545-550.

[10] Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2011). Performance-based metamodel for healthcare facilities. *Earthquake Engineering & Structural Dynamics*, *40*(11), 1197-1217.

[11] Pianigiani, M., Przelazloski, K., Christovasilis, I. P., Cimellaro, G. P., De Stefano, M., Filiatrault, A., ... & Tanganelli, M. (2014, August). A comprehensive methodology for evaluating the seismic resilience of health care facilities considering nonstructural components and organizational models. In *Second European Conference on Earthquake Engineering and Seismology, Istanbul, Turkey*.

[12] Joshi, A. J., & Rys, M. J. (2008). *Study on the effect of different arrival patterns on an emergency department's capacity using discrete event simulation* (Doctoral dissertation, Kansas State University).

[13] Fawcett, W., & Oliveira, C. S. (2000). Casualty treatment after earthquake disasters: development of a regional simulation model. *Disasters*, *24*(3), 271-287.

[14] Fiedrich, F., Gehbauer, F., & Rickers, U. (2000). Optimized resource allocation for emergency response after earthquake disasters. *Safety science*, *35*(1-3), 41-57.

[15] Ceferino, L., Mitrani-Reiser, J., Kiremidjian, A., Deierlein, G., & Bambarén, C. (2019). Effective Plans for Hospital System Response to Earthquake Emergencies.

[16] Abrahamson, N. A., Silva, W. J., & Kamai, R. (2013). *Update of the AS08 ground-motion prediction equations based on the NGA-West2 data set*. Pacific Earthquake Engineering Research Center.

[17] Xu, H., & Gardoni, P. (2018). Improved latent space approach for modelling non-stationary spatial–temporal random fields. *Spatial Statistics*, *23*, 160-181.

[18] Vanmarcke, E. (2010). *Random fields: analysis and synthesis*. World Scientific.

[19] Gardoni, P. (2018). *Routledge handbook of sustainable and resilient infrastructure*. Routledge.

[20] Gardoni, P. (2017). Risk and Reliability Analysis. In *Risk and Reliability Analysis: Theory and Applications* (pp. 3-24). Springer, Cham.

[21] Gardoni, P., & LaFave, J. M. (2016). Multi-hazard approaches to civil infrastructure engineering: Mitigating risks and promoting resilence. In *Multi-hazard approaches to civil infrastructure engineering* (pp. 3-12). Springer, Cham.

[22] Gardoni, P., Der Kiureghian, A., & Mosalam, K. M. (2002). Probabilistic capacity models and fragility estimates for reinforced concrete columns based on experimental observations. *Journal of Engineering Mechanics*, *128*(10), 1024-1038

[23] Bruce R. Ellingwood, Harvey Cutler, Paolo Gardoni, Walter Gillis Peacock, John W. van de Lindt & Naiyu Wang (2016) The Centerville Virtual Community: a fully integrated decision model of interacting physical and social infrastructure systems, *Sustainable and Resilient Infrastructure*, **1:3-4**, 95-107. doi: 10.1080/23789689.2016.1255000

[24] Guidotti, R., Chmielewski, H., Unnikrishnan, V., Gardoni, P., McAllister, T., & van de Lindt, J. (2016). Modeling the resilience of critical infrastructure: The role of network dependencies. *Sustainable and resilient infrastructure*, *1*(3-4), 153-168.

[25] Jayaram, N. and Baker, J. W. (2009), Correlation model for spatially distributed ground-motion intensities. Earthquake Engng. Struct. Dyn., 38: 1687-1708. doi:10.1002/eqe.922

[26] FEMA (2015) *Hazus 2.1 technical and user's manuals*, available at https://www.fema.gov/medialibrary/assets/documents/24609 (last accessed 21 February 2018)

[27] Gostin, L. O., Viswanathan, K., Altevogt, B. M., & Hanfling, D. (Eds.). (2012). Crisis Standards of Care: A Systems Framework for Catastrophic Disaster Response: Volume 1: Introduction and CSC Framework (Vol. 3). National Academies Press.

[28] der Heide, E. A. (2006). The importance of evidence-based disaster planning. *Annals of emergency medicine*, *47*(1), 34-49.

[29] Assistant Secretary for Preparedness and Response. (2014). *Hospital Surge Evaluation Tool*.

