ssessing Hospital System Resilience to Disaster Events involving Physical Damage and Demand Surge

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bstract: This paper investigates the effectiveness of formalized collaboration strategies through which patients can be transferred and resources, including staff, equipment and supplies, can be shared across hospitals in response to a disaster incident involving mass casualties and area-wide damage. Inflicted damage can affect hospital infrastructure and its supporting lifelines, thus impacting capacity and capability or, ultimately, services that are provided. Using a discrete event simulation framework and underlying open queuing network conceptualization involving patient flows through 9 critical units of each hospital, impacts on critical resources, physical spaces and demand are modeled and the hospital system's resilience to these hazard events is evaluated. Findings from numerical experiments on a case study involving multiple hospitals spaced over a large metropolitan region replicating a system similar to the Johns Hopkins Hospital System show the potential of strategies involving not only transfers and resource sharing, but also joint capacity enhancement alternatives to improve post-disaster emergency health care service delivery through joint action.

Keywords: Healthcare resilience; Hospital operations in MCI; Collaboration; Interhospital coalition; Disaster preparedness; Discrete event simulation; Queueing networks

Introduction

n urban disaster event can lead to sudden surge demand for regional health care services. In 2017 in the U.S. alone, events, including the mass shooting in Las Vegas and Hurricanes Irma and Harvey, have highlighted the need for efficient hospital response to incidents involving high numbers of casualties, i.e. Mass Casualty Incidents (MCIs). In these hurricanes, casualties were estimated at 129, including 44 direct and 85 indirect fatalities (Kay, 2018), and 82 (Moravec, 2017), respectively. In the mass shooting event, however, the numbers were of significantly greater magnitude at over 500 injured and 59 deaths (Blankstein, 2017). Consequently, an expectation of significant demand increase in emergency department visits compared to demand in ordinary circumstances can be expected in MCIs. Simultaneously, the capability to supply health care services may be diminished due to structural damage, reduced workforce, or loss of critical support systems (power, water supply, transportation, cyber, sanitation and more) and supplies produced by the disaster event. Illustrative of this, in the U.S. Virgin Islands, Hurricane Irma led to a reduction in a single hospital's workforce by 150 of 600 employees (llen, 2018). lso in Hurricane Sandy of 2012, damage to electrical systems, emergency and exam rooms, and elevators was incurred, resulting in reduced capacity for admitting new patients in several hospitals in the region (Evans, 2012). Thus, efficient use of available health care resources is necessary to address the unexpected spike in demand for urgent care despite diminished service capacities. Such efficiency is required to achieve minimum fatality rates at individual hospitals and in the wider healthcare network.

In previous work, Tariverdi et al. (2018a) studied the role of capacity enhancing actions (i.e. modified operations and alternative standards of care) for a single hospital, along with transfers out by patients who would not be seen in reasonable time, in the responsiveness of a single hospital to circumstances involving mass casualties. They developed a patient-based, resource-constrained, multi-unit hospital modeling approach. This paper extends their approach to investigate the effects of diminished capacities and potential responses to these reductions when faced with physical damage to the hospital infrastructure and its supporting lifelines. In addition to capacity enhancing actions, the potential of coordinated response by two or more hospitals in the form of formalized collaboration is also investigated here. Coordination in this study includes the sharing of physical spaces, resources (personnel, equipment or supplies) and information, as well as patient demand handling in the form of on-scene patient assignment to hospitals or transfer of patients who otherwise would not receive timely service at their origin hospital.

Numerous works in the literature consider performance of specific units, such as emergency departments (EDs), operating rooms (ORs), intensive care units (ICUs), pharmacies, neonatal care, and mental health care departments for conventional circumstances within individual hospitals (e.g. Draeger et al., 1992; Duguay and Chetouane, 2007; Kaushal et al., 2015; Komashie and Mousavi, 2005, Jun et al.,1999). Cimellaro and Pique (2016) employed a discrete event simulation (DES) platform with Monte Carlo simulation results to estimate parameters for a metamodel of resilience to disaster for the emergency department of a single hospital. Recent comprehensive reviews can be found in (Lakshmi and ppa Iyer, 2013; Saghafian et al., 2015).

These works provide methods for quantifying the capacity (physical) or capability (services) in the studied units by such measures as waiting times for patients to be seen and patient throughput.

few works quantify performance of individual hospitals in an MCI (TariVerdi et al., 2018a), and fewer quantify performance of a health care network in such events (specifically, Yi et al., 2010; TariVerdi et al., 2018a). Yi et al. calibrated a parametric regression model from simulation results for capacity planning of hospitals operating independently within a region in relation to an earthquake event or other similar disasters. TariVerdi et al. (2018b) propose a multi-stage stochastic optimization model for measuring resilience of a network of healthcare facilities where collaboration involves optimal patient assignment to hospitals and patient transfers between hospitals. The model accounts for the hospital's dependence on interdependent water, power and transportation lifelines and seeks optimal resilience enhancing actions in both preparedness and post-event stages of a disaster with potential physical damage and mass casualties. Other related works consider intra-unit coordination within a single hospital (Warren et al., 2004; Nyssen et al., 2007).

While very few works consider the performance of a whole hospital or wider health care network, the importance of analyzing the larger system has been recognized (Barbisch and Koeing, 2006; Dai and Tayur, 2019). Barbisch and Koeing note the important potential role of our Incident Command System (ICS), i.e. the National Disaster Medical System (NDMS), in hospital system performance for an MCI. Dai and Tayur (2019) discuss the need for modeling interactions across key entities of complex healthcare ecosystems in place of considering the operations of a single entity in isolation. Several works describe preparedness actions, such as disaster training for health care workers (Hsu et al., 2006) or assessed their preparedness for evacuating a hospital in a natural hazard event (e.g., Schultz et al., 1996 , Wabo et al., 2012 and Chen et al., 2015). Kaji and Lewis (2006) surveyed hospital preparedness strategies for Los ngeles County.

Since the number of casualties and injury types could vary significantly across hazard event categories, health care providers must be prepared to respond to the variety of hazards and range of event impacts that their geographic regions may face, whether induced by a malicious act, a natural hazard event, or an accident, e.g. train derailment or industrial chemical release. The Federal Emergency Management gency (FEM) provides a list of disasters for which states must be prepared. The list includes biological and chemical threat, drought, earthquake, fire, flood, heat, hurricane, landslide, radiation and nuclear accidents, tornados, tsunami, volcano, wildfire, and winter storms. These events may overwhelm any single health care facility, thus triggering a need for formal or informal collaborations across the system.

In terms of collaborations, Wang (2009) assessed coordination between hospitals and the Center for Disease Control for improved tuberculosis (TB) control in China. Van Eyk and Baum (2002) studied the role of prior interactions between personnel in facilitating collaboration within a given hospital of the benefits of such intra-hospital coordination. It appears that only TariVerdi et al. (2018b) proposes tools for quantifying the performance of two or more hospitals operating within a coalition or specific analysis of such systems. Further, quantification techniques to assess hospital performance where physical damage is incurred is also uniquely addressed in their paper.

Their mathematical modeling approach can only roughly account for the effects of a disaster impact on the structures and supporting lifelines and uses a simplistic collaboration with patient transfers and a single patient type. No resource sharing is modeled. Capacity enhancing actions are included only through uniformly faster service rates.

To address these gaps and a need to consider a wide variety of disaster types, a DES framework with underlying open queuing network conceptualization is proposed to model disaster impacts on critical resources, physical spaces and demand, and assess the resilience of a hospital system given various actions, including coalition formation and implementation of capacity enhancement strategies under varying disaster scenarios. This DES conceptualization herein builds on earlier work by Tariverdi et al. (2019) in which a patient-based, resource-constrained, multi-unit hospital modeling approach was proposed for evaluating the performance of a single, stand-alone hospital in routine and surge demand scenarios. Findings from their numerical experiments on a case study that replicates key elements of the five main hospitals in the Johns Hopkins Healthcare System (JHHS) in the Greater D.C. and Baltimore areas, based on publically available information, show the potential (i.e. reduced losses and wait times) of strategies involving resource sharing, patient transferring and joint capacity enhancement alternatives (i.e. cancellation of scheduled operations, longer shifts for staff, lower staff-to-patient ratios). In the next section, coalition strategies proposed in the literature are discussed and strategies considered in the case study are described.

Coalition Policies

In a formal regional health care coalition operating in a MCI, member hospitals prepare to pool physical and personnel resources, as well as share information pertaining to situational awareness. This enables efficient re-allocation decisions and distribution of urgently needed supplies during the incident. These activities can be facilitated through an ICS, which connects health care network entities within the coalition. Such coalitions can be very effective. From the analysis of data associated with the management of triage, surge demand and resources just after an event involving an attack on the Underground in London in 2005 that involved 775 casualties and 56 deaths (ylwin et al., 2006), it was found that the critical mortality rate was lower than expected as a consequence of efficient pre-hospital response and in-hospital, cross-department management of surge (ylwin et al., 2006). ylwin et al. noted that six of 12 emergency departments in London that were put on alert received casualties. The casualties were distributed to these hospitals based on proximity to the incident and updated hospital capacity and capability.

Participation in a coalition is consistently suggested in hospital preparedness planning guidelines, and coalitions are now a significant consideration in MCI and disaster preparedness planning within the U.S. In addition, the existence of Level-1 trauma centers (hospitals equipped with highest care levels) reduce risk of death in severely injured patients (McConnell et al., 2003). Regional response efforts can incorporate this risk factor in patient assignments; otherwise, all health care entities in the area could anticipate receiving such patients. Despite this recognition of the importance of coalitions, it appears that no prior study in the published literature has sought to quantify benefits of hospital participation in a coalition in routine or MCI conditions.

Patients may enter the health care network independently, choosing a particular facility, or they may be brought in from a disaster scene by emergency personnel. In the latter case, with a coalition in place, centralized allocation decisions on the assignment of patients to individual facilities may be made similar to the case in the London Underground attack, or with even greater coordination and efficiency. In favor of such coordination efforts, Jarvis et al. (2016) argue that rapid and effective triage enables efficient patient flows by member hospitals and improved overall system performance. To a community, efficient response by the wider health care system is as vital as the performance of each individual facility.

Formal coalition agreements or advanced health collaboratives between regional health care facilities can aid in joint preparedness planning. This unified approach is facilitated through communications and transportation, mechanisms for exchanging services, sharing resources and information, and transferring patients or moving staff between facilities. The role a specific facility plays within the coalition may depend on incident characteristics. For example, one facility may have a burn unit while another may have an isolation unit. Moreover, patient needs are a function of incident type. Consider that in an earthquake, the number of severely injured patients needing operating room facilities would likely be greater than that found in a flood event. Non-formalized collaborations, such as joint emergency preparedness and response planning, even in the absence of official agreements between regional hospitals, are also valuable. The National Capital Region (NCR) Health Care Coalition in the Washington, D.C. Metropolitan area involves 10 hospitals across Maryland, Virginia and the District, and is an example of an advanced health collaborative. This coalition was designed for joint operations in a regional disaster or an MCI where the resources of one hospital might become overwhelmed. The collaborative involves hospitals from different hospital systems, public and private. In addition to regional collaborations, some hospitals are part of a larger health care system in which they share some services and human resources, supply warehouses, and operational strategies. Member hospitals in such coalitions are not necessarily spatially proximate. JHHS is one such system in the U.S. Moreover, JHHS with five hospitals in the Washington-Baltimore area is its own system. Finally, many teaching hospitals, medical schools and faculty practice plans are organized within cademic Medical Centers (MCs) and many of these are organized across multiple universities (Levine, 2018). These historical partnerships can enable collaboration during disaster events, particularly when they are in close proximity. Levine discusses various financial arrangements used within MCs. These arrangements may differ from that described by Levine during post-disaster operations and can affect post-event alliance performance.

This study seeks to quantify the potential of various coalition agreements in a regional health care system in routine and emergency circumstances. Four policies for such agreements are envisioned as described next. They are studied further in coming sections. Whether coordination involves only information sharing or a centralized allocation scheme with sharing of resources, the agreement shapes a queuing network conceptualization used here to model hospital system operations and response capabilities. The agreement affects operational policies that determine which server is assigned (which department in which hospital) and effectively the order in which customers are served.

The system of hospitals is conceived as a network of open queuing networks (one for each hospital). From this perspective, each hospital is a server. Patients (customers) arrive to the hospital (server) according to an arrival distribution that is a function of the specific disaster event. Each patient is prioritized according to need. For example, those in need of immediate care will receive service earlier than those who are in less critical condition. Thus, a priority queuing discipline with preemption is employed. Total system capacity for serving additional patients is given as c and is computed from the sum of available beds at the constituent hospitals. Each of these four policies can be represented as a *GI/G/H/GD/c* queue, meaning that interarrival and service times are independently and identically distributed, both of which are governed by general distributions (GI and G) associated with the disaster type, with H servers (hospital nodes), a general queue discipline (GD), which is specified by the policy (1-4), and a total system capacity of c. The following policies are tested; these policies affect arrival rates and queue disciplines.

Policy 1. No coordination: Under this policy, all health care entities operate independently with their own patient queues and resource pools. Patients at the MCI scene are presumed to walk in or arrive by Emergency Medical Service (EMS) vehicles to the closest hospital where initial triage is completed. Minor injuries are presumed to be treated at the scene. Patients can choose to leave a hospital to seek faster service elsewhere when arriving and finding queues for entering triage to be excessively long. With no cooperation between hospitals, neither patients nor resources are transferred or shared. In the queuing network conceptualization, this policy is modeled using a set of independent resource pools, one pool per hospital. Each hospital has its own set of independently functioning queues for its various units. The queueing network topology of a health care system operating under this policy is shown in Figure 1-a.

Policy 2. EMS-only coordination: Under this second policy, hospitals operate largely independently, but it is assumed that real-time information on hospital capacities for facilities in the area are available to EMS through the Incident Command System (ICS). EMS chooses the closest hospital to handle each patient from those with available capacity. Once a patient enters a hospital, she is treated at that hospital. She cannot be transferred. There is no transfer of resources from one hospital to another. Urgent care clinics are not considered as recourse to handle excess demand. queuing network topology that would be associated with this policy would be similar to Policy 1 and is depicted in Figure 1-b. Only arrival rates would differ. For an MCI with a large number of casualties, this policy might be adjusted to use a combination of the amount of capacity for taking new patients with given needs and distance for a globally optimal assignment.

Policy 3. Health care coalition response: The U.S. Department of Health and Human Services recommends the use of Health care Coalition Response Teams (HCRT) operating through an ICS for coordinating coalition member organizations. The primary purpose of HCRT is to provide situational awareness for its members. In addition to providing incident information, the HCRT assists with the allocation of internal resources and distribution of aid from other organizations (US Department of Health and Human Services, 2019). This policy models the health care system that benefits from aid of the HCRT as a central coordinating entity.

In this policy, health care entities are assumed to communicate with each other, patients can be transferred between facilities, and resources can be shared. Patients with less severe injuries facing high wait times may be transferred to the next closest facility within the coalition that can accept new patients. Secondary facilities may serve as primary care units or clinics for patients with minor injuries. Some specialized outpatient facilities, such as ambulatory surgical centers, can provide excess Operating Room (OR) capacity for affiliated hospitals. Hospitals coordinate with EMS for patient transfers as necessary to exploit the excess capacity. This policy benefits from dynamic patient assignments based on available capacity information and expected waiting times for cooperating facilities, which are assumed to have direct communication with other health care entities in the coalition. In the queuing network conceptualization, this policy is modeled using a single shared resource pool. Each hospital maintains its own set of independently functioning queues for its various units. similar arrival pattern to that in Policy 1 is assumed. The queueing network topology of a health care system operating under this policy is shown in Figure 1-c. The JHHS might operate under this policy.

Policy 4. Centralized processing: Even excellent communications and exceptional responsiveness will not prevent fatalities at the MCI scene. However, rapid patient transfer to the best-suited hospitals based on prehospital triage and information on hospital capacities can increase efficiency by utilizing limited resources and reduce losses. This policy presumes that prehospital triage is conducted at the MCI scene or at a few locations within the area for MCIs affecting larger geographical areas. Patient allocation decisions are also made at the scene. ll decisions are made centrally with full information about hospital capabilities and current capacities for handling new patients with varying injury types and severities. Jotshi et al. (2009) provide a data-enabled methodology for dispatching emergency vehicles in a disaster to transport casualties to nearby hospitals based on available capacity and proximity. Their approach can support a modern method for dispatching in a system cooperating to enable a centralized policy. Like Policies 1 and 2, this policy is modeled using a set of independent resource pools, one pool per hospital, within the queueing network conceptualization. Each hospital has its own set of independently functioning queues for its various units. Different from these policies, however, two-stage patient transfer from the MCI scene to triage and then to a health care facility is implemented. The queueing network topology of a health care system operating under this policy is shown in Figure 1-d. Washington's (NCR) Health Care Coalition might follow this policy.

Policies 1 and 2, thus, are similar in that they do not share resources or patients. However, in Policy 2, on-scene medical assistants have information on available hospital capacities, which they use in the allocation of patients to hospitals. dditionally, Policies 3 and 4 are similar in that patients are assigned to hospitals using a centralized processing approach. Commonalities and differences across the four policies are depicted in figure 2. The potential combinations are shown in the intersections of the Venn diagram in the figure. The next section describes the modeling platform and modeling implications of applying these policies.

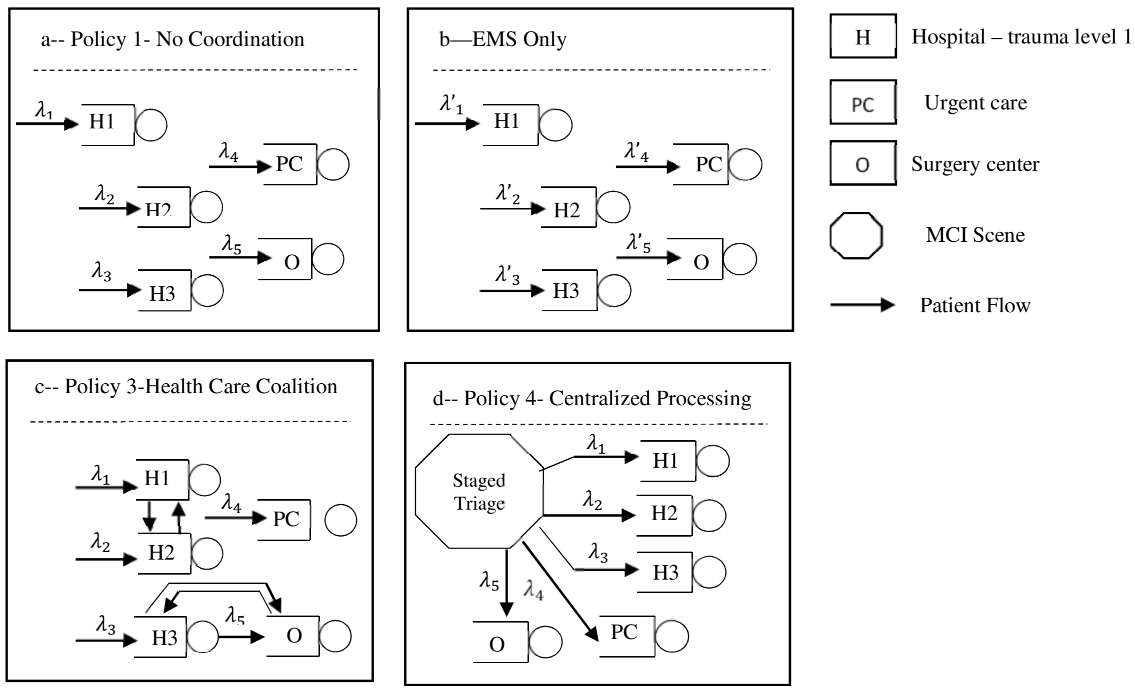


Figure 1- Regional Healthcare Network Layout under Different Policies

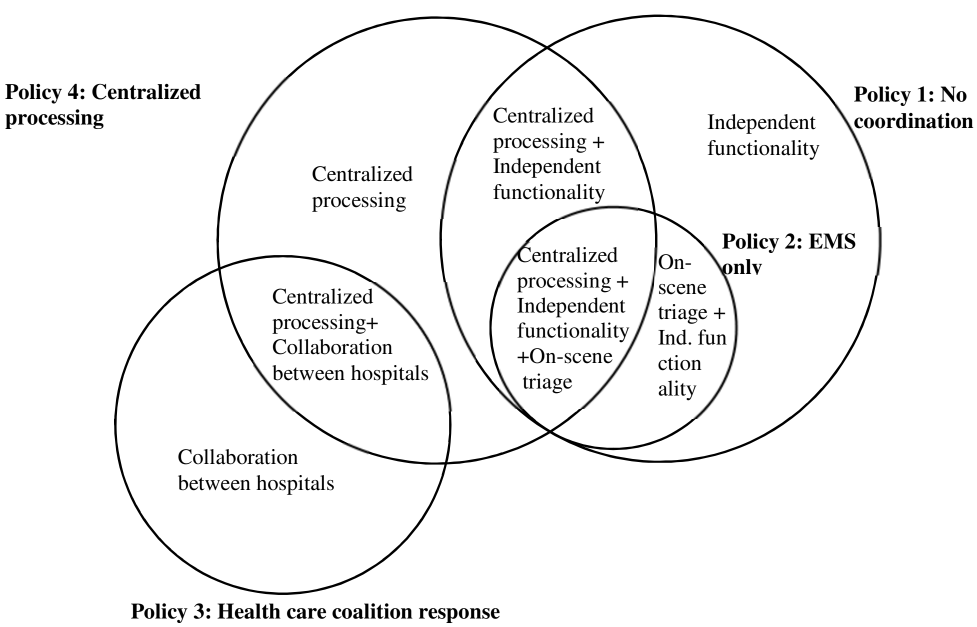


Figure 2- Venn Diagram of Policy and their Relations

Experimental Platform

Individual hospitals along with transfer paths for patients coming from specific units of one hospital in transferring to a second hospital (i.e. hospital interconnections), shared resources and guiding policies for patient assignment to care paths within a hospital were modeled within the ExtendSIM microscopic discrete event simulation platform. ExtendSim's dvanced Technology libraries, including value, item, rate and plotter, are used extensively in model creation and results analysis. lso used in results analysis and error checking is a two-dimensional option to help follow patient flows inside and between hospitals.

The modeling approach here expands on existing modeling capabilities that use a patient-based, whole-hospital (including 9 critical units), resource-constrained modeling approach developed for a single generic, urban hospital of trauma level-1 or -2 (TariVerdi et al., 2019) to multiple, interacting hospitals. Details of the modeling approach taken, including for example, by delineation of patient care paths, simulation of patients, tracking of pooled resources, shifts for staff, for an individual hospital operating under ordinary, surge and extraordinary (MCI) demand scenarios can be found in (Tariverdi et al., 2018a).

The modeling framework is applied to replicate a system of five hospitals with similar geographic proximity and characteristics to the five main hospitals in JHHS. These hospitals are set to have 1194, 440, 318, 282 and 222 beds representing The John Hopkins Hospital, Bayview Medical Center, Sibley Memorial Hospital, Howard County General Hospital, and Suburban Hospital, respectively. The distances between hospitals in this system range from 20 to 65 miles. Such distances can be key factors in decisions associated with the assignment of patients to hospitals from a disaster scene.

Each independent hospital is a queuing network into itself, and can be represented within a simulation module known in ExtendSIM as a hierarchical block. Details of each hospital, including inputs of each of the five hospitals, outputs and activities are tracked. Each hospital block includes subblocks that replicate processes and resources maintained within that hospital. For example, a shift block can be used to maintain staff shifts for a given hospital. Likewise, queue blocks can maintain details of each queue. Each queue block has an input and a results tab. The maximum allowable queue length, i.e., queue capacity, resources required to provide associated services, and renege options (maximum time patients will wait before leaving) are defined for each queue in an input tab. Information on queue length, waiting time, number of arrivals or departures, and number reneging is recorded within a results tab. Some queues, such as the registration queue, contain patients, while others, such as the radiology queue, are associated with services. Patients do not generally physically wait in specific queues, but their overall time in the system is determined by their time waiting for such services (along with service and exit times). For each hospital, 40 queues are tracked (Tariverdi et al., 2019) and their average wait times are computed and recorded.

The numerical experiments are designed to assess collaboration strategies under four hazard types: (1) pandemic, (2) earthquake, (3) flooding, and (4) MCI. Each hazard event may impact each hospital in different ways. For example, based on the type of disaster and its scale, patient arrival patterns, along with impacts on resources, unit capacities and lifeline support for the hospital building may vary significantly. These factors are explained further next.

Patient arrival patterns: Patients arriving to a hospital are categorized by an Emergency Severity Index (ESI) based on physical need, specifically injury type and severity. ESI-5 patients have less urgent needs and are discharged without being treated, while ESI-1 are in need of immediate care. Patient ESI level and care needs are a function of the hazard category and event severity, and these needs affect the care paths they take. For some scenario classes, e.g. pandemic and flooding, patients are assumed to walk in on their own. They go through the triage process, are diagnosed and assigned an ESI level, and are sent along appropriate care paths for the needed services. In an earthquake, however, there are likely to be larger numbers of ESI-1 (e.g. with head trauma) or -2 patients who are in need of urgent care. When on-scene triage is completed, as is likely the case in an MCI such as in Las Vegas, the patient enters the hospital post-triage, thus accelerating service to these patients and relieving the burden on the triage unit. Details of patient arrivals are given in ppendix 6.

Impacts on Resources: Resources (number of nurses, doctors, technicians by skill, equipment (x-ray machines, Computerized xial Tomography (CT) scans) and supplies (oxygen, blood)) can be affected by a hazard event. Pandemic, earthquake and flooding scenarios were assumed to directly affect the availability of human resources. For example, flooding and earthquake will result in fewer nurses, technicians and doctors. llen (2018) found that 25% (150 out of 600) of hospital workers did not attend work during flooding arising from Hurricane Irma in 2017 due to impassable roadway conditions. Thus, a reduction in personnel by 25% over the simulation run associated with flooding for affected hospitals was presumed. Similarly, a reduction in personnel was noted during an avian flu outbreak, as 38% of hospital workers chose not to attend work (Martinese et al. 2009). Thus, a 38% reduction in personnel in all hospitals in the region was presumed in the pandemic scenario. Cone and Cummings (2006) found that 79% of hospital workers were willing to work after an earthquake; thus, for the earthquake scenario runs were made under the assumption that 21% fewer personnel, including Emergency Department (ED) doctors and nurses and operating room (OR) doctors, at affected hospitals would attend work as a result of damage to roadways, schools or homes. n earthquake scenario involving moderate damage, considered Grade-2 in (chour et al., 2011), was modeled. Consistent with this grade level, the scenario runs involved a reduction in functionality by 20% of physical resources, including OR, Operation Preparation Unit (PreOp) and general ward beds, lab equipment, excluding Computed Tomography (CT) scan and magnetic resonance imaging (MRI) machines, at affected hospitals.

Effects on unit capacities/capabilities: Earthquake and flooding scenarios involve physical damage to part of the affected hospital building in several scenarios, and this damage results in loss of functionality of some units. Unit capacities depend on the disaster scenario type. Pandemic and MCI events are non-physical type hazards and, thus, it is presumed that building structures and supporting lifelines are undamaged and units work at their full capacities or reduced capacity due to personnel shortages in the case of a pandemic. In earthquake and flooding scenarios, the building will also be impacted and loss of functionality of some units is expected. In the runs, it was assumed that the service rates of the OR units of any affected hospital decrease by 30% in these scenarios. dditionally, the flooding scenarios presumed that a storm would affect a portion of Howard County that is historically susceptible to flooding, leaving Howard County General Hospital with a loss in functionality by 20%. In this scenario, thus, 20% of routine arrivals are rejected.

Lifelines: power outage at an affected hospital is modeled in the earthquake scenario, reflecting the impact of disaster events on lifeline support of a hospital building. The hospital relies, thus, on back-up generators. The generators can only support limited functions, and are usually reserved to maintain power to critical units. In the runs, thus, the OR units and ED continue to run as normal, but other units are presumed to have reduced functionality. This reduction is modeled by a decrease of 20% in service rates. It is assumed that the generators can be refueled throughout the simulation runs; however, one might test scenarios where the generators run out of fuel in only 24-48 hours.

Numerical experiments designed and run to assess the potential benefits of considered capacity enhancement strategies under the disaster scenarios with these impacts on physical structures, supporting lifelines and resources are described next.

Experimental Run Design

20 different sets of numerical runs (each set with 50 replications) were conducted with the aim of evaluating potential benefits of capacity enhancement (modified operations and alternative standards of care) and collaboration strategies. ll reported results are averages of the 50 runs. Patient arrivals at the ED were assumed to follow an exponential distribution for both the baseline and surge scenarios. Service times for all services were presumed to follow an exponential distribution. Specific details of these distributions and their parameters can be found in Table 3 of (TariVerdi et al., 2018a). Four disaster scenarios along with four types of capacity enhancement strategies are combined to form these runs. For each hazard event, average queue waiting times number who Leave Without Being Seen (LWBS) and expired patients (i.e. patients who enter a hospital through the OR and whose wait times exceed a given acceptable threshold, thus failing to receive adequate care) were collected and compared considering the implementation of resource sharing, patient transfers and capacity enhancement strategies. These are depicted pictorially in Table 1. Unless stated otherwise, runs studying transfers were made assuming 40% of LWBS and 60% of expired patients are transferred. smaller portion of LWBS are assumed to be transferred, because LWBS patients walk in and, thus, are likely to be able to wait longer (up to 8 hours in the model), than expired patients who are in need of immediate care. Each run is over 27 days of which the first 20 days serve as the warm-up period. Thus, all results, including number of LWBS

and expired patients (together referred to as the unmet demand) and average waiting times are computed over 7 days. The experiments were designed to answer a number of questions pertaining to disaster impact performance effects and the potential of various strategies to address these impacts. Runs were also completed to evaluate hospital system resilience to multiple hazard event scenarios for the case study. dditional input specifications are provided in ppendix 6.

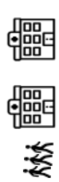
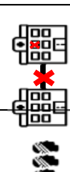
Results and analysis

Results and analyses provided next are organized according to the questions that are investigated.

What are the impacts of disasters on hospital system performance? Results of the runs show that physical damage to the hospitals themselves and/or supporting lifelines can cause an increase in unmet demand. Reductions in personnel had less, but also significant, impact. Figure 3 shows a case where physical damage causes a 50% decrease in the functionality of PreOp, Post nesthetic Care Unit (P CU) and OR units. This reduction led to an increase in system-wide unmet demand by 9%. dditionally, reductions in personnel alone for the same units, specifically a 50% decrease in the number of PreOp, P CU and OR doctors and nurses, led to 7% system-wide increase in unmet demand.

Qureshi et al. (2005) surveyed hospital workers to investigate the potential for a staff shortage under different disaster scenarios. They noted that in the case of an MCI, environmental disaster, chemical release event, smallpox epidemic, radiological event, sudden acute respiratory distress syndrome outbreak, and a severe snow storm, 83%, 81%, 71%, 69%, 64%, 64% and 49% of healthcare workers indicated that they would be able to show up for work, respectively.

Table 1- Effects of Different Hazard Events

Disaster Event	***Pictograph***	***Demand Surge***	***Reduced Staff/ Stuff***	***Structural Damage***	***hospital down in system***	***Routine Operation***	***Capacity Enhancement Strategy***	***Patient Transfer***	***Resource Sharing***
Pandemic-Baseline		✓	✓			✓			
Pandemic 1		✓	✓				✓		
Pandemic 2		✓	✓					✓	✓
Pandemic 3		✓	✓						
Pandemic 4		✓	✓					✓	✓
Pandemic 5		✓	✓				✓	✓	✓
Earthquake-Baseline		✓	✓	✓		✓			
Earthquake 1		✓	✓	✓			✓		

Earthquake 2		✓	✓	✓				✓	
Earthquake 3		✓	✓	✓					✓
Earthquake 4		✓	✓	✓				✓	✓
Earthquake 5		✓	✓	✓			✓	✓	✓
Flooding-Baseline		✓	✓		✓	✓			
Flooding 1		✓	✓		✓		✓		
Flooding 2		✓	✓		✓			✓	
Flooding 3		✓	✓		✓				✓
Flooding 4		✓	✓		✓			✓	✓
Flooding 5		✓	✓		✓		✓	✓	✓
MCI-Baseline		✓				✓			
MCI 1		✓					✓		
MCI 2		✓						✓	
MCI 3		✓							✓
MCI 4		✓						✓	✓
MCI 5		✓					✓	✓	✓

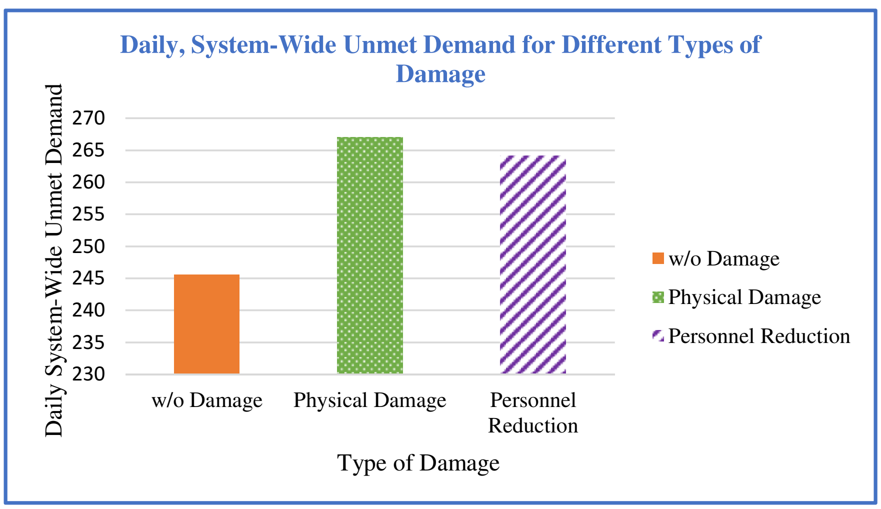


Figure 3- Effects of Physical Damage and Personnel Reduction on Total, System-wide Daily Unmet Demand

Which policy is most effective: no coordination, EMS-only coordination, health care coalition or centralized processing? Results of the numerical experiments indicate that all three policies involving some form of coordination (EMS-only coordination, health care coalition and centralized processing) significantly decrease daily, system-wide unmet demand as compared to a baseline of no coordination. Results from the implementation of Policy 1 in the pandemic scenario, wherein the surge demand is evenly split across the five hospitals, are given in Figure 4. The savings ranged from 27 (EMS-only) to 59 (health care coalition) additional patients who receive help, for an improvement by as much as nearly 24%. Thus, 32 additional patients were treated by allowing transfers (using the health care coalition policy) compared to EMS delivering patients to hospitals with available capacity but forbidding the transfer of patients once entering a hospital. ssigning patients to hospitals in proportion to the number of available beds (a proxy for wait time) resulted in five additional treated patients as compared to delivering patients to hospitals with any remaining capacity. Similar results were found for other scenarios.

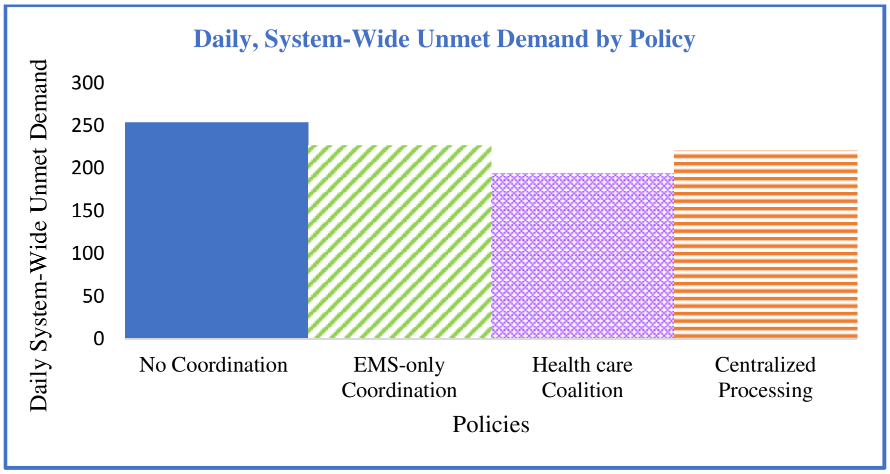


Figure 4- Effects of Physical Damage or Personnel Reduction on Total, System-Wide Daily Unmet Demand

re collaboration and capacity enhancement strategies useful in times of disaster? The results also indicate that patients entering a damaged hospital or a hospital handling a comparatively significant increase in demand will have a greater chance of surviving due to reduced average waiting times when the damaged hospital collaborates with other hospitals. Further, when the hazard event causes damage to the structure, forming a coalition that permits patient transfers and resource sharing, and simultaneously implementing capacity enhancement strategies, will cause a reduction in system-wide unmet demand (LWBS and Expired patients) by up to 13% (the earthquake scenario) compared to a baseline without similar collaboration. When there is no damage to any structure, i.e. the disaster event affects only resources and demand, implementation of capacity enhancement strategies and coalition formation led to a reduction in unmet demand by as high as 27%, which occurred in the earthquake scenario. lso, when there is a surge in demand, collaboration decreases system-wide unmet demand by up to 14% (earthquake scenario). Figure 5 provides further insights into the effectiveness of collaboration on reducing unmet demand in cases with (earthquake scenario) and without (pandemic scenario) damage.

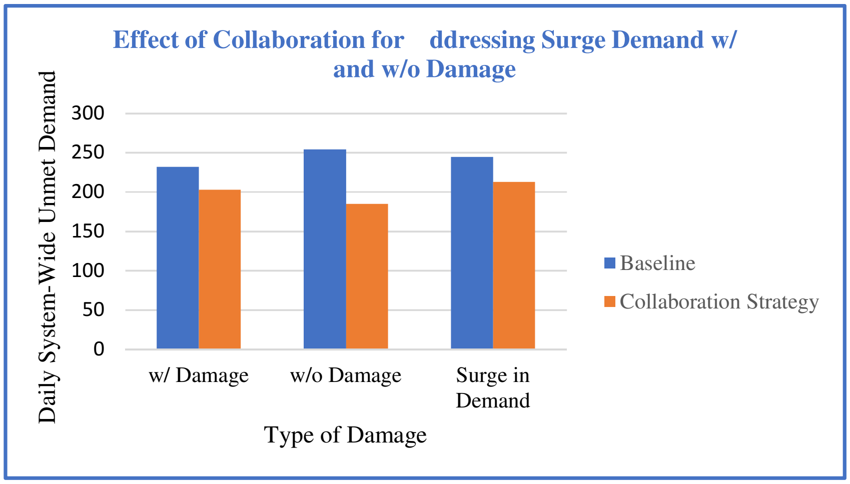


Figure 5- Effects of Collaboration Strategy on Daily Unmet Demand with Physical Damage or Surge in Demand

Which collaboration strategy (patient transfer vs. resource sharing) works best under which scenarios? In the pandemic scenario, implementing capacity enhancement strategies creates a 23% system-wide decrease in unmet demand. In the earthquake, flooding and MCI scenarios, resource sharing is most effective, creating a decrease of 39, 45 and 23% in system-wide unmet demand, respectively. Yet, in all scenarios, a combination of patient transfers and resource sharing along with the implementation of capacity enhancement strategies resulted in additive benefits, leading to significant decreases in unmet demand. Figure 6 shows these results by disaster scenario.

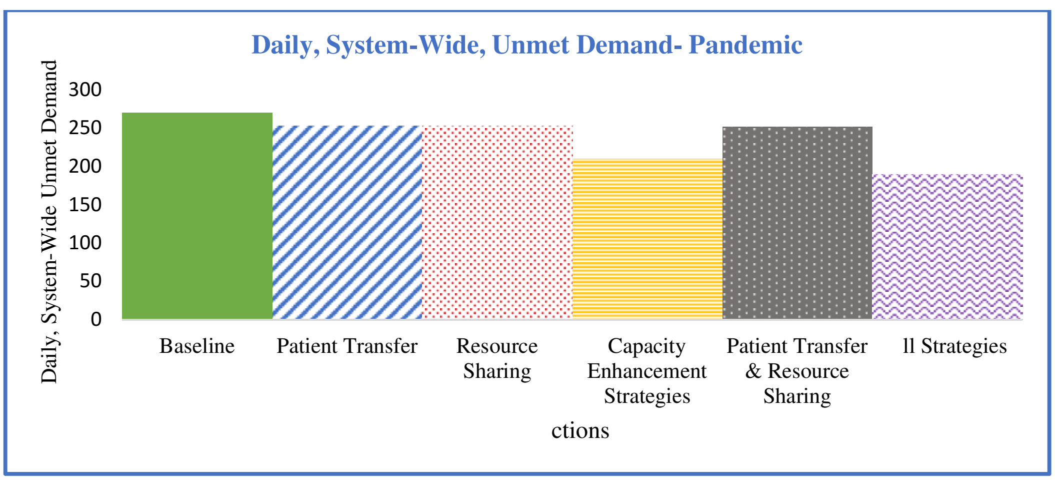


Figure 6a- Daily System-Wide Unmet Demand in Pandemic

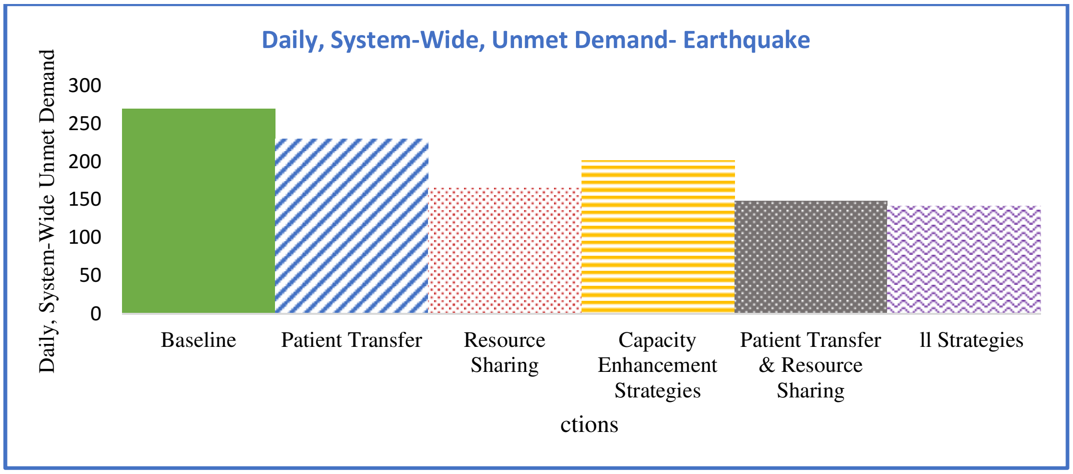


Figure 6b- Daily System-Wide Unmet Demand in Earthquake

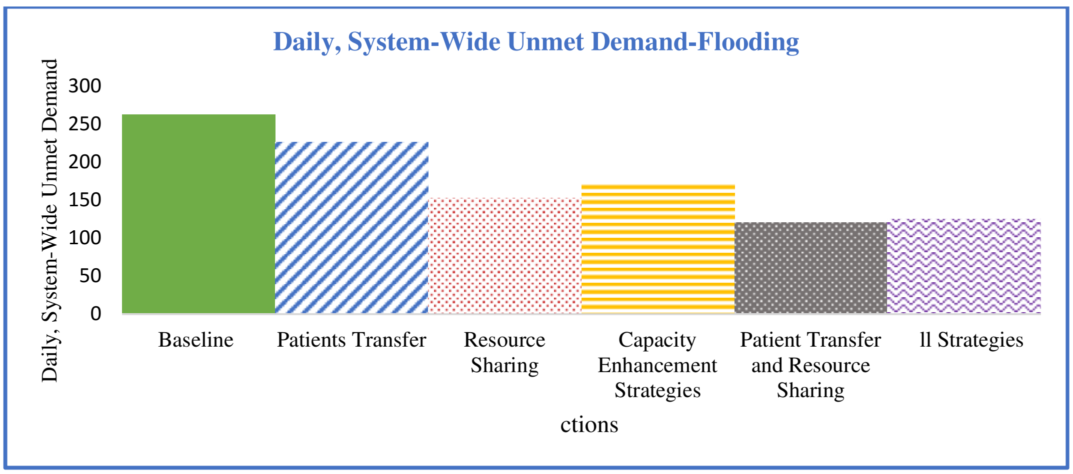


Figure 6c- Daily System-Wide Unmet Demand in Flooding

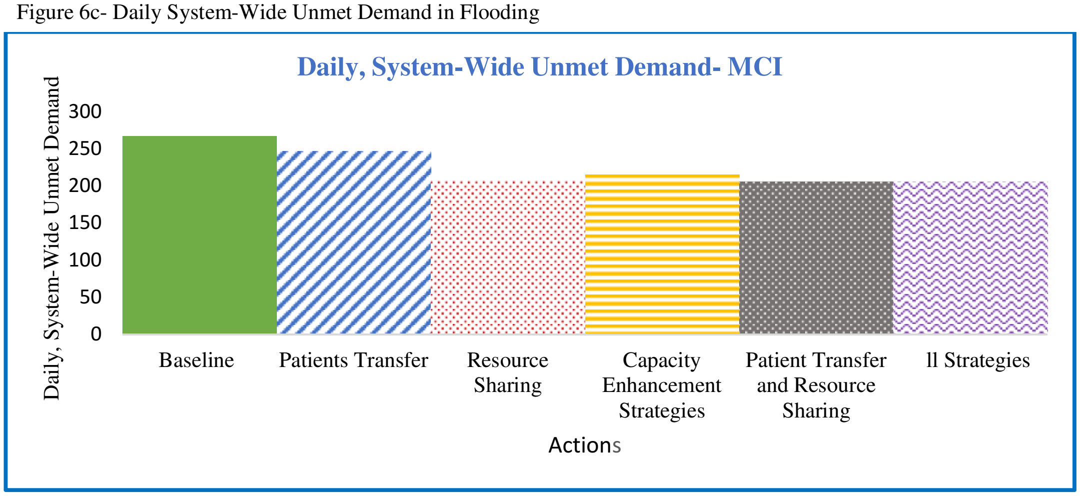


Figure 6d- Daily System-Wide Unmet Demand in MCI

Figure 6 provides system-wide effects by permitted response strategy. While the system performance is improved by all actions, some hospitals fair better than others. For example, a hospital transferring out patients will have less unmet demand than a hospital receiving the transfers. Changes in daily system-wide unmet demand for the pandemic scenario for each of three affected hospitals are shown in Table 2. Here, Bayview Medical Center and John Hopkins Hospital incur a surge in demand as a result of a pandemic. Simultaneously, they experience a shortage in personnel. Howard County General Hospital, on the other hand, receives patients from these two hospitals. The results indicate reductions in unmet demand at the affected hospitals by up to 88% for 106 people at Johns Hopkins Hospital and Bayview Medical Center combined. Simultaneously Howard County General Hospital incurs an increase by 47% (or 40 people). Thus, system-wide, total unmet demand is reduced by 66 people when all capacity enhancement and collaboration strategies are permitted.

Table 2- Changes in Daily, Unmet Demand for Different Hospitals inside Coalition

Name of Hospital	Percent of Change in Daily Unmet Demand for Different ctions in Pandemic				
	Patient Transfer	Resource Sharing	Capacity Enhancement Strategies	Resource Sharing and Patient Transfer	ll Strategies
Bayview Medical Center	-10%	-7%	-1%	-13%	-26%
Johns Hopkins Hospital	-10%	-11%	-68%	-13%	-88%
Howard County General Hospital	19%	9%	15%	22%	47%

Where within a hospital should patients be sent when transferring between hospitals? Runs were conducted to assess the effectiveness of allowing transfer patients to enter a second receiving hospital post-triage. Results of these runs show (Figure 7) that patients with less severe care needs (ESI-4, 5) should enter the second hospital before triage and more urgent patients (ESI-2, 3) should enter the second hospital after triage to reduce unmet demand. These runs were made for a baseline with no surge in demand or physical damage.

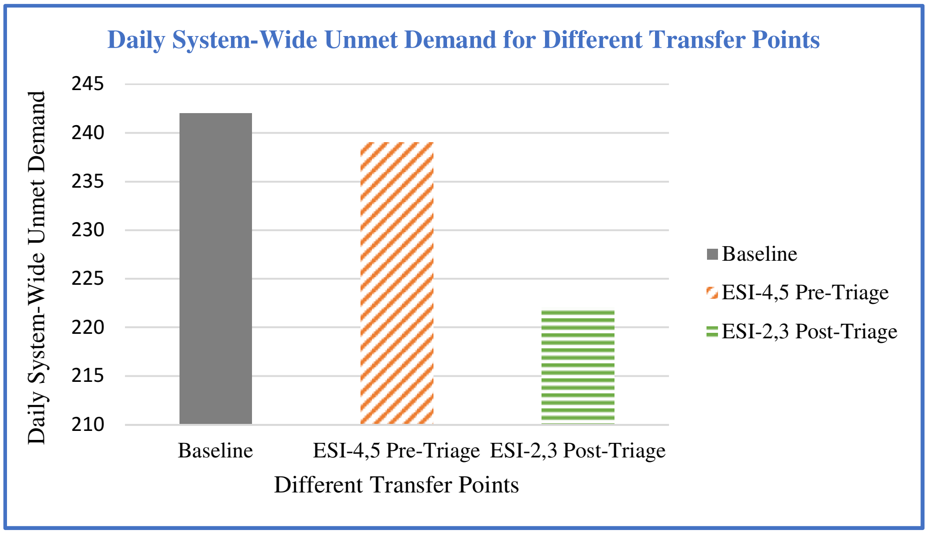


Figure 7- Transferring ESI-4,5 pre Triage and ESI-2,3 post Triage – No Damage or Demand Surge

What portion of patients can be sent to other hospitals from an affected hospital? Consistent with expectations, results reveal that the greater the number of patients transferred from a damaged hospital as in the pandemic scenario, the less the unmet demand in the originating hospital, but the greater the unmet demand in the receiving hospital(s). When deciding what percent of patients to transfer between hospitals, the capacity of the receiving hospital and whether or not it is in close proximity to the hazard event play important roles. Figure 8 depicts the impact on unmet demand of the number of patients transferred for the earthquake scenario where there is surge demand, reduced personnel and damage both to the structure itself and its supporting lifelines. When only 10% of LWBS and expired patients are transferred out of a hospital, total system-wide unmet demand decreased by 22%. However, if 90% of LWBS and expired patients are transferred out, a 41% decrease in total system-wide unmet demand can be expected. Transferring nearly all LWBS and expired patients from the originating to a receiving hospital can be difficult in reality. Transfer is thus critical to these patients if they cannot be seen in a timely manner. In the runs, time for completing a transfer between hospitals ranged as a function of distance and patient ESI level. Transfer times were assumed to be twice as long for patients with more severe injuries to account for special equipment and staff needs. dditional details of provided in ppendix 6.

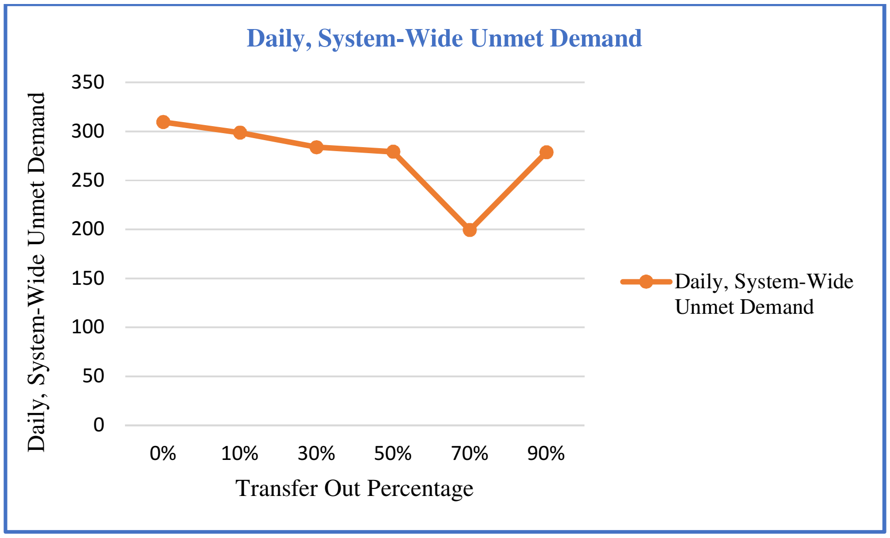


Figure 8- Effect of Transfer-Out Percentage Changes on Daily Unmet Demand in Earthquake Scenario

How much benefit are modified operations and alternative standards of care strategies when implemented alongside collaboration strategies? Results suggest that the best outcome is achieved when capacity enhancement strategies are combined with both resource sharing and patient transfer. In pandemic, earthquake, flooding and MCI scenarios, there was a decrease of 30%, 48%, 53% and 23%, respectively, in system-wide daily unmet demand when collaboration strategies, including patient transfer and resource sharing, are combined with capacity enhancement strategies. lone, patient transfer resulted in a decrease of only 7%, 15%, 42% and 8% in pandemic, earthquake, flooding and MCI, respectively, in daily unmet demand. Correspondingly, resource sharing produced a decrease of 7%, 39%, 42%, and 23% in daily unmet demand. Likewise, combining patient transfer along with resource sharing caused a decrease of 7%, 45%, 54%, 24% and capacity enhancement strategies alone produced a decrease of 23%, 26%, 35%, and 19% in system-wide unmet demand. Thus, patient transfer was most effective in the pandemic scenario, while resource sharing was most critical in earthquake and flooding scenarios. The benefits of combining these collaboration options and including capacity enhancement strategies produced very significant gains over their independent implementations. Figure 9 shows the results in a single diagram. Note from the figure that combining all strategies may not always be worth the cost of doing so. For example, in the flooding scenario, patient transfer and resource sharing resulted in a 53% decrease in daily unmet demand while all strategies combined led to only 0.4% additional improvement. These results indicate that specifying the strategy combination for a given circumstance can provide nearly the same benefits as gained from applying all strategies, but with significant savings.

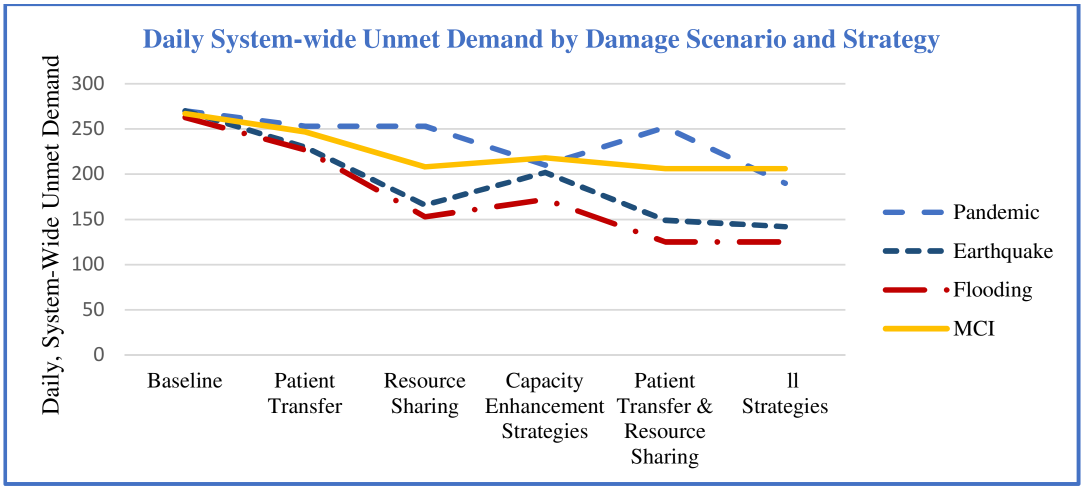


Figure 9- Percent of Decrease in Unmet Demand for Different Collaboration and Capacity Enhancement Strategies

How can resiliency be measured and what are the effects of collaboration and capacity enhancement strategies on resiliency? Resiliency of any system can be described in terms of the system's ability to maintain continued operations post-disruption.   health care system is resilient under different hazard scenarios if it can serve patients with a performance level near to that of routine conditions. The performance of the JHHS can be measured using unmet in the system. Unmet demand can serve as a surrogate for fatalities and is the basis herein for measuring the resilience of the hospital system.

Let Z_j represent hospital system performance under scenario *j* and Z_B be the baseline for which capacity enhancement or collaboration strategies are implemented and no damage is incurred. Resilience is measured as in equations 2-4 for $\mathrm{Udemand_j}$ the unmet demand, or LWBS and expired patients, for hospital *j*. The closer this resilience measure is to 1, the more resilient the health care system is to hazard event *j*. Table 3 provides resiliency estimates for this 5-hospital system under different hazard events and capacity enhancement and collaboration strategies.

$$\mathrm{Z_j} = \sum_{\mathrm{j}} \mathrm{Udemand_j}|scenario \qquad \text{(Eq 2)}$$

$$\mathrm{Z_B} = \sum_{\mathrm{j}} \mathrm{Udemand_j} \qquad \text{(Eq 3)}$$

$$\left(\frac{\mathrm{Z_j}}{\mathrm{Z_B}}\right)^{-1} \qquad \text{(Eq 4)}$$

Table 3- Resilience Values for Hospital System under Varying Hazard Events for Baseline B

daptive Strategy	*Pandemic*	*Earthquake*	*Flooding*	*MCI*
Patient transfer	0.98	1.15	1.22	1.04
Resource sharing	1.06	1.34	1.04	0.93
Resource sharing and patient transfer	1.03	1.34	1.17	1.02
Capacity enhancement	1.13	1.09	1.17	1.05
ll strategies combined	1.15	1.27	1.34	1.04

Note that some of the values are greater than 1. This is because the capacity enhancement and collaboration strategies, Table 3 provides even greater service rates than are needed to address the event. However, even in routine conditions, there can be unmet demand at the hospitals and enabling these adaptive strategies can mitigate the unmet demand. Let $Z_{B'}$ be the baseline in which all capacity enhancement and collaboration strategies are implemented, but no damage is incurred. Resilience estimates for this second baseline are shown in Table 4. In this case, no value exceeds 1 as the adaptations are identical.

Table 4- Resilience Values for Hospital System under Varying Hazard Events for Baseline B'

daptive Strategy	*Pandemic*	*Earthquake*	*Flooding*	*MCI*
Patient transfer	0.96	0.89	0.72	0.88
Resource sharing	0.61	0.64	0.61	0.58
Resource sharing and patient transfer	0.85	0.91	0.53	0.86
Capacity enhancement	0.94	0.83	0.79	0.89
ll strategies combined	0.85	0.74	0.50	0.85

Taking the expectation over all hazard events, assuming an equal probability of each scenario occurring and that all adaptive strategies are identically enabled under the different scenarios as appropriate to the hospital, results in an overall expected resilience level of 1.12 (for baseline B) or .78 (for baseline B') for the hospital system. If the JHHS does not prepare to enable any of the considered adaptive strategies, the overall expected resilience level is 0.48. This latter measurement is a measure of the system's inherent coping capacity and provides a baseline for understanding the importance of taking adaptive measures.

The number of additional patients treated can be seen as a short-term performance metric as it is meant as a surrogate for fatalities. One might also consider longer-term economic effects, issues of equity and other social welfare metrics. Such metrics would require monetary loss estimates, including the cost of a patient's death, costs and risks of transferring patients between hospitals, costs associated with sharing resources between hospitals, and more.

Inconsistencies in the resilience values in these two tables were noted, as the resilience value for combined strategies is not always higher than one used in isolation. This is appears to be due to the effects of aggregation over the five hospitals. Results for individual hospitals are provided in the ppendix. Finally, additional study would be needed to compute a baseline, Z_B, for resilience computation in which patient transfer is permitted in disaster events where the transfer times reflect the additional needed time given that no coalition agreement exists.

Conclusions

Few works that quantify hospital preparedness for disaster seek to quantify the benefits of inter-hospital collaboration, or evaluate hospital performance where a hospital system is faced with a surge in demand and simultaneously a loss in system functionality. This paper seeks to fill these gaps. To achieve this, the impacts of disaster events were modeled through the effects on physical space and resources in terms of unit functionality. In addition to capacity enhancement strategies that were previously modeled for a specific hospital (TariVerdi et al., 2018a), patient transfers, resource sharing and various coalition strategies, such as centralized processing, were implemented through joint resource pools and flows across inter-hospital linkages.

Results from systematically designed numerical experiments replicating five hospitals in a metropolitan region with characteristics that are based on those of the JHHS revealed a number of important insights that may have general utility in actual post-disaster response. For example, physical damage was noted to have greater effect on hospital operations compared to reductions in personnel. Collaboration can be effective in cases with such physical damage or reduced staff. It can be concluded from the results that in a pandemic or earthquake, patient transfer is the most effective strategy of those tested; while in a flood, resource sharing will likely create the largest decrease in daily unmet demand. In the former, the strain on the hospitals is more likely to come from patients with high care needs; whereas, in the latter, greater damage to the facilities is expected. This difference in patient arrival patterns and damage scale across scenarios is a likely cause of this finding. dditionally, in a MCI, capacity enhancement strategies tended to have the best outcomes among tested approaches. Results also suggest transfers based on ESI level is an effective strategy. Specifically, ESI-4 or 5 patients should enter the second hospital before triage while ESI-2 or 3 patients should be permitted to skip triage in the second hospital, accelerating their service rates. mong the four tested policies, the health care coalition policy led to the greatest decrease in daily unmet demand followed by centralized processing and EMS-only coordination and no coordination. Centralized processing, wherein a hospital's distance from the scene and its proportion of remaining capacity is accounted for in patient allocation among hospitals, can be effective in reducing unmet demand while avoiding patient transfers. Such an approach may have significant utility in real operations, and would be well-supported by entering into a coalition. It can also be concluded that while combining all possible strategies will lead to the greatest decrease in daily unmet demand, the benefits of taking every such action may not be worth the cost in time, training or money.

This paper also presented a resilience measure for assessing hospital system preparedness. The measure takes a weighted sum of average waiting time and unmet demand and compares this value to a baseline where there is no damage and no collaboration between hospitals. Results indicate, for example, improved resilience under a patient transfer strategy for post-event adaptation for the studied pandemic and earthquake scenarios, but improved resilience in flood and MCI events through implementing capacity enhancement strategies. More generally, preparing to enable the implementation of the studied adaptive strategies is crucial in maintaining a resilient hospital system.

dditionally, in the best case, in the flooding scenario, when combining patient transfers, resource sharing, modified operations and alternative standards of care under a healthcare coalition response policy (policy 3), 138 additional emergency patients are treated, leading to a 53% reduction in unmet demand occurring as a consequence of the event. Taking expectations over all scenarios assuming occurrence probability of 0.25, 0.25, 0.4, and 0.1 for pandemic, earthquake, flooding and MCI, respectively, results in treatment of 113 additional patients, or a 43% reduction in unmet demand. Given the same scenario occurrence probabilities, only 30 additional patients are treated when patient transfers and resource sharing only are permitted, while 80 additional patients would be treated if only resource sharing is allowed. The latter may have greater benefits due to shorter in-system times and reduced resource needs.

The numerical results obtained in this study are limited by the specific details of the case study hospital system, chosen hazard event scenarios and set of potential strategies for post-event adaptation. Future studies might consider a wider range of scenarios and strategies. Monetary losses may be incurred by a hospital that rejects or transfers a patient or shares its critical resources; thus, mechanisms for compensation for operating coalitions in disaster events are needed. Future models might take such compensation schemes into account.

cknowledgments: This work was funded by the National Science Foundation. This support is gratefully acknowledged, but implies no endorsement of the findings

ppendix

Table A1- Resilience Values for Hospitals in Hospital System under Varying Hazard Events for Baseline B under the Patient Transfer ction

Patient Transfer	***Johns Hopkins Hospital***	***Bayview Medical Center***	***Sibley Memorial Hospital***	***Howard County General Hospital***	***Suburban Hospital***	***System-wide***
Pandemic	0.13	1.51	1.11	1.02	1.13	0.98
Earthquake	1.06	1.06	1.38	1.09	1.18	1.15
Flooding	0.99	1.47	1.14	1.49	1.20	1.22
MCI	7.78	0.99	0.91	0.57	0.98	1.04

Table A2- Resilience Values for Hospitals in Hospital System under Varying Hazard Events for Baseline B under the Resource Sharing ction

Resource Sharing	***Johns Hopkins Hospital***	***Bayview Medical Center***	***Sibley Memorial Hospital***	***Howard County General Hospital***	***Suburban Hospital***	***System-wide***
Pandemic	71.57	141.43	91.14	39.00	159.71	0.98
Earthquake	4.28	1.09	1.23	1.18	1.28	1.15
Flooding	0.88	0.85	1.17	1.38	1.19	1.22
MCI	0.53	0.86	1.10	0.95	1.31	1.04

Table A3- Resilience Values for Hospitals in Hospital System under Varying Hazard Events for Baseline B under Capacity Enhancement Strategies ction

Capacity Enhancement Strategies	***Johns Hopkins Hospital***	***Bayview Medical Center***	***Sibley Memorial Hospital***	***Howard County General Hospital***	***Suburban Hospital***	***System-wide***
Pandemic	0.97	1.13	1.17	1.00	1.12	1.13
Earthquake	5.04	0.83	1.08	1.10	1.00	1.09
Flooding	5.94	0.97	1.18	1.32	0.98	1.17
MCI	7.67	0.75	1.05	0.98	0.99	1.05

Table A4- Resilience Values for Hospitals in Hospital System under Varying Hazard Events for Baseline B under Patient Transfer and Resource Sharing ction

Patient Transfer and Resource Sharing	***John Hopkins Hospital***	***Bayview Medical Center***	***Sibley Memorial Hospital***	***Howard County General Hospital***	***Suburban Hospital***	***System-wide***
Pandemic	1.00	0.95	0.98	0.87	1.21	1.03
Earthquake	5.61	1.27	1.07	1.07	1.24	1.17
Flooding	1.30	1.03	1.21	1.30	1.20	0.93
MCI	12.60	0.71	0.86	0.70	1.16	1.04

Table A5- Resilience Values for Hospitals in Hospital System under Varying Hazard Events for Baseline B under All Actions

ll daptations	Johns Hopkins Hospital	Bayview Medical Center	Sibley Memorial Hospital	Howard County General Hospital	Suburban Hospital	System-wide
Pandemic	7.56	1.12	1.06	0.57	1.09	1.15
Earthquake	7.90	1.53	1.01	1.09	1.00	1.27
Flooding	8.67	1.47	1.20	1.28	1.02	1.34
MCI	7.78	0.99	0.91	0.57	0.98	1.04

Table A6- Details of Runs for Disaster Scenarios

	Surge to	Transfer to	Midday Travel Time	ESI-4,5 Travel Time	ESI-1,2,3 Travel Time	Functionality Loss??	Patient rrival Time Distribution	Statistical Parameters (1^{st} Originating Hospital) - Walk-in Patients	Statistical Parameters (1^{st} Originating Hospital) - Severe Patients	Statistical Parameters (2^{nd} Originating Hospital) Walk-in Patients	Statistical Parameters (2^{nd} Originating Hospital) Severe Patients
Pandemic	John Hopkins Hospital, Bayview Medical Center	Howard County General Hospital	40 min, 40 min	1 hour, 1 hour	2 hours, 2 hours	Not pplicable	Exponential	Not pplicable	Mean: 0.02	Mean: 0.06	Not pplicable
Earthquake	Bayview Medical Center	John Hopkins Hospital	11 min	30 min	1 hour	Not pplicable	Exponential	Not pplicable	Mean: 0.12	Not pplicable	Not pplicable
Flooding	Bayview Medical Center	John Hopkins Hospital	11 min	30 min	1 hour	Howard County General Hospital- 20%	Exponential	Mean: 0.06	Mean: 0.12	Not pplicable	Not pplicable
MCI	John Hopkins Hospital, Bayview Medical Center	Howard County General Hospital	40 min, 40 min	1 hour, 1 hour	2 hours, 2 hours	Not pplicable	Exponential	Mean: 0.04	Mean: 0.04	Mean: 0.06	Mean: 0.06

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