Dynamic Team Deployment in Urban Search and Rescue

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16. Abstract

Continuing population growth and increased urbanization within disaster-prone areas have led to greater numbers of mass casualties and economic losses caused by natural hazards. The identification of an effective policy for managing limited emergency response resources in this environment, where every moment is crucial, will enable quick, life-saving decision-making. This work conceptualizes this real-time urban search and rescue team deployment problem as an M/G/c priority and preemptive spatially distributed queueing system with roving servers. Prioritization schemes that require minimal, on-site, real-time computation for operating the system are proposed and compared through numerical experiments conducted on disaster instances based on events from the 2010 Haitian earthquake.

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Executive Summary

Continuing population growth and increased urbanization within disaster-prone areas have led to greater numbers of mass casualties and economic losses caused by natural hazards. The identification of an effective policy for managing limited emergency response resources in this environment, where every moment is crucial, will enable quick, life-saving decision-making. This work conceptualizes this real-time urban search and rescue team deployment problem as an M/G/c priority and preemptive spatially distributed queueing system with roving servers. Prioritization schemes that require minimal, on-site, real-time computation for operating the system are proposed and compared through numerical experiments conducted on disaster instances based on events from the 2010 Haitian earthquake.

Of the 16 considered policies, seven policies were found to be promising under two selected performance measures. Two of these policies were particularly notable. The first of these prioritizes based on the lowest service time and highest number of live entrapped victims adjusted for losses while waiting for the USAR teams to arrive. The second ranks the worksites based on shorter service time and higher rate of change in survival likelihood, measures that together are representative of life expectancy.

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1. Introduction

Continuing population growth and increased urbanization within disaster-prone areas have led to greater numbers of mass casualties and economic losses caused by natural weather and geophysical events (Center for Research on the Epidemiology of Disasters, 2011). In such events, immediate response is required to reduce the number of casualties; hence, every moment in these post-disaster circumstances is crucial. However, local response capabilities are often not sufficient, and national and international resources are required to serve the acute demand for response and rescue. In this situation, even large numbers of responders cannot guarantee a successful rescue mission in the absence of appropriate management of critical limited resources. For instance, in response to the 2003 Bam earthquake in Iran, in addition to the local responders, more than 44 international organizations sent rescue teams to the disaster region. Due to lack of coordination, however, the number of fatalities may have been unnecessarily high. Casualties were estimated at more than 35,000 people (Ramezankhani and Najafiyazdi, 2008). High levels of casualties and damage were incurred more recently in, for example, the 2010 Haitian earthquake also due to difficulties with mobilizing available resources. These difficulties arose from inoperable infrastructure and communications means, which negatively impacted response and relief operations (Margesson and Taft-Morales, 2010).

Early in the response stage, experts must make decisions based on insufficient data, since evaluation of the disaster impacted area takes time. However, such information, particularly as it relates to the conditions of the civil and healthcare infrastructures, is essential to efficient decision-making during this stage. Important considerations include: condition of roadways and remaining capacities of healthcare facilities, number and location of possible victims and their medical conditions, and structural damage to buildings with probable live entrapped victims, i.e. the worksites.

Countries around the world have developed emergency response protocols to prioritize rescue actions and accelerate decision processes. Decisions must be made in real-time with available information, and for expedient response, Urban Search and Rescue (USAR/US&R) teams must be immediately informed of their tasks. The United Nation's International Search and Rescue Advisory Group (INSARAG) and Federal Emergency Management Agency (FEMA) have put in place prioritization-based methodologies for quick evaluation of the disaster area and rapid deployment of resources (USAR teams and equipment) to worksites. These methods rely on input from reconnaissance and initial structural triage.

To prioritize response to the worksites, scoring methods that evaluate such factors as building materials, condition of voids (influenced by structural design and collapse pattern), usage type and special occupancy information, potentially trapped building inhabitants, known live victims, and accessibility to victims are used in FEMA's approach. See Section 4 for additional details. Their protocol uses a simplified scoring method for prioritization, allowing quick, manual computation (National US&R Response System Field Operations Guide, 2003). This method, however, does not account for all of the factors, e.g., travel time between worksites that affect response. INSARAG's method uses similar input to assign priorities to the worksites, but instead of quantifying the inputs, existence or nonexistences of specific circumstances are used to attribute priority levels. By exploiting the capabilities of widely available computer technologies and new information sources (including evolving information on building conditions and probable survivors), important problem complexities and additional key characteristics not considered in the FEMA and INSARAG methods can be captured in the decision-making process.

This work conceptualizes the USAR team deployment problem as an M/G/c (M = Poisson arrivals, G = generally distributed service times, c = number of servers) priority and preemptive spatially distributed queueing system with roving servers. This interpretation of the problem helps to examine and suggest modifications to existing INSARAG and FEMA prioritization schemes to take advantage of these new information sources. Moreover, developed prioritization schemes also address issues of dependence among contributing factors, assumptions of additivity, issues of subjectivity, scaling inconsistencies, and assumptions of constancy (specifically that the number of live entrapped victims present during the prioritization will not change by the time the team travels to and accesses these potential survivors) present in the existing schemes. Prioritization schemes for operating the queueing system are proposed and tested. These policies can be used directly to enable quick decision-making in real-time USAR operations.

A review of related studies to the USAR team deployment problem and discussion of key problem aspects are provided in Section 2. Details of the modeling framework, system performance measures and approximation methods for their quantification, and design of a simulation platform for demonstrating and testing this framework are given in Section 3. In Section 4, the FEMA prioritization scheme is explained and alternative policies are introduced. The prioritization schemes or policies were tested and compared on disaster instances based on events from the 2010 Haitian earthquake. These instances are described in Section 5. This is followed by results from numerical experiments conducted in the simulation environment on the Haitian instances in Section 6. Analysis and insights are also provided. Additional comparison to optimal deployment decisions under perfect information is made. The number of live entrapped victims extracted in an optimal response provides an upper bound for assessing the individual proposed policies. Conclusions and extensions are given in Section 7.

2. Prior Literature on Optimal Team Deployment in Post-Disaster Situations

The general topic of emergency management has been widely studied; however, few works have focused on the deployment of rescue resources with the aim of maximizing the number of saved lives post-disaster. The most relevant work is by Chen and Miller-Hooks (2012). Their work addresses the USAR team deployment problem with the objective of maximizing the total expected number of survivors (i.e. entrapped victims who are successfully extricated while still alive). They proposed a Multistage Stochastic Program (MSP) to model and conceptualize the USAR team deployment problem accounting for evolving information as situational awareness improves. To solve the MSP, the problem is decomposed into a series of interrelated two-stage stochastic programs that are solved exactly in a rolling horizon framework. The procedure exploits real-time information as it is received over decision epochs. While pertinent to conceptualizing the USAR team deployment problem under real-time information, their approach is not suitable for real-time application due to excessive computational and memory requirements. In fact, simply enumerating feasible scenarios needed for this approach is difficult given that the number of scenario instantiations which may arise can be exceptionally large. Thus, while this earlier work provides a framework from which to understand the team deployment problem, it has limited utility in practical, field applications.

A second closely related study is by Fiedrich et al. (2000). Their work modeled the problem of optimal post-disaster allocation of rescue resources as a type of dynamic resource allocation problem. Their formulation seeks an optimal allocation of resources in response to information on survivor locations with the goal of minimizing the number of casualties over a time horizon. Casualties are incurred in three stages of the rescue operation: at the disaster site, in the transfer time to the hospital, and at the hospital. The formulation does not account for the possibility of receiving updated information on the disaster scene, nor does it consider many of the other situation details. Two specialized heuristics for its solution were proposed.

There are several classes of optimization problems with relevance to the USAR team deployment problem, including problems in: dynamic routing and scheduling, dynamic resource allocation and team orienteering. Their relevance to the USAR team deployment problem is discussed by Chen and Miller-Hooks (2012). They note that each of these problem classes differs from the USAR team deployment problem in specific and important problem characteristics. That is, each omits one or more of the following problem facets: decreasing survival likelihood for entrapped victims; need to maximize the number of survivors; that service times or required resources depend on the order in which service is provided; and that steady state cannot be reached within the finite and limited decision time horizon of post-disaster rescue operations. The focus of this work is to develop real-time solution policies for USAR team deployment considering these features as well as uncertainty in future conditions and possible benefits from updated information over a rolling time horizon. The proposed alternative method to conceiving the USAR team deployment problem based on queueing provides a platform for both conceptualizing and evaluating existing and proposed resource allocation strategies.

3. Queueing System and Simulation Platform

3.1 Conceptualization as a Queueing System

The M/G/c priority and preemptive spatially distributed queueing system with roving servers conceptualization of the USAR team deployment problem is presented in this section. In this conceptualization, USAR teams are modeled as servers that move to the customers over the disaster region. The order in which customers are served is determined by an operational policy. Common policies used in queueing system modeling include, for example, first-in first-out (FIFO) or last-in first-out (LIFO). The FEMA prioritization scheme offers an alternative policy with specific application to USAR operations. In this context, worksites will enter the waiting queue. They will be ranked based on the chosen policy and the teams will generally attend to victims at those worksites with highest rankings first. The considered queueing system allows preemption. Preemption permits redeployment in the event that new information arises indicating that moving to an alternative site would be beneficial despite that work at the current site is incomplete. In the current National US&R Response System Field Operations Guide (2003) there are instructions for how to treat and mark preempted worksites and preemption decisions are to be made by response planners. The system is considered over a time horizon during which the system state (i.e. position of USAR teams and unserved worksite locations) changes. Survival likelihood, arrival of new USAR teams, service time estimates, and estimates of travel time between worksites may change stochastically depending on post-disaster relief activities and investigations.

Alternative operational policies are devised in the next section. These policies can be used in real-time to prioritize the worksites. To choose a best policy, the alternatives can be compared through an evaluation of the queueing system operations under the devised operational policy. Ideally, such an evaluation would be performed analytically. Such analytical assessment is described next. The following nomenclature is employed in this description.

i, j	:	Index of worksites
k	:	Index of the USAR team deployment policies
t	:	Decision time
w_i	:	Worksite i
AP^k	:	Assignment Policy k of USAR teams
S_{it}	:	Service time at worksite i estimated at time t (time to access victims once on site)
B_{it}	:	Drop in survival likelihood of live entrapped victims at worksite i at time t
$tt_{i,j}$	:	Travel time between worksites i and j plus equipment set-up time once on site
r_i	:	Initial estimate of number of live entrapped victims at worksite i
$\Delta SL_{it,\, it+\Delta t}$	:	Change in survival likelihood of live entrapped victims at worksite i between time t and $t+\Delta t$
P_{fi}	:	FEMA priority value for worksite i
$V(AP^k)$	:	Value of Policy k by the end of the decision horizon
W_{qi}^k	:	Waiting time of worksite i under Policy k
N_{wt}	:	Number of worksites waiting in the queue at time t

Note that set-up time is the time that USAR teams need to place the heavy equipment (e.g. cranes) safely at the site and decide on the best rescue path. Service time for each worksite is defined as the time that USAR teams require to extricate the live entrapped victims from under the debris. It includes the time to set-up needed equipment.

Typically, queueing systems are assessed in terms of average waiting time in queue, average number of customers in the queue or in the system, total time required to serve a given number of customers or number of customers that can be served in a given time period. Analytical results, including steady-state exact formulae and approximations for these measures, have been published previously for many types of queueing systems. See, for example, (Kleinrock, 1976). The majority of results are for stationary customer-to-server queueing models, where customers line up to be served. Results associated with queueing systems with roving servers (server-to-customer systems) are given in (Larson and Odoni, 1981) and more recently in (Boyaci et al., 2011). As these systems are complex, derived results are limited by a variety of assumptions, including the existence of only a single server and very simple prioritization schemes or multi-server models with no preemption and priority.

The mean waiting time and number of customers in the queue at steady-state conditions are derived in (Larson and Odoni, 1981) for a non-preemptive server-to-customer spatial queueing system with one server and FIFO ordering. This work further showed that the mean number of customers and mean waiting time in the queue depend on the means and variances of two service time distributions: service time of the busy period and all succeeding periods. If these two service time distributions have identical mean and variance, the performance measures of the queueing system in steady-state can be computed using equations that are very similar to that of standard M/G/1 queueing systems using Pollaczek-Khintchine formulae.

For multi-server spatial queueing systems, Larson (1974) proposed the hypercube queueing model. This model applies where travel times are insignificant in comparison to on-site service times, and thus, service times are independent of location. He showed that travel times can be included within this framework using a calibration strategy. Even with the assumption of insignificant travel times, it is recognized that the number of states grows exponentially with number of servers (e.g. Boyaci et al., 2011). Boyaci provides a review of performance measure estimation methodologies associated with hypercube models devised for a variety of such multi-server systems. However, it appears that there are no analytical results for multi-server, server-to-customer spatial queueing systems with priorities and preemption.

While travel times may be negligible for many emergency response applications, in circumstances involving large-scale regional disaster events, travel times between worksites may be significant and the order in which trips between worksites are taken can affect system performance. To incorporate travel times in queueing models, travel times can be included in service times. However, this creates order-dependent service times, and no methodologies exist for the computation of performance metrics in this context. This order dependence arises, because service times at worksites depend not only on the time spent at each site, but the time spent in transit from prior sites. This is further complicated by the arrival of worksites that were not previously known.

3.2 Performance measures

In the context of USAR team deployment, a critical performance measure is the number of survivors. In fact, survival likelihood is monotonically decreasing with varying rates depending on the building material, collapse patterns, condition of voids, building usage and physical condition of victims as discussed in Coburn et al. (1991). The time until worksites are served by the teams (i.e. the waiting time in queue) depends on the sequence of visited worksites, service times at previous worksites and travel time between worksites. Moreover, the sequence affects the number of survivors. Thus, the number of survivors at the end of the decision horizon depends on the team deployment strategy, that is, the prioritization method used in the queueing model. $V(p^k)$, the sum of survivors from all the identified worksites at the end of the search and rescue period T can be computed as in equation (1).

$$V(P^k) = \sum_{t \in T} \sum_{i \in N} r_i (1 - \beta_{it} W_{qi}{}^k) \tag{1}$$

An additional performance measure of interest is the time-averaged number of worksites waiting in the queue (N_{wh}). This is given in equation 2.

$$N_{wh} = \sum_t N_{wt} / T \tag{2}$$

This measure is of particular importance where reliable information on live entrapped victims at the known worksites is not present. Its value is also a function of prioritization schemes employed in the queueing model.

While equations 1 and 2 provide structure for computing the number of live entrapped victims or worksites served, derivation of equations for specific elements of these formulae, e.g. W_{qi}^{k}, have been formidable. Thus, an alternative simulation-based technique is employed.

3.3 Discrete-Event Simulation Framework

A discrete-event simulation framework was developed using the Python programming language. Simulation design is based on a queueing system conceptualization developed in this section.

In the simulation environment, a customer represents an identified worksite. The state of the system at each point in time is described by the number of worksites for which service is not yet completed and location and status of the USAR teams (idle, busy, in transit). Possible events include: receiving an update on the characteristics of a worksite, identification of a new worksite, arrival of a new USAR team to the disaster impacted area, and completion of service at a worksite. Priority rankings are reexamined upon each event, and team deployment decisions are updated allowing for preemption where found to be beneficial.

Simulation design is based on 3 routines: Service Request, Server Assignment, and Arrival. Key to the simulation model are priority computation and replication of preemption decisions. The Service Request routine schedules tasks given preemption decision rules and new information on worksites. Preemption can require that a team leave a worksite before completing service or be redeployed while in transit to a worksite to serve a worksite with higher priority. Priorities are computed within the Server Assignment routine. The Arrival routine records arrival times of servers at customers and updates the server status from “in transit” to “at location.” Flowcharts of all three simulation routines are presented in Figures 1 and 2.

In the simulation model, when an event occurs that raises the priority of unserved sites beyond that of sites that are in service or to which teams are in transit, a team may be redeployed. The decision to redeploy is made with a predefined probability for worksites suffering from light or moderate structural damage with no heavy equipment requirements. If service is preempted, that portion of service time that was completed is credited when the site is revisited. However, survival likelihood diminishes as time passes and, thus, the number to be saved from that site may be smaller than if the service to the site was completed as initially designed. A second USAR team can complete the service; that is, service upon return to the site need not be completed by the same USAR team that began work at the site.

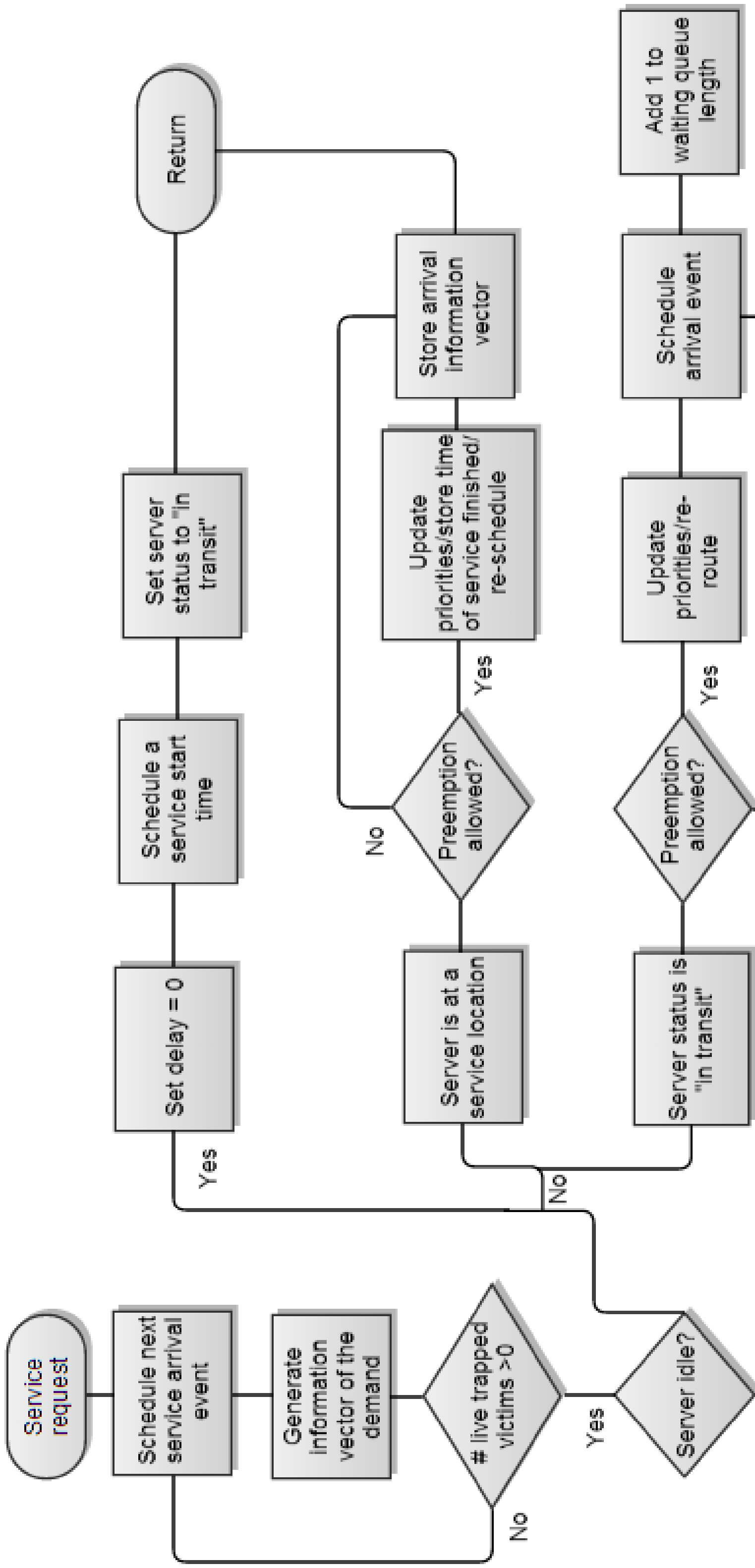

Figure 1 Flowchart of Service Request Routine

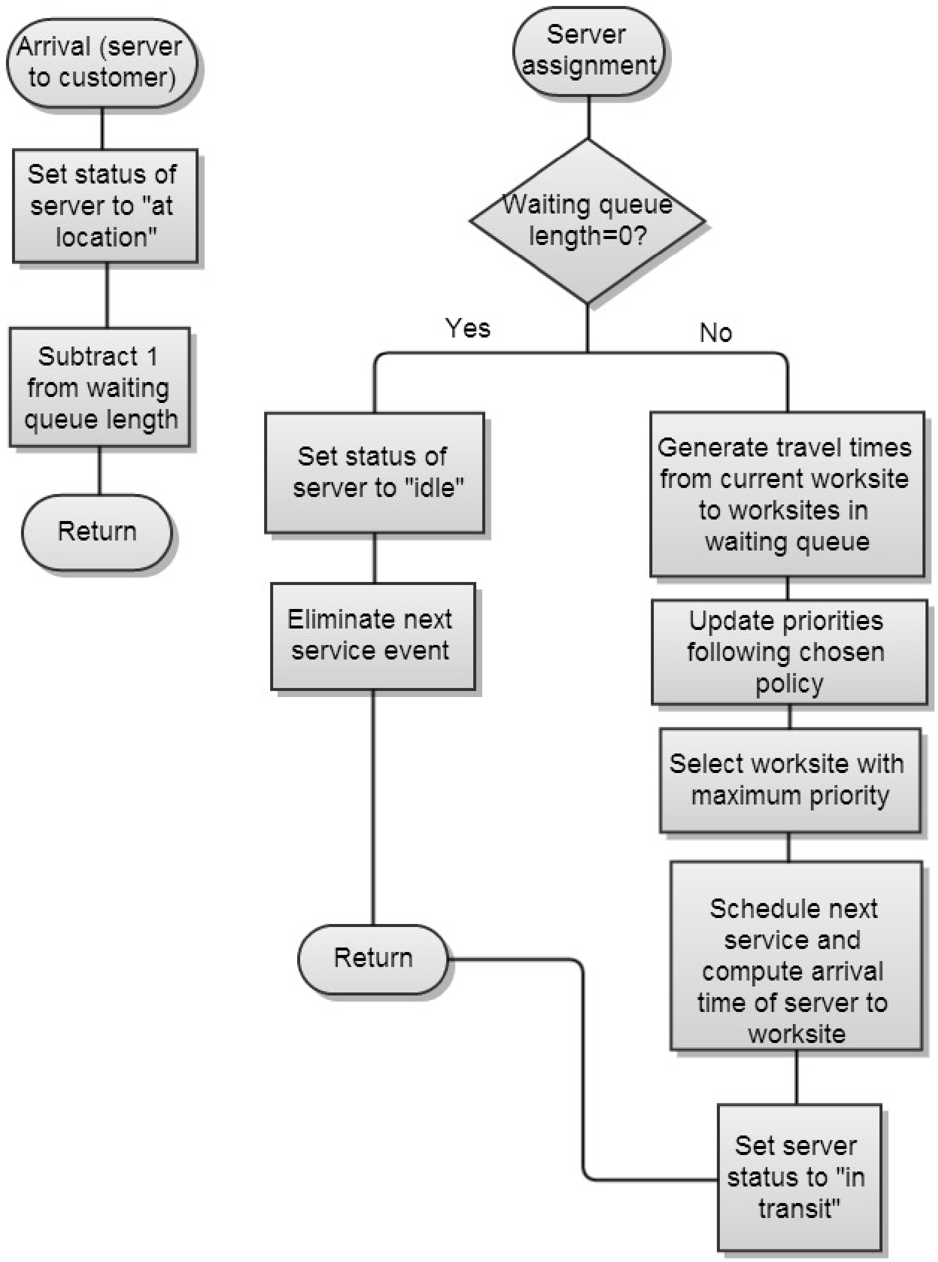

Figure 2 Flowchart of Arrival Routine (left) and Server assignment (right)

4. Proposed Deployment Policies

Search and rescue missions begin with assessment of the disaster impacted area. Initial investigations provide insight to USAR team managers to create an efficient response plan. FEMA suggests two general search and rescue approaches (National US&R Response System Field Operations Guide, 2003). The first option applies to small areas of impact wherein the area is divided into sectors and a team is deployed to each sector. It is assumed that there is sufficient response capabilities for the impacted region. For large affected regions, where response capacities are exceeded and thus resources are inadequate, worksites requiring response are prioritized.

Sixteen prioritization schemes are proposed here and described in Table 1. Each scheme can serve equivalently as the operational policy employed within the spatial queueing system model of Section 3. Thus, to assess and compare the performance of these policies, performance of the queueing system under the different policies can be evaluated.

The policies consider a variety of characteristics. These characteristics include: worksite detection times and locations, service times, travel times, diminishing survival likelihoods and urgency for serving worksites due to changes in survival likelihood, or surrogates thereof. Factors included in the policies were chosen based on their anticipated impact on prioritization performance in terms of number of survivals. Single factor experiments were conducted to determine if each considered factor would serve best in the numerator or denominator. For example, ranking based on highest and lowest service times were tested. It was found that assigning higher priorities to worksites with shorter service times significantly improves the total number of survivals, and thus, service times were included in the denominator. A similar choice was made with respect to travel times. Additionally, adjustments for loss are made in comparison to the FEMA prioritization. With these guiding principles for policy creation in mind, more than 25 policies were created. Based on results from preliminary experiments, 15 of these policies were selected for further analysis as exhibited in Table 1.

Team-to-worksite assignment decisions are updated when information on new worksites is received, estimates on current worksites are updated or a USAR team finishes its service at a location. These serve also as the events within the discrete-event simulation (DES) environment. Let the set $T=[e_{0=0}, e_1, e_2, \ldots, e_n]$ be the set of event times, one such event time denoted by e_n, for $n = 0,\ldots,T$ during the rescue period. Relative priority scores with respect to the location of USAR teams for all worksites are re-calculated using the suggested formulae from Table 1 upon each event, e_n. Available teams are then assigned to the worksites with highest rank.

Table 1 Proposed USAR Team Deployment Policies

Policy (PA^k)		Priority Computation	unit
FEMA	FEMA scoring Scheme	P_{fi}	score
FAL	FEMA Adjusted for Loss	$P_{fi} - r_{i.} \cdot \Delta Sl_{it,\, it+tt(ij)}$	score
FAST	FEMA Adjusted by Service Time	P_{fi}/S_{it}	score
FALS	FEMA Adjusted for Loss and Service Time	$P_{fi} - r_i \cdot \Delta Sl_{it,\, it+tt(ij)}/S_{it}$	score
FATT	FEMA Adjusted by Travel Time	$P_{fi}/tt(ij)$	score
FALR	FEMA Adjusted for Loss Rate	$P_{fi} - r_{i.} \cdot \Delta Sl_{it,\, it+tt(ij)}/ \Delta Sl_{it,\, it+tt(ij)}$	score
NW	Nearest Worksite	$1/tt(ij)$	$hour^{-1}$
LST	Lowest Service Time	$1/S_{it}$	$hour^{-1}$
HE	Highest Number of Live Entrapped Victims	r_i	*# of people*
HEAL	HE Adjusted for Loss Rate	$r_i \cdot (1- \Delta Sl_{it,\, it+tt(ij)})$	*# of people*
CS	Critical drop in Sl_{it}	$\Delta Sl_{it,\, it+tt(ij)}$	*# of people / hour*

RCS	Reverse of Critical Drop in Sl_{it}	$1/\ \Delta Sl_{it,\ it+\ tt(ij)}$	*hour / # of people*
HRCS	HE and RCS	$r_i/\ \Delta Sl_{it,\ it+\ tt(ij)}$	*hour*
LRCS	LST and RCS	$1/(S_{it}\ \cdot \Delta Sl_{it,\ it+\ tt(ij)})$	*1/ # of people*
HLRCS	HE and LRCS adjusted by loss due to travel	$r_i\ \cdot(1\text{-}\ \Delta Sl_{it,\ it+\ tt(ij)})/\ (S_{it}\ \cdot \Delta Sl_{it,\ it+\ tt(ij)})$	*1*
HEALS	HEAL and LST	$r_i\ \cdot(1\text{-}\ \Delta Sl_{it,\ it+\ tt(ij)})/S_{it}$	*# of people / hour*

The FEMA priority value, P_{fi}, associated with each worksite i is taken as the sum of individual scores by category listed in Table 2. The structural triage team must provide an estimate of scores for every individual building affected by the disaster following the US&R Response System, Field Operations Guide (2003). This information can be modified during the response phase by further investigations and more thorough structural testing. This prioritization scheme accounts for some factors that affect survival likelihood at each worksite and likely number of survivors present. It implicitly assumes that these factors are additive with equal weight. The main idea of this FEMA prioritization scheme is that worksites with better structural condition and stability get higher rank. However, some key factors affecting survival likelihood, such as physical condition of the live entrapped victims, are not included.

Table 2 FEMA Prioritization Guideline (retrieve from US&R Response System, Field Operations Guide, Structure Triage Form, 2003)

General Category	Included Factors	FEMA Scores
Estimated Number of Live Entrapped Victims	Potential number of live entrapped victims	1 to 50 (divided by 5) known live entrapped victims (add +5)
	Demographic distribution*	Building type (Schools/Hospitals add 25)
Structural Characteristics	Structural material	Wood, concrete, steel, masonry, precast concrete
	Condition of voids	Very compact, separate layers to partial collapse (scale between 1 to 20)
	Time to get to the victims	24 hours to 2 hours (scale between 1 to 20)
	Chance of further collapse	Low to high chance (scale between -1 to -20)

* Schools and hospitals are given higher priority

This FEMA prioritization method does not account for travel time between or to worksites from the emergency operations center (EOC). In unreliable and heavily damaged environments, travel between worksites can take very significant time. Moreover, during the response phase, significant effort to clear debris and open passages in the region will be underway (e.g. Koike et al., 2004), and travel time between worksites will be changing over the course of the response phase. Obtaining travel time estimates in disaster scenarios has become less problematic in recent years. In fact, in the 2010 Chilean earthquake in Bio-Bio (Caminoschile, 2013), individuals created a coded Google map using social media applications. This map provided updated information on the damage-level to the transportation infrastructure in the disaster region after the earthquake. As time passes, the number of live entrapped victims diminishes. Thus, it is essential to consider time to access these victims (i.e. service time) in the prioritization.

The additional 15 policies defined in Table 1 seek to overcome some of the omissions or simplifications of the FEMA prioritization scheme. All inputs required by the proposed protocols except travel time between worksites and an explicit survival likelihood function are currently required for use in the FEMA response procedures as indicated in Table 2.

FAL, FALS, FALR, HEAL, CS, RCS, HRCS, LRCS, and HLRCS policies incorporate survival likelihood and/or changes in the rate of this likelihood. Note that survival likelihood functions used in these policies can be empirically derived from data associated with previous events, laboratory structural tests, and experience in the field. A few works have developed probabilistic models to estimate post-disaster injury severity of the victims involved in a building collapse. The models use information on structural type and earthquake intensity (e.g. Frolova et al., 2011). Coburn et al. (1991) studied survival likelihood progression over time for varying structural materials.

With the exception of CS and RCS, these policies also consider travel and set-up times, the latter of which will vary by worksite. These policies prioritize according to survival likelihood computed from the point in time that the USAR team starts the task, instead of the time that the dispatching decision is made. That is, it captures the reduction in survival likelihood due to access times. FAL, FALS, and FALR policies are modifications of the FEMA policy, while HEAL, LRCS, and HLRCS are based on estimated number of live entrapped victims, service times and changes in survival likelihood during the time it takes for the USAR teams to travel between worksites.

The FATT policy modifies the FEMA prioritization approach to account for travel time and set-up times between worksites, but survival likelihood is omitted. By following this policy, worksites that are in relatively better structural condition with simultaneously shorter required access times will have higher rank. By comparison, the NW policy focuses directly on the travel and set-up times, omitting the FEMA score elements.

The impact of service times is investigated through the inclusion of the FAST policy. When there is a tie in P_{fi} for two worksites, higher priority will be given to the worksite with the lower estimated service time. FALS combines aspects of two policies: FAL and FAST. It adjusts P_{fi} for the arrival time of a USAR team at the worksites while giving higher priority to the worksites with lower service times.

The benefits corresponding to prioritizing worksites with greater number of live entrapped victims in better physical condition is investigated in the LRCS policy by giving higher weight to those worksites with lower service times and flatter survival likelihood functions. In addition to factors included in the LRCS policy, the HLRCS policy adjusts for loss incurred during the USAR team's travel to the worksites.

Additional simpler policies, including LST, HE, CS, and RCS policies, are also suggested for comparison purposes. Comparison of queueing system performance under these simpler policies to performance under other suggested policies will enable a deeper understanding of the importance of access and service times to a best policy creation.

5. Experimental Setting

The performance of the spatial queueing system described in Section 3 is assessed under each of the proposed operational policies presented in Section 4. The assessment is completed within the simulation platform presented in Section 3. The numerical experiments were performed on a Windows 7 personal computer with one 3.20 GHz CPU processor and 6.00 GB RAM. Results and analyses are provided in Section 6.

5.1 Problem instance setting

The queueing system was evaluated under each policy for 5 replications of approximately 6,000 randomly specified problem instances derived from publically available information, including structural failure data, associated with the 2010 earthquake in Port-au-Prince, Haiti. The problem instances follow the case study setting in (Chen and Miller-Hooks, 2012) as closely as possible, noting some differences in assumptions.

110 worksites were identified from satellite images as depicted in Figure 3. Building use (school, government, hospital, other) and damage level were presumed for each worksite. 58 buildings were identified as potential worksites from the start of the rescue period based on the existence of visible damage, indicated by circles in Figure 3. Identification of the remaining worksites was assumed to follow a Poisson distribution with mean 0.83 worksites per hour over the decision horizon (Chen and Miller-Hooks, 2012). These worksites are shown in Figure 3 by dashed circles. The EOC was assumed to be located at the Toussaint Louverture International Airport in Port-au-Prince, indicated by a square mark in Figure 3..

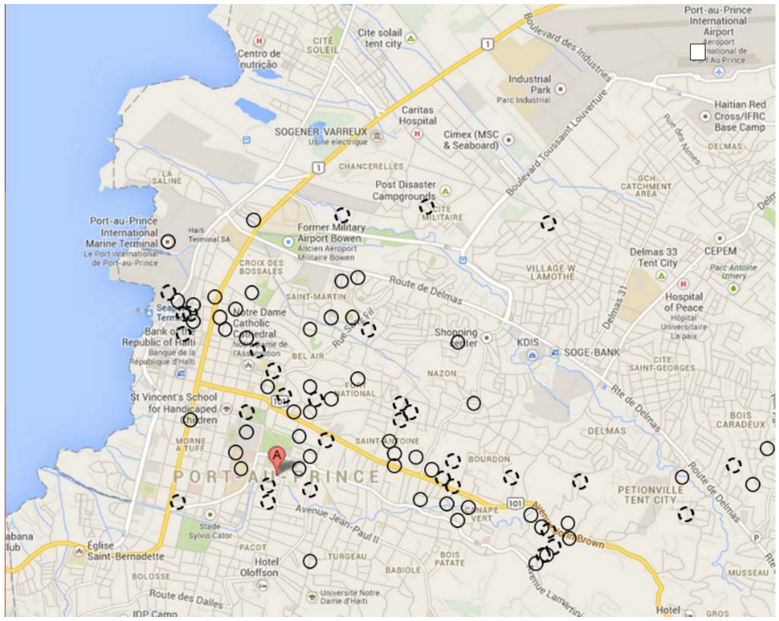

Figure 3 Identified Worksites in Port-au-Prince, Haiti, Overlaid on Google Map (adapted from Chen and Miller-Hooks, 2012)

Survival likelihood was assumed to be one at the beginning of the rescue period, and the survival likelihood function is presumed to be negative exponentially distributed as in (Coburn et al., 1991). At each time instance, a maximum of one USAR team was assigned to each worksite. Individual teams work 12 hours per day; although, the response effort is carried out 24 hour per day until its conclusion. It is further assumed that no time is lost in changing shifts. Five USAR teams are available at the beginning of decision horizon, and five additional teams arrive over the first 24 hours of the response phase. Their arrival times are known in advance. The rescue period is assumed to be five days or 120 hours. Euclidean distances on a plane were employed in estimating initial travel times with an assumed constant travel speed of 40 miles/hour (Chen and Miller-Hooks, 2012). Travel times were designed to vary under different problem instances. To create the random travel times, initial travel times were multiplied by a random variable with distribution ~U[0.5,2] hours.

To simulate the number of live entrapped victims in each affected building, random variates were generated for time-of-day (probability 0.23 during working/school hours) and earthquake magnitude (5 to 9 with equal probability).

Considering the different damage levels and building uses shown in Figure 3, an estimate of r_i is made for each identified worksite assuming that the number of survivors at the given point in time is uniformly distributed on [0, specified upper bound]. The upper bound was calculated from the product of the number of estimated persons present in the building just prior to the earthquake equation and the demand generation ratio given in Table 3.

Table 3 Parameters of Entrapped Victim Generation (from Chen and Miller-Hooks, 2012)

Damage Level	School	Government	Hospital	Others
Destroyed	0.6	0.54	0.48	0.42
Severely Damaged	0.80	0.72	0.64	0.56
Moderately Damaged	1.00	0.90	0.80	0.70
No Visible Damage	0.50	0.45	0.40	0.35

Results from (Frolova et al., 2011) on the physical condition of live entrapped victims are employed to estimate the initial condition of people trapped in a building in the disaster region. In their work, Florova et al. analyzed empirical data on casualties from historically strong earthquakes. They suggested the use of Equation 3 for estimating the probability of injuries and fatalities for a given building.

$$P_{C_k}(I) = \sum_{i=1}^{5} P_{B_i}(I) P(C_k \mid B_i), \tag{3}$$

where $P_{C_k}(I)$ is the probability that a person located within a given building is injured or dead given an earthquake with intensity I. $P_{B_i}(I)$ is the probability of damage state *i*, i$\in\{1,\ldots,5\}$ for a given building type *B* under an earthquake with intensity *I*, and $P(C_k \mid B_i)$ is the survival likelihood (for C_1 = injury, C_2 = casualty) of people in building of type *B* under damage state *i* as derived from regional empirical data. As an example, estimates from (Frovola et al., 2011) for $P_{C_k}(I)$ in a building made from massive stone, unreinforced bricks, concrete blocks, or reinforced concrete floors (buildings of type MMSK-86) are given in Table 4.

Table 4 $P_{C_k}(I)$ for a Building of Type MMSK-86 under Different Damage States (Retrieved from Frovola et al., 2011)

Social losses C_k	**Damage states**		
	3	4	5
Fatalities (*k*=1)	0.02	0.23	0.6
Injured (*k*=2)	0.09	0.37	0.37
Total	0.11	0.6	0.97

To generate random problem instances herein, $P_{C_k}(I)$ was estimated from building material type, collapse patterns and condition of voids consistent with building damage state. For example, to score the condition of predicted voids for an unreinforced masonry building with pancake collapse pattern a random score from a uniform distribution of 1 to 5 is generated. For a reinforced concrete structure that will likely have triangular-shaped voids, this value is assumed to be uniformly distributed on [15, 20]. Three damage states of 3, 4, and 5 (representing the intensity of earthquake) were generated randomly from a uniform distribution with equal probability.

To predict the physical condition of live entrapped victims over time, survival likelihood functions associated with different building types presented in (Coburn et al., 1991) were employed. These functions account for building material type and capture hourly changes in survival rate. $\Delta Sl_{it,\ it+\Delta t}$ is randomly generated from a skewed normal distribution according to suggested functions for each building material type.

Service time at each worksite is assumed to be independent of other criteria and uniformly distributed on [0, 24]. Service times are estimated upon identification of a worksite and may be randomly updated (by up to plus or minus 20%) at event intervals.

6. Experimental Design, Results and Analysis

Four sets of numerical experiments were conducted based on replications derived from the 2010 Haitian earthquake case study described in Section 5. The first seeks to identify a best policy from those considered based on statistical analysis of system performance under the given policies. The second compares the performance of each policy to the *a posteriori* optimal solution under a decision framework, and determines how close to optimal results are from following a single, easy-to-implement policy. In a third set of experiments, sensitivity analysis was conducted on those policies identified as performing best. Finally, possible improvements to the best performing policy were investigated in a fourth set of experiments.

6.1 Comparison of Policies

Assessing the policies on number of survivors

To evaluate the performance of the defined queueing system under each operational policy, the total number of survivors saved by the end of the rescue period and the time-averaged number of worksites waiting in queue over the rescue period were analyzed.

The D&D method was applied here to identify a best operational policy from those policies tested in terms of the number of survivors (Dudewicz and Dalal, 1975). D&D is a two-stage procedure that uses an indifference zone approach. It is designed for selecting the best of k systems with respect to the mean. The D&D method requires that the performance measures be strongly normally distributed over the simulation runs. The distribution of the total number of survivors achieved under each policy over the many replications were tested and found to be normally distributed as required.

The D&D method involves a two-stage sampling approach. In the first stage, a small sample of problem instances is tested (40 such instances were tested herein) to estimate first-stage sample mean and variance ($\bar{X}_i^{(1)}(40), S^{2\,(1)}_i(40)$). Results from the initial estimates provide the minimum number of samples needed in the second stage to conduct the D&D ranking under each policy. Weights used to compute final population mean and variance from runs of both stages as required by the D&D method were computed based on the procedure described in (Dudewicz and Dalal, 1975). Results of first- and second-stage sample size and population mean for a confidence level of 95% are shown in Table 5.

Table 5 D&D Ranking Results for Total Number of Survivals

AP^k	$\bar{X}_i^1(40)$	$s_i^2(40)$	N_i	$\bar{X}_i^2(N_i - 40)$	w_{i1}	w_{i2}	$\tilde{X}_i(N_i)$
HEALS	599	101.29	1062	574	0.045	0.955	**575**
HEAL	596	99.69	1029	571	0.047	0.953	**573**
HLRCS	595	99.62	1027	569	0.047	0.953	**570**
HRCS	593	99.69	1029	567	0.047	0.953	**568**
LRCS	589	98.63	1007	564	0.048	0.952	**566**
RCS	586	95.96	953	562	0.051	0.949	563
FALS	585	99.74	1030	560	0.047	0.953	561
FAL	581	99.27	1020	557	0.047	0.953	559
HE	578	99.25	1020	555	0.047	0.953	556
FALR	579	97.40	982	554	0.049	0.951	556
FAST	575	99.69	1029	548	0.047	0.953	549
LST	563	98.33	1001	542	0.048	0.952	543
FEMA	560	92.84	892	538	0.055	0.945	539
FATT	556	95.76	949	533	0.051	0.949	535
NW	538	97.49	984	516	0.049	0.951	517
CS	454	107.65	1199	435	0.040	0.960	435

* Bold font indicates those policies that performed best for the indifference zone of 10 survivors and a 95% confidence level.

The results indicate that the HEALS policy that involves the highest number of live entrapped victims adjusted for loss rate and lowest service time, would lead to the largest expected number of survivors, and the HEALS, HEAL, HLRCS, HRCS, and LRCS policies tied for best given the indifference zone of 10 survivors and a 95% confidence level.

Policies HEAL and HEALS consider the number of live entrapped victims existing at each site at the potential arrival times of the USAR teams to these sites. This is accounted for through consideration of the survival likelihood rate of change over time. The HEALS policy also attributes higher priority to worksites with shorter service times. As both policies perform among the best, it can be concluded that the estimated number of live entrapped victims at the worksites at expected team arrival times should play an important role in site prioritization. Note that the HE policy, which is not identified as a best policy, considers the same factors as the HEAL policy, but uses estimates of number of live entrapped victims at the time of deployment and not the estimated arrival of the USAR teams. Consequently, it does not perform as well. Two additional best performing policies, Policies HRCS and HLRCS, similarly account for this factor. The LRCS policy is the only one of the five best policies to not directly consider the number of live entrapped victims upon team arrival. Different from the other four top policies, this policy considers only changes in the survival likelihood rate as opposed to actual expected number of live entrapped victims. All top policies consider survival likelihood rate of change as an important factor. It is also worth noting that the FEMA prioritization scheme results in 36 (6.2%) fewer survivors in terms of the D&D score than the best performing policy.

To compute the relative probability of performing best, $P_{Win}(AP^k)$, of each policy P^k, that is, the frequency with which the policy will outperform all other considered policies, results from five replications of 3,000 additional problem instances were obtained as provided in Table 6. Confirming earlier findings, Policy HEALS outperforms other policies with probability $P_{Win}(p^{HEALS})$ = 0.37. The second best policy, Policy HEAL, has probability 0.27 of performing best. This is followed by Policy HRCS with a probability of performing best of only 0.08. Note that the FEMA policy would outperform other policies with only probability 0.003. One might also notice that the LRCS policy performs better than other policies 5.9% of the time.

Table 6 Relative Probability of Policies p^k Performing the Best

	HEALS	HEAL	HRCS	LRCS	HLRCS	RCS	FALS	FAL
$P_{Win}(p^k)$	0.376	0.27	0.077	0.059	0.057	0.047	0.029	0.028
	HE	FALR	FAST	LST	FEMA	FATT	NW	CS
$P_{Win}(p^k)$	0.026	0.009	0.009	0.006	0.003	0.001	0.001	0

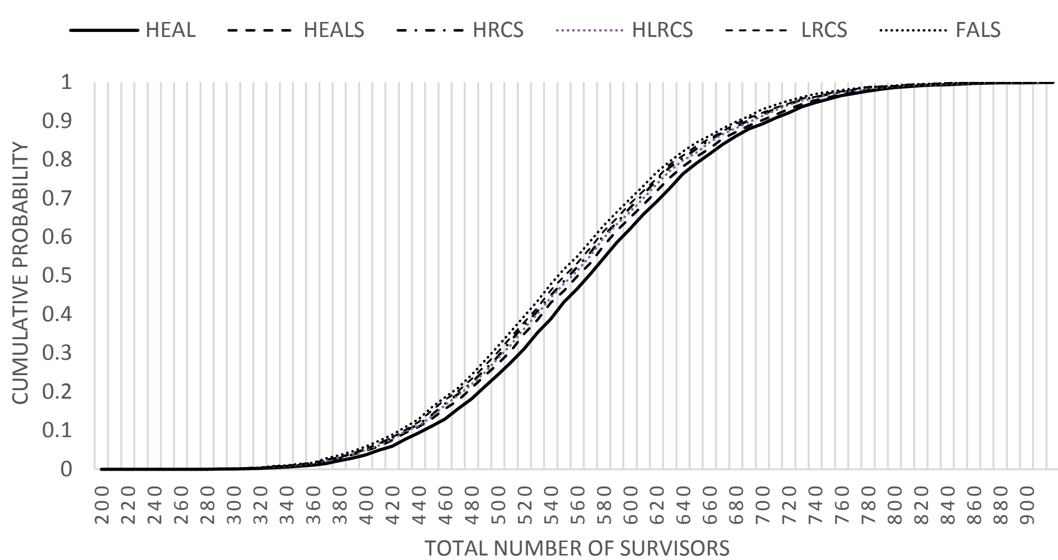

Figure 4 CDF of Total Number of Survivors

Using the same set of 5 replications of 3,000 problem instances, the cumulative distribution function (CDF) of the number of survivors was computed for the five best policies along with the best FEMA adjusted policy, FALS. Results are shown in Figure 4. Policies HEALS and HEAL stochastically dominate the other 4 policies, as their CDFs are completely to the right of the CDFs for the other policies.

Assessing the policies on time-averaged number of worksites waiting in queue

In addition to total number of survivors, time-averaged number of worksites waiting in queue is studied. The D&D method is applied once more to choose the best policy with respect to this second performance measure. The distributions of this second performance measure over the many replications and policies were tested and were found to be normally distributed for every policy as required by the methodology. Results are provided in Table 7 for an assumed confidence interval of 95% and indifference zone of 2 worksites.

Table 7 D&D Ranking Results for Time-average Number of Worksites Waiting in the Queue

AP^k	$\bar{X}_i^1(40)$	$s_i^2(40)$	N_i	$\bar{X}_i^2(N_i - 40)$	w_{i1}	w_{i2}	$\tilde{X}_i(N_i)$
LST	7	3	41	7	1.131	-0.131	7
LRCS	8	3	41	8	1.084	-0.084	8
FAST	9	3	41	9	1.040	-0.040	9
CS	12	4	56	11	0.709	0.291	11
FAL	12	4	63	11	0.632	0.368	11
FATT	12	4	58	11	0.690	0.310	11
FEMA	12	4	59	11	0.678	0.322	11
FALR	12	4	63	11	0.635	0.365	11
NW	12	4	62	11	0.645	0.355	12
HRCS	12	4	53	11	0.751	0.249	12
HE	12	4	55	11	0.724	0.276	12

HEAL	12	4	61	11	0.654	0.346	12
RCS	12	4	60	11	0.668	0.332	12
FALS	15	5	72	14	0.552	0.448	14
HEALS	16	5	80	14	0.503	0.497	15
HLRCS	16	5	81	15	0.494	0.506	16

Three policies (LST, LRCS, and FAST) were found to perform best with respect to this second performance measure. All three policies prioritize worksites based on estimated service times. Policy LST gives higher priority to worksites for which shorter service times are expected. In addition to allocating higher priority based on lower expected services times, the LRCS policy also includes the impact of change of rate in survival likelihood function on priority scores. The FAST policy is equivalent to the FEMA policy, but is rescaled to capture the benefits of lower service times. Only the LRCS policy performs among the best with respect to both performance measures. Likewise, the HEALS, HEAL, HLRCS and HRCS, all of which account for estimated number of live entrapped victims, perform among the worst under the second performance measure.

In circumstances where the worksites are similar in terms of use, material and likely damage, the probability of a given number of survivors at each worksite will be similar. In such cases, it would be best to follow a policy that performs well in terms of minimizing the time-averaged number of worksites in queue. The LRCS policy offers advantages under both performance considerations.

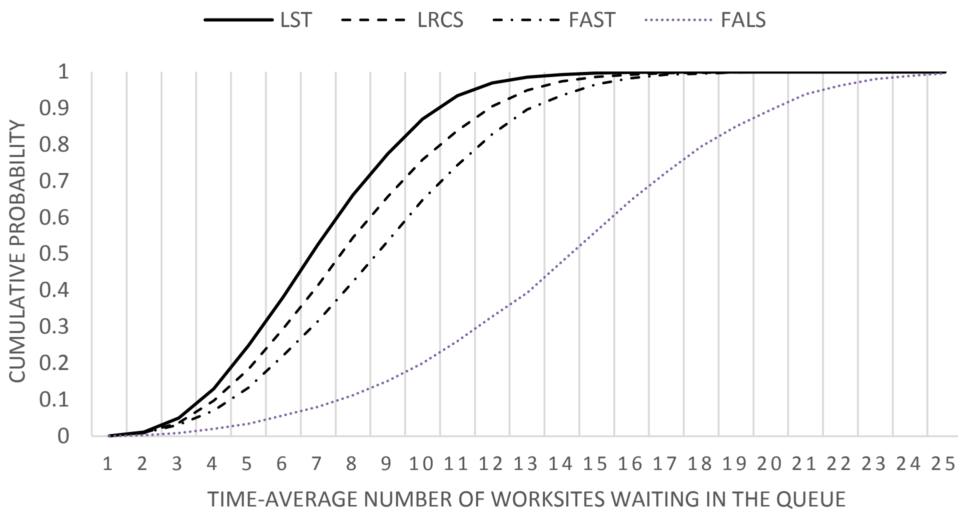

Figure 5 CDF Time-Averaged Number of Worksites Waiting in the Queue

The CDFs associated with the best performing policies given the time-averaged number of worksites waiting in queue were computed on the 5 replications of 3,000 problem instances mentioned above. The CDFs are graphed in Figure 5. The LST policy stochastically dominates the other considered policies. While both FEMA-based policies have the worst performance in these experiments, the FALS policy is noticeably suboptimal.

6.2 Policy Performance Compared with Decision Approach

In the previous section, the performance of 16 policies is assessed. The best of these policies would, using the D&D estimate, save as many as 575 people (Table 1) in the context of the case study. While this policy produces significantly more survivors, if there might exist an alternative policy that would produce even better results is not known. Thus, an upper bound on policy performance can be obtained by determining the optimal number that can be saved given available resources and other problem properties (e.g. survival function rates of decline), as well as perfect knowledge of the problem characteristics. That is, this number is determined *a* *posteriori* assuming perfect knowledge of the situation in hindsight. The optimal achievable number will not likely follow from a single prioritization scheme.

To determine the *a posteriori* optimal deployment of teams to worksites so as to maximize the number of survivors, the USAR team deployment problem with perfect information is modeled herein as a multi-team extension of the Multiple Tour Maximum Collection Problem with Time-Dependent Rewards (MTMCPTD). The MTMCPTD is a generalization of the team orienteering problem, a comprehensive review of which can be found in Vansteenwegen et al. (2011). It was introduced in Tang and Miller-Hooks (2007) in the context of the scheduling planned maintenance tasks to be performed by a single technician over a multi-day planning horizon for a company with geographically distributed equipment. Since they showed that the MTMCPTD is NP-hard, a tabu search heuristic embedded in an adaptive memory procedure and run over a rolling horizon was proposed. The procedure was shown to obtain near-optimal solutions on a real-world case study through the use of theoretical bounds. This procedure was extended to multiple agents (i.e. teams) for use herein and was employed to solve the USAR team deployment problem over 10 Haitian problem instances.

The first 24 hours of the rescue mission were simulated. Table 8 displays the average total number of survivors produced under each policy and a percentage difference from the *a posteriori* optimal number of survivors that could be obtained under perfect information and using a decision approach rather than a single policy. Using the existing FEMA policy, 50.7% of the optimal *a posteriori* number of survivors is achieved. Employing Policy HEALS (highest number of live entrapped victims adjusted for loss rate and lowest service time) increases this performance by 35.7 percentage points to achieve 86% of optimality. On average, incorporating the impact of decreasing survival likelihood, with its degree of change over time, during the transit time of USAR teams and service times improves the total number of survivors by between 15 and 35 percentage points.

Table 8 Policy Comparison to *a Posteriori* Solution

Policy	Survivors	Percent from *a Posteriori* Optimal	Policy	Survivors	Percent from *a Posteriori* Optimal
HEALS	844	86.0	LST	589	60.0
FALS	745	75.9	RCS	575	58.6
HLRCS	680	69.3	FAL	571	58.2
HEAL	676	68.9	HE	544	55.4
FAST	645	65.7	FEMA	498	50.7
LRCS	644	65.6	FATT	462	47.1
HRCS	641	65.3	NW	387	39.5
FALR	595	60.6	CS	160	16.3
Upper Bound			981		

6.3 Sensitivity Analysis

The five best performing policies, HEALS, HEAL, HRCS, LRCS, HLRCS, along with the FALS policy, were further investigated. Specifically, the sensitivity of the number of survivors achieved under each such policy to service time, travel time and the survival likelihood function was considered. A goal of this sensitivity analysis is to determine if one of the best policies identified in Section 6.1 in terms of the first studied performance function, average number of survivors, stands out above the others. It is worth noting that the HEALS policy, a top performing policy, is similarly structured to the best FEMA-based policy, the FALS policy.

Policy performance on five replications of each of 3,000 randomly generated Haitian problem instances was investigated for seven service time distributions: ~U[1,24], ~U[24,48], ~U[48,72], ~N(24,6.92), ~N(48,6.92), ~N(72,6.92), ~N(24,13.48), ~N(48,13.48). Travel times were assumed to be uniformly distributed on the interval [1,4], ~U[1,4]. Survival likelihood functions were presumed to be negative exponentially distributed with rate 90%. Setting the rate parameter of the distribution function to 90% infers survival of at most 10% of live entrapped victims by the end of the first 24 hours.

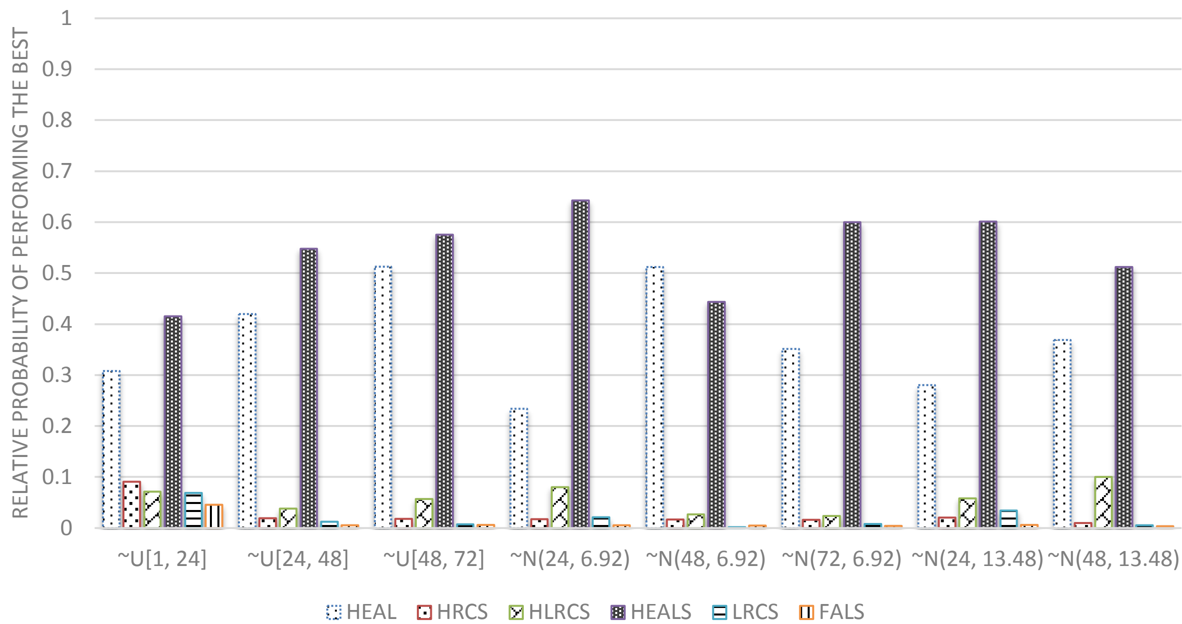

Figure 6 Sensitivity Analysis of Policy Performance under Alternative Service Time Distributions

Figure 6 shows the relative probability of performing the best, $P_{Win}(AP^k)$. This probability is based on the frequency with which the studied policy outperforms all other considered policies under each service time distribution.

The results indicate that the HEALS policy (highest number of live entrapped victims adjusted for loss rate and lowest service time) outperforms other policies under all but one studied service time distribution: ~N(48,6.92). The HEAL policy performs best under this service time distribution and second best in all other cases. Moreover, increasing the mean service time from 12 to 24 or 48 hours under a uniform distribution improves the relative probability of being the best for Policy HEAL. The relative improved performance of the HEALS policy compared with the HEAL policy is even greater under normally distributed service times, which in comparison to uniformly distributed service times has a peak and generally lower variance, but the general relative performance differences between all studied policies are minor. As mean service time increases, the difference in performance between HEAL and HEALS policies diminishes. The relative performance of the HLRCS policy improves with increased variance in service time.

The impact of changing the rate in the survival likelihood functions on the performance of the studied policies is investigated further under uniform service and travel time distributions, ~U[1,24] and ~U[1,4], respectively. The rate was varied between a 90% and 20% in the first 24 hours. Results of these runs are given in Figure 7.

From the figure, it can be observed that the lower the rate (i.e. closer to 20%) the better the relative performance of the HEALS policy. At the highest rate (90%), performance of the HEAL policy is nearly as good as that of the HEALS policy. This observation suggests that under conditions with higher survival likelihood and lower rate of change in this likelihood, it is more important to include service time in the prioritization. That is, priority should be given to those worksites with low service times. In conditions where rate of survival is dropping quickly, those worksites with more live entrapped victims should have the highest priority.

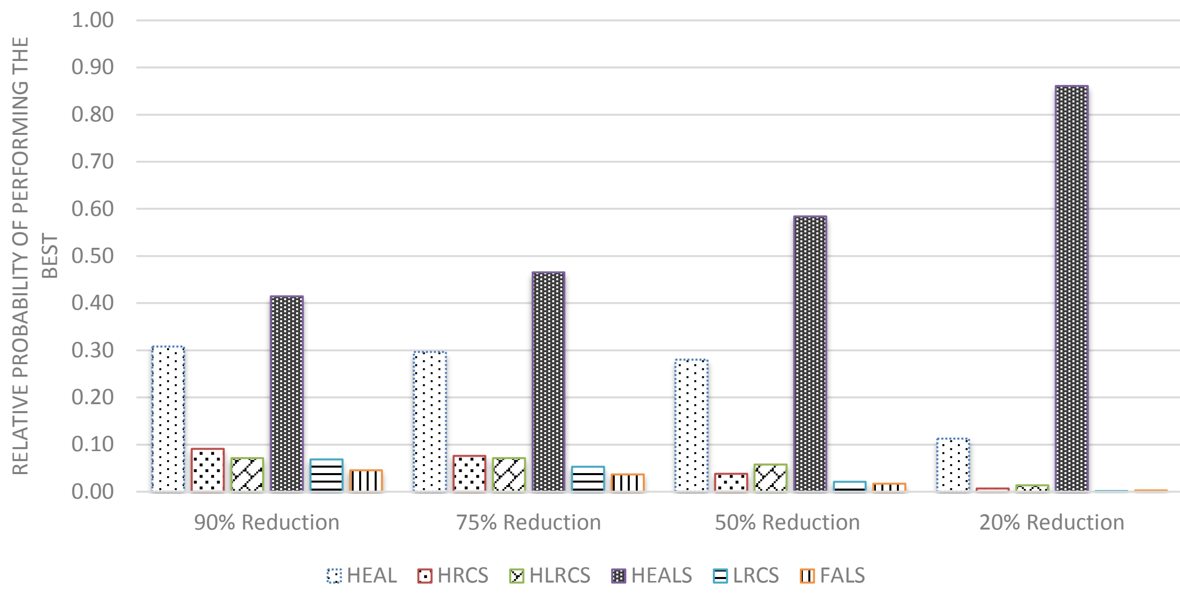

Figure 7 Sensitivity to Reduction in Survival Likelihood Rates Given by Reduction in First 24 Hours

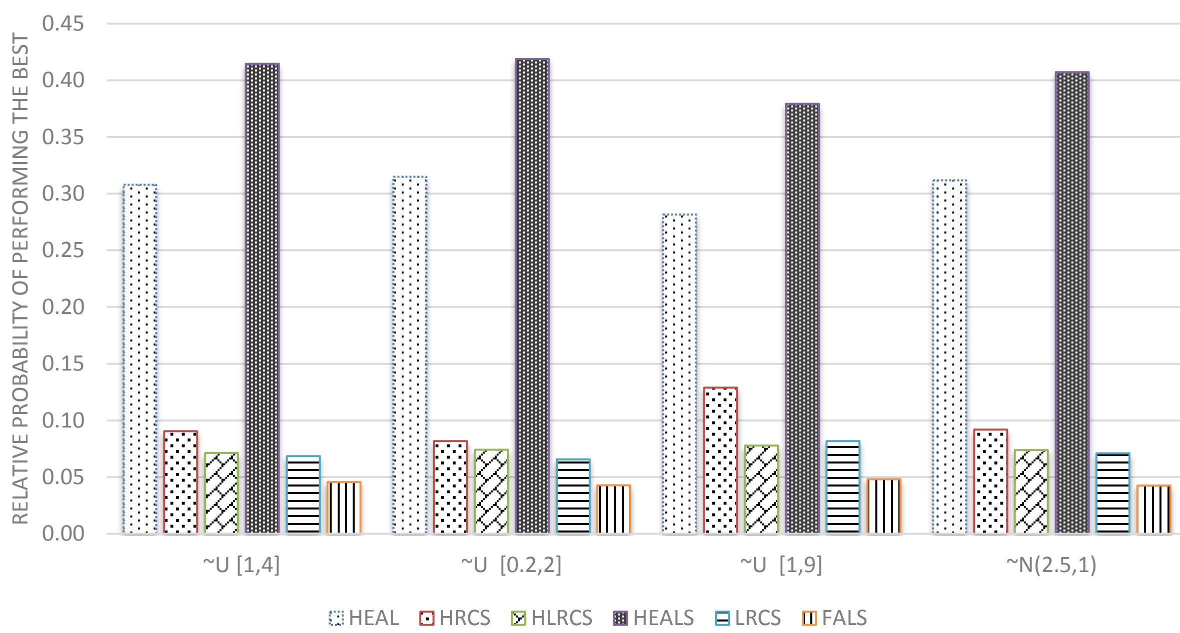

Figure 8 Sensitivity to Travel Times

Finally, given a service time distribution that is ~U[1,24] and negative exponentially distributed survival likelihood function with rate 90%, policy performance in terms of number of survivors under varying travel time distributions was studied. Results from these experiments, given in Figure 8, suggest that changes in travel time mean, variance and distribution have little effect on the relative probability of performing the best, $P_{Win}(AP^k)$, among considered policies. Again, policy HEALS outperforms other policies.

6.4 Further Investigation of Policy FALS

The FALS policy was further investigated through parameterizing its numerator and denominator: $(P_{fi} - r_i \cdot \Delta Sl_{it+tt_{ji}})^{\alpha} / S_{it}{}^{\beta}$. Five replications of 1,000 problem instances were completed for varying values of the parameters. Considering four different service time distributions, (~U[1, 48], ~U[0,3], ~N(24, .6.92) and ~U[L,U] for integer L between 5 and 8 hours and $U = L + 8$). While for a few settings of α and β (e.g. $\alpha = 1.3, \beta = 1.8$) a statistically significant difference in performance was noted at a 95% confidence interval, the actual difference in number of survivors is trivial (e.g. an increase of less than one to perhaps two survivors).

7. Conclusions and Extensions

The problem of optimally deploying USAR teams to worksites in a disaster region requires quick evaluation of the disaster scene and rapid decision-making on the deployment of limited resources. These allocation decisions directly affect the number of people who can be extricated and, therefore, the number to survive. In this work, the idea of implementing a single policy for allocating USAR teams to worksites is explored. The use of a single policy is particularly pertinent in real-time operations and requires a minimal level of on-site, real-time computation. Moreover, prioritization based on a single policy reduces confusion that can arise in such difficult, emergency-related situations.

In this paper, this allocation of limited emergency resources to worksites is conceptualized as a M/G/c priority and preemptive spatially distributed queueing system with roving servers. Sixteen policies were proposed for operating the queueing system. These policies provide a mechanism for prioritization of worksites (e.g. collapsed buildings) in the field. The policies were tested on thousands of randomly generated problem instances developed on a real-world based case study application.

Of the 16 considered policies, seven policies were found to be promising under two selected performance measures, two of which, specifically HEALS and LRCS policies, were particularly notable. The first of these two policies prioritizes based on the lowest service time and highest number of live entrapped victims adjusted for losses while waiting for the USAR teams to arrive. The second ranks the worksites based on shorter service time and higher rate of change in survival likelihood. As time passes, survival likelihood diminishes. Thus, effectively, these factors together provide a measure of life expectancy.

A comparison between Policies HEAL and HEALS shows that service time alone is not enough. Better policies give priority to worksites with larger numbers of live entrapped victims and, therefore, possible survivors. Further comparison of the HE and HEAL policies shows the added improvement of considering loss in number of live entrapped victims during the time it takes to travel to the worksite and set up needed equipment. That is, the number of live entrapped victims at the worksites should be estimated from the time when USAR teams begin the actual rescue work rather than when deployment decisions are made.

Alternative approaches to this problem of real-time USAR team deployment might be considered. In particular, methods that view the problem as an online routing problem may be useful. Consider, for example, the Online Traveling Salesperson Problem (OTSP). The objective of the OTSP is to minimize the total waiting time of a select subset of customers who are chosen to be served while simultaneously minimizing penalties incurred from rejecting other customers. Jaillet and Lu (2011) introduced a polynomial time algorithm for an offline version of this problem. They further developed an optimal c-competitive online algorithm for requests on a metric space where c is found to be approximately 2.28. This is a difficult problem class for which solutions can be obtained under restrictive assumptions, including the omission of preemption and priorities based on factors other than time of arrival to the system.

The well-known Online K-server Problem on a metric space may also have some applicability here (Borodin and El-Yaniv, 1998). This problem seeks to minimize the total distance that servers must travel from one customer to the next to serve all incoming requests. While algorithms exist for several variants of this problem, e.g. the Work Function Online Algorithm, no algorithm has been developed that considers real-world complexities, such as prioritization, preemption and that not all customers can be served in the planning horizon. The advantage of these approaches is that they can model dynamic worksite arrivals; however, neither modeling approach considers the effects of time evolution on problem characteristics, including service times and potential rewards received from serving customer locations.

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