Challenges of Modeling Community-Driven Disaster Operations Management in Disaster Recurrent Areas: The Example of Portsmouth, Virginia

Josey Chacko
Mount St Mary's University
chacko@msmary.edu

Christopher W. Zobel
Virginia Tech
czobel@vt.edu

Loren P. Rees
Virginia Tech
lrees@vt.edu

ABSTRACT

Although one of the dominant paradigms in managing disaster operations is that of modeling decisions around the activities of humanitarian organizations, recent literature has highlighted the importance of managing disaster operations from the perspective of the affected community. Modeling community-driven disaster operations has a unique set of challenges, however, several of which are highlighted in this research effort. These include engaging the community and coordinating amongst multiple decision makers, defining a clear community objective, and planning with long decision horizons. Using the urban area of Portsmouth, Virginia as a case study, this work in progress paper demonstrates a decision support system-based approach which addresses these critical elements of community-driven disaster operations management.

Keywords

Community-Driven Disaster Operations, Disaster Management, Community Engagement, Recurrent Disasters, Resilience.

INTRODUCTION

Although the importance of managing disaster response and preparedness cannot be understated, managing disaster operations is a challenging process. First of all, technical disaster operations activities must be carried out in complex environments that are characterized by both uncertainty and urgency (Bealt & Mansouri, 2018; Chacko et al., 2016). Secondly, there is the challenge of coordinating a network of diverse and geographically separated stakeholders (Comfort, 2007; Balcik, et al., 2010; Dubey & Altay, 2018). Additionally, these diverse stakeholders may have different, and possibly conflicting, goals, some of which will be dependent on their roles in the process (Balcik, et al., 2010; Chacko, 2015). Given this complexity, it is critical for researchers to continue developing decision support systems that can lead to more timely and effective decision making.

Since much of the literature surrounding the management of disaster operations is generally motivated by planning for a specific disaster event (Overstreet et al., 2011; Chacko, Zobel, and Rees, 2014; Chacko et al., 2016), discussions on goals have typically focused on the immediate needs associated with a current emergency. While there recently has been a shift towards alleviating human suffering (See Holguin-Veras et al., 2013), much of the focus of such work still deals with managing the 'disaster at hand,' with an emphasis on humanitarian and disaster-relief organizations (Bealt & Mansouri, 2018). As a result, it misses out on the opportunity to also consider information about long-term community stability and viability in a disaster-prone area (Habsburg-Lothringen, 2015; Bealt & Mansouri, 2018).

The literature on community-driven disaster operations, i.e. disaster efforts motivated by the needs and capacities of the affected community, is limited and is only now emerging (Bealt & Mansouri, 2018). To our knowledge, only Bealt & Mansouri (2018) and Chacko et al. (2016) explicitly emphasize the importance of community-driven disaster operations. Bealt & Mansouri (2018) focus on using local collaborative networks to support disaster operations while Chacko et al. (2016) focus on modeling mitigation and long-term recovery for communities. This current study, in turn, focuses on discussing the unique challenges that arise when modeling community-driven disaster operations management. Thus, the main purpose of this paper is to explicate some of these challenges and to discuss how they can be addressed, using the urban area of Portsmouth, Virginia as a specific case study. We begin our discussion by providing a brief survey of the literature on community engagement in disaster operations, and introduce objectives for community viability over longer-term decision horizons. We then present the case study and discuss the possible implementation of the proposed modeling approach in that context.

SURVEY OF RELATED LITERATURE

The first official US assessments of disasters occurred around 1964 and led, in part, to a conceptual shift from an engineering/structural perspective of disasters to one *more inclusive of data about the human and social dimensions.* This also included a shift from vulnerability models, which emphasized risk reduction, to models that were more active in placing responsibility of actions/decisions on people, rather than models that simply reacted to nature (Cutter et al., 2008). This shift emphasized the placement of the affected community at the forefront of disaster operations, emphasizing the community's goals - community stability and viability over the long-term (Pearce, 2003; NRC, 2006). This emphasis results in a few unique challenges, however, including the definition of clear community objectives, long decision horizons, and engagement and effective coordination with other stakeholders (Chacko, 2015). In the following sections, we'll review the literature to explicate these challenges.

Community Engagement & Coordination

One of the dominant paradigms in managing disaster operations is that of modeling decisions around the activities of humanitarian organizations (Chacko, 2015; Bealt & Mansouri, 2018). This emphasis begs the question, however, of whether the needs of the affected communities are truly addressed in such situations (Saab, Maitland, & Tapia, 2008; Bealt & Mansouri, 2018). In order to broaden the effectiveness of disaster operations, it is necessary to consider and directly engage with the affected community (Sheppard et al., 2013; Bealt & Mansouri, 2018), including stakeholders such as the local government, etc. In fact, Birkmann (2008) argues that community engagement when managing disaster operations makes the community more resilient. This raises a unique challenge: in what areas should the community specifically be engaged? Pearce (2003) & NRC (2006) suggest that engaging the affected community on their values and goals is an important area. In addition, it can be important to engage the community in ascribing levels of importance to various disaster operations activities (NRC, 2006).

A critical challenge that arises from community engagement is how to coordinate relevant disaster operations actors to work towards the goals of the affected community. Though much of the coordination in disaster operations is driven by the bureaucratic model (National Response Framework (NRF)), such a paradigm has critical limitations, specifically that 'it is not likely to accommodate the multi-dimensional crisis situation found in large-scale disasters' (Majchrzak, Jarvenpaa, & Hollingshead, 2007, p. 159). Critically, Bealt and Mansouri (2018) highlight from their study that effective coordination occurs when information sharing is facilitated by the affected community. This is because the local community has local knowledge - a better understanding of local needs, the local context, and available local resources (Bealt & Mansouri, 2018). This fits well into the context of the broader literature on coordination amongst inter-dependent actors, which asserts that effective coordination occurs through shared goals (Gittell, 2006; Bealt & Mansouri, 2018), information sharing (Comfort et al., 2004; Gittell, 2006; Dubey, Altay, & Blome, 2017; Balcik et al., 2010; Bealt & Mansouri, 2018), and mutual respect (Gittell, 2006; Dubey, Altay, & Blome, 2017).

If such coordination among actors is facilitated by the affected community, then it is important to consider how the community clearly defines their goals and values and how they can appropriately share them internally.

Defining a Clear Community Objective

Defining and quantifying appropriate outcomes from the viewpoint of those who are impacted is critical to disaster operations management since the affected community has a very personal stake in such outcomes (Miskel, 2008; Holguin-Veras et al.'s, 2013). Moreover, including the community in the process of defining the objectives of those operations is also critical for gaining their acceptance, since they often will not want to follow, much less embrace, the process otherwise (Berke et al., 1993; Pearce, 2003). It is also important, however, to consider the community's objectives within the larger context of regional impacts, in order to avoid solutions that may be locally optimal but globally inappropriate. The question therefore arises, if the community is included in defining such objectives, then what kind of framework should be used to do so?

If the defined objective(s) are consistent with the community's values (in the broadest sense), then we might expect them to focus on the community's stability and viability over the long-term. This is both naturally consistent and consistent with findings from applied research (see Habsburg-Lothringen, 2015). With such an emphasis on long-term stability and community viability, there is a subsequent need to widen the focus to include broader system linkages that are external to the disaster event. If this is the case, then a sustainability framework becomes appropriate, in which possible community objectives such as Economic Development, Quality of Life Concerns, and Ecological issues are all considered in tandem (NRC, 2006; Smith and Wenger, 2007).

Within this broader context, it is important to define clear objectives not only to recover from disasters and to build back from disaster impacts in accordance with community values, but also to bounce back *quickly*. In other words, time plays a critical role when defining community objectives because the longer a community is under duress the more it suffers (see Holguin-Veras et al.'s (2013) seminal work on objectives for humanitarian relief work). In order to determine the extent to which the objectives have been achieved they must be quantified, so that the relative extent of the loss suffered, and the speed of the recovery process, can be assessed. As a result, the concept of resilience becomes an important aspect of the discussion.

Resilience is a useful measure for focusing on a system's coping and recovery capacity, for the purpose of reducing the amount of loss that an entity suffers over time, in response to the impacts of a disaster event (Zobel and Khansa, 2012; 2014). To measure such resilience with respect to the various defined objectives of a community, we adopt the approach of calculating the area under a time series loss curve as a percentage of the total area Q^* available if no loss occurs (Bruneau et al., 2003; Zobel, 2011): $R = \left(\int_{t_0}^{t_1} q(t)dt\right)/Q^*$, so that $R \in [0,1]$, where $q(t)$ is the time curve of the community functionality being measured, and t_0 and t_1 are the beginning and end points, respectively, over which the measurement is taken. Because the quantity Q^* depends on specifying a decision horizon over which this functionality should be considered, taking a long-term view implies that we must also adopt a long decision horizon.

Long Decision Horizons

Much of the current disaster operations management literature underplays the recurrent nature of many hazards and focuses instead on the impacts of a single hazard within a relatively short time period (Salmerón and Apte, 2010; Kappes et al., 2012; Chacko, Zobel, & Rees, 2014, Chacko et al., 2016). Particularly when taking a longer-term view, however, it is very important to consider such recurrence in order to emphasize reducing repetitive disaster damages (e.g. rebuilding in flood plains) (Godschalk & Salvesan, 2004; Salmerón and Apte, 2010). This argument is often echoed in a real-world context and by disaster management professionals (City of Portsmouth, 2010; Mitchell et al., 2013). In particular, a long decision horizon adds a new challenge - the need to manage disaster operations (including both the data and decision making) from the perspective of multiple hazards. This is because over a longer time frame various different disasters and their epiphenomena (cascading effects of primary disasters resulting in secondary disasters) may affect a given community in different ways that need to be captured (Basher, 2006; Kappes et al., 2012; Zhang, Li, & Liu, 2012; Chacko, Zobel, & Rees, 2014, Chacko et al., 2016). By addressing disasters within a longer time window, inter-temporal factors may be included in the analysis across multiple events (Mileti, 1999; Psaraftis et al., 1986; Van de Walle and Turoff, 2008). As an example of this, Mitchell et al. (2013), in their applied research of flooding in the tidewater region of Virginia, recommend a suitable decision horizon of 20 to 30 years.

MANAGING COMMUNITY-DRIVEN DISASTER OPERATION CHALLENGES

Given this context of long-term disaster operations management to support community viability in the face of possibly recurrent disasters, we propose a two-step decision making methodology within the context of a decision support system environment.

Step 1: Engaging with the Community & Identifying Appropriate Goals

The first step in our methodology explicitly acknowledges community involvement in specifying appropriate long-term goals. This initial step requires the community to determine three sets of inputs to be included in the analysis to follow: (1) the resilience based *measures* that the community can use to assess the achievement of their goals (2) the list of possible candidate projects/activities that could be implemented to achieve their goals; and (3) the list of policies that reflect the community's various and sometimes competing long-term goals. In addition, the relative importance of each of the policies being considered, along with any additional policies that the community wants to include in its analysis, and the community's "posture" (see below) in enacting these policies.

The *measures* that reflect the community's long-term critical goals will be maximized or minimized as objective functions in a mathematical optimization problem that will be run under a variety of different possible scenarios. Stated conversely, if the community does *not* include a measure in its objective specification, the community should not care if that measure is paid no attention in the analysis that ensues. The candidate disaster operation projects may range from the small to the large. For example, a community may contemplate a project to place curbing along a river or a canal; to build an earthen berm, or a low concrete wall. There might be a variation of the previous project that provides a high concrete wall. A further project might suggest buying back (i.e., moving out) houses and property in the floodplain, in particular those structures that repeatedly are "hit" over and over by successive disasters. Another project of a different ilk might involve the relocation of a disaster supply depot.

The community's "posture" in enacting the most relevant policies represents an *a priori* indication of whether it wants these policies to be "set in stone" over the whole 20-year (say) study horizon, or whether they can be altered given the latest set of conditions and events. For example, a community may decide in advance that it is committed to prioritizing the ecological sustainability," no matter *what*; regardless of the disaster circumstances that ensue, i.e., the populace may say that they refuse to further damage the environment in response. Or, a community may insist it will be equitable in its treatment of its citizenry regardless of what the disaster brings; hence, every socio-economic group will receive equal support in response to damage regardless of political power, influence, etc. Conversely, the community may decide to remain committed to its objective measures and thus, whenever a disaster occurs, to choose (mathematically) the policy that best fulfills the objective function values as expressed by the community.

Step 2: Modeling

In the methodology's second step, a discrete-event simulation model is invoked to generate a large number of independent *disaster sequences* that, in turn, get presented to a planning model for analysis of what to do following the occurrence of each consecutive disaster. A resource allocation model is then run immediately *after each disaster event* to determine how best to proceed, given what has just transpired and what is *expected* to transpire in the future. The model and plan are then adapted based on these results so that an "optimal" path is followed until the next disaster occurs. The state of affairs at the end of the sequence (i.e., the end of the study horizon) is then examined, and the results are stored for each community measure of interest. This is repeated for each disaster sequence. Finally, the mean, median, mode, spread, etc. across all independent sequences are calculated. The results can be presented to the community for feedback and for reconsideration, or validation, of the specified set of measures and of the community's current "posture." Because the quality of the results depends on the quality of the collected data, it is very important to include explicit consideration of the associated uncertainties, including sensitivity analyses within the individual optimizations, in order to properly compare the effectiveness of the different policies over time. Only by examining the results of such multiple replications across a long study horizon can a community properly ensure that it has examined the best set of disaster operation decisions across the policies it cares about.

Case Study: Portsmouth, Virginia

Portsmouth, VA, provides a good example of a community that has been the source of recurrent disasters, particularly flooding, over the past 100 years (City of Portsmouth, 2010; Mitchell et al., 2013). A Google map rendering of Portsmouth with a FEMA risk-of-flooding overlay is shown in Figure 1; red shading in that figure indicates high-flooding risk areas, whereas pink shading represents regions of moderate flood risk.

To enhance this example, we divide the Portsmouth community into four homogenous regions based on median income and location, as shown in Figure 2. The unique characteristics of these regions provide some interesting notes: Region 1 is characterized by being in the floodplain; regions 2, 3, and 4 are *not.* Also, note that region 2 does not abut water (although flooding may occur there); hence it makes no sense to mitigate there with sea walls. Finally, we identify region 4 (along the waterfront) as the business district.

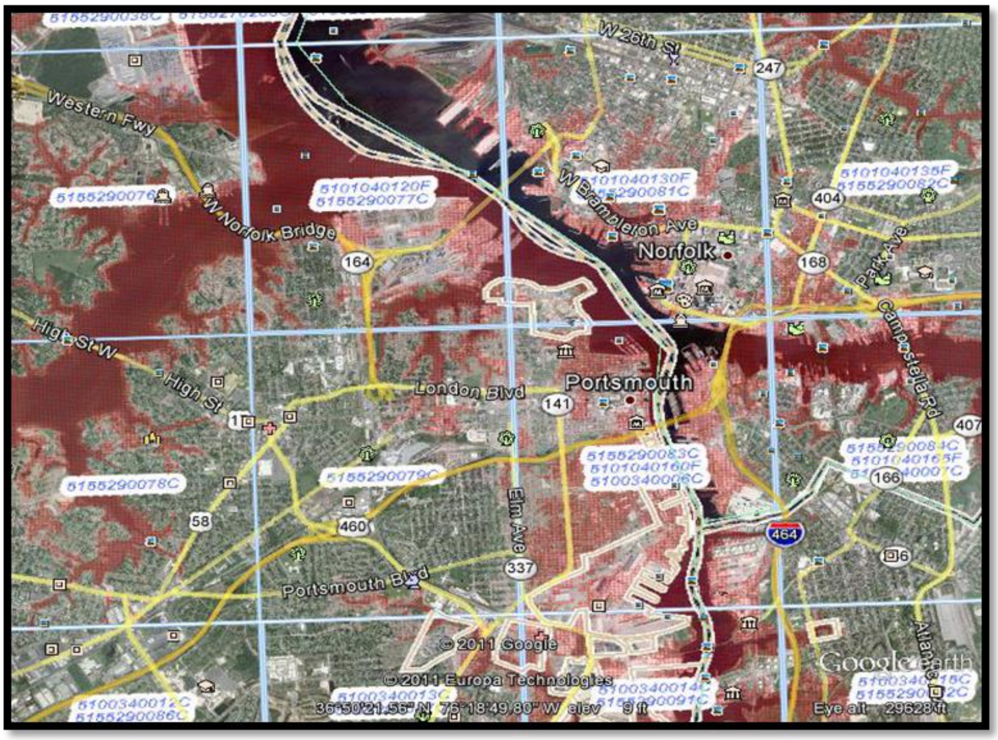
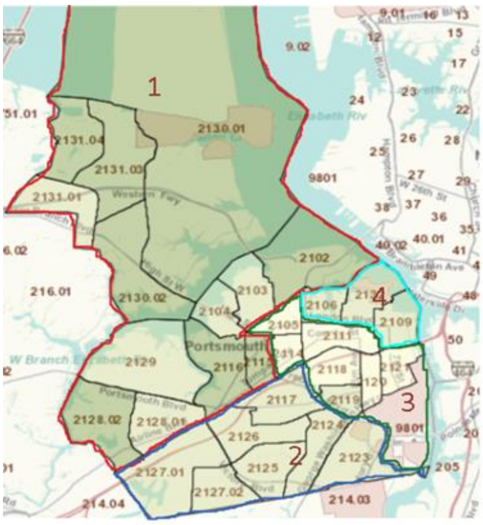


Figure 1. Google Map Image of Portsmouth, VA (USA) with a Flood Hazard Overlay

Source: Google Earth, Version 7; Flooding Risk Overlay provided by FEMA's "Stay Dry," Version 3.



Region	Description
1	Wealthy; in floodplain
2	Middle median income
3	Lowest median income
4	Business district

Figure 2. The Four Defined Portsmouth, VA, Regions

Source: U.S. Census Bureau, 2006-2010 American Community Survey

Proposed Solutions to Community-Driven Disaster Operation Challenges

To analyze the disasters to be faced by Portsmouth, we may generate the inter-arrival times and severity of storm damage from data collected from Mitchell et al. (2013), reflecting Portsmouth's history of storm damage. To further demonstrate the capability to model different types of disasters, we may classify Portsmouth storms into two different *types*. The first storm type consists of tropical storms, Nor'easters, and category 1 and 2 hurricanes, whereas the second consists of category 3 and higher hurricanes. Based on historical storm data for the past 100 years, we may then fit triangular distributions for both severity and inter-arrival times for each type of storm, with different parameters representing the most likely, the smallest, and the largest values occurring.

Because the sequences of disasters discussed above will be drawn from distributions based on historical data and/or expert opinions of both severity intensities and inter-arrival times, plots of the impact of the events on the community's chosen objectives over time do not necessarily follow closed-form expressions. However, if we assume (essentially) instantaneous disaster effects and linear recoveries from them (or that nonlinear recoveries may be approximated by piecewise linear functions), we may generate curves q(t), as in Figure 3, to represent changes in these measures over time. Using Chacko et al., (2016), we may then calculate resilience as a function of the piecewise area under q(t). This piecewise-linear approximation of the response is particularly appropriate because of the long time frames being considered, however, it is not strictly necessary for calculating the area beneath the response curve since there are a variety of numerical integration methods that could be used for this purpose if a different approach were adopted.

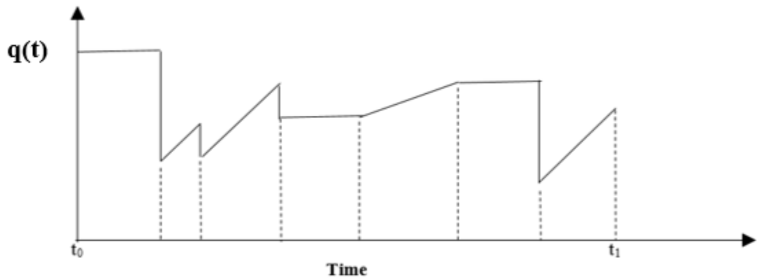


Figure 3. Computational approach for calculating resilience.

The methodology is implemented via a basic resource-allocation mathematical model, where both long-term mitigation and long-term recovery projects are mathematically drawn from among a pool of possible disaster operation projects. These projects are categorized either under long-term mitigation projects or long-term recovery projects, and they are allocated resources in order to meet the community's goals and objectives while implementing community-specified, significant policies. The form of the model may generally be written as

Pursue Objective(s)		*(1a)*
subject to:	*physical constraints*	*(1b)*
	long-term mitigation project constraints	*(1c)*
	long-term recovery project constraints	*(1d)*
	policy constraints	*(1e)*
	non-negativity constraints, etc.	*(1f)*

The objective in this model is to maximize the community's chosen objectives, or community values, including such options as *equity among social classes; preferential treatment for the elderly; preferential treatment for businesses; measures reflecting safety*, etc., through investment of limited resources into mitigation and recovery decision options. These various values may be considered singly, as a group of independent objectives detailed lexicographically, or in the form of a weighted combination (with weighting specified by the stakeholders), that combines to a single objective. The function *q(t)* then represents the extent to which the objective or objectives are being achieved at each time *t*, relative to a given target value of 100% achievement. This may be calculated by using either proxy variables or direct measurements, depending on the nature of the objective under consideration. The resource limitations are primarily financial and construction-related, and are functions of both time and region, but any additional resource constraint that obtains in a particular scenario can and should be included.

Taking such an approach can allow the community to assess the range of possible outcomes it is likely to see over the planning horizon for each policy it considers, both through the quantitative results of the analysis and through visualizing the long-term trajectory of the community with respect to their chosen objectives. The community thus may choose the policy that most effectively accommodates its long-term wishes. Alternatively, however, the community may instead determine that none of its proposed measures, policies, and project combinations provides a satisfactory solution, given the disasters it expects to face. It is critical that communities be able to make this assessment before, rather than after, facing a sequence of disasters. In such cases, new/different projects, resources, etc., must be considered with the model being re-run and re-assessed.

CONCLUSIONS

This research highlights the challenges of modeling community-driven disaster operations management, specifically the challenges of: engaging the community and coordinating amongst multiple decision makers, defining a clear community objective, and planning with long decision horizons. Using the urban area of Portsmouth, Virginia, this research demonstrated, as a work in progress, a decision support system approach which addresses critical elements of community-driven disaster operations management. The proposed approach provides data informing answers to multiple, general questions, from which the community then must engage in open, informed discussion, considering interactively-determined tradeoffs, before it specifies its recommended course of action for mitigating against and responding to upcoming disasters.

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