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Abstract

Volunteer convergence refers to the mass movement of volunteers toward affected areas following disaster events. Emergency management professionals sometimes refer to volunteer convergence as "the disaster within the disaster," which is an indicator of the tremendous challenge that managing the post-disaster influx of spontaneous volunteers presents. In order to develop effective strategies for managing volunteer convergence, it is imperative that emergency managers and coordinators understand the nature of convergence from a quantitative perspective. This paper presents a case study of volunteer convergence following the April 2011 tornado disaster in Tuscaloosa, Alabama, and represents the first academic study to rigorously analyze volunteer convergence data. Specifically, we characterize selected stochastic variables that are relevant to volunteer task assignment within the context of a disaster relief warehouse environment using data collected during tornado relief efforts in May 2011. Time series analysis and a hierarchical clustering method based on the Kruskal-Wallis test revealed both non-stationarity and non-homogeneity in the data with respect to time of day, day of the week, and number of weeks past the disaster event. We also discuss the implications of our findings with respect to modeling relief center convergence as a queuing system.

Keywords: *Humanitarian logistics, volunteer convergence, case-study, data analysis, disaster relief center, queuing system.*

1 Background

Convergence within the context of disaster management refers to "the mass movement of people, messages, and supplies toward the disaster-struck area" (Fritz and Mathewson, 1957). This definition identifies three major forms of convergence that can occur following a disaster: *personal convergence* (the physical movement of people), *informational convergence* (the movement or transmission of messages), and *material convergence* (the physical movement of supplies and equipment). The focus of this study is a special case of personal convergence that addresses the influx of spontaneous volunteers following a large-scale disaster. In particular, this paper investigates the convergence of volunteers who are not necessarily affiliated with the organized relief efforts of police, paramedics, FEMA, Red Cross, or other official responders. Lowe and Fothergill (2003) describe these spontaneous volunteers as "...those individuals who contribute on impulse immediately after a disaster."

Spontaneous volunteerism represents one of many forms of volunteerism often associated with emergency and disaster response situations. Whittaker et al. (2015) review frameworks for classifying disaster volunteerism that have been proposed by the academic literature. One of the most well-known classifications by Quarantelli (1966) and Dynes (1970) categorize organizational responses to disaster as (i) established, (ii) expanding, (iii) extending, or (iv) emergent. *Established organizations* perform routine tasks within existing infrastructures. Examples include police, fire departments, and paramedics. The Salvation Army is an example of an *expanding organization:* an agency whose routine tasks are relief-related (e.g., feeding those in need), but not always in an emergency context. Expanding organizations often engage the services of spontaneous volunteers, which constitutes an expanding personnel infrastructure. Expanding organizations may also take on additional tasks to support relief efforts (i.e., an expanding set of tasks). Thus expansion can occur in terms of infrastructure and/or the types of activities performed. Unlike established and expanding organizations, *extending organizations* operate outside of the formal emergency management infrastructure and have expertise in areas not uniquely related to relief activities. However, extending organizations may perform tasks that are either within or beyond their areas of expertise in response to a crisis situation. Examples include a logging company who donates bulldozer operators and equipment to support debris clearance efforts, and sporting clubs who deliver food to disaster survivors (Whittaker et al., 2015). The fourth category, *emergent organizations*, is the one that is most closely related to our study. Similar to extending organizations, emergent groups also function outside of the formal emergency management system. Moreover, emergent groups lack a collective expertise and therefore inherently take on unfamiliar tasks. They are often on the scene before established, expanding, and extending organizations, and they perform various first responder tasks such as search and rescue.

Perhaps the most relevant framework for the purposes of this study is Shaskolsky (1965), who identifies four forms of disaster volunteerism: (i) anticipated individual, (ii) anticipated organization, (iii) spontaneous individual, and (iv) spontaneous organization. Doctors who volunteer their expertise to help disaster survivors are considered *anticipated individual* volunteers, while the services of Red Cross is an example of an *anticipated organization* response. Both types can be expected in response to large-scale disaster events, hence the designations as "anticipated". As mentioned previously (Lowe and Fothergill, 2003), *spontaneous individual* volunteers typically self-deploy based on impulse during the early stages of response. On the other hand, *spontaneous organization* volunteers partner with expanding, extending, or emergent organizations on a temporary basis to support post-disaster relief activities. This study examines the spontaneous volunteer response, both individual and organization, in Tuscaloosa, Alabama USA following the record setting 2011 tornado outbreak (e.g., Knupp et al., 2014).

The terms *unofficial, unaffiliated,* and *informal* have also been used in reference to spontaneous volunteers (Whittaker et al., 2015). With the exception of Lowe and Fothergill (2003), definitions of spontaneous volunteerism seem to come from practitioners exclusively. In Cottrell (2012), spontaneous volunteers are "*those who seek to contribute on impulse - people who offer assistance following a disaster and who are not previously affiliated with recognized volunteer agencies, and may or may not have relevant training, skills, or experience.*" Similarly, according to the Australian government, "*Potential spontaneous volunteers are individuals or groups of people who seek or are uninvited to contribute their assistance during and/or after an event, who are unaffiliated with any part of the existing official emergency* *management response and recovery system and may or may not have relevant training, skills or experience*" (Australian Red Cross, 2010). In the United States, the position of the Federal Emergency Management Agency (FEMA) is that "*Unaffiliated volunteers, also known as spontaneous volunteers, are individuals who offer help or self-deploy to assist in emergency situations without fully coordinating their activities. They are considered 'unaffiliated' in that they are not part of a disaster relief organization*" (FEMA, 2013).

The convergence of unaffiliated volunteers represents a disaster management paradox as shown in Table 1. On one hand, spontaneous volunteers perform a variety of critical relief activities such as search and rescue, debris removal, and distribution of food and supplies (e.g., Wenger, 1991; O'Brien and Mileti, 1992). In fact, Glass (2001) and Oberijé (2007) report that the majority of disaster victims are rescued by spontaneous volunteers, largely because official responders are unable to reach disaster sites in time. Unaffiliated volunteers who live near affected areas can also be the best sources of information to official responders because of their knowledge of the impacted locale (Oberijé, 2007) and ability to accurately report the conditions and needs of the community (Brennan et al., 2005). In addition, Fernandez et al. (2006a) (citing Lowe and Fothergill, 2003; FEMA, 2005, respectively) point out that spontaneous volunteers can relieve professional responders of menial tasks so that they can attend to more specialized relief activities, and that the economic benefit of spontaneous volunteers can be up to eight times the return for states (in the US) who cost share disaster expenses with the federal government.

On the other hand, volunteer convergence introduces several challenges that can potentially impede disaster relief efforts. In fact, volunteer convergence can be so problematic that it has been referred to as the "disaster within the disaster" by emergency management professionals (Points of Light Foundation, 2002). The source of this so-called disaster within the disaster, particularly for events that are covered extensively by the media, is simply that personal convergers show up in large unmanageable numbers, which has also been referred to as the "mass assault" (Allen, 1969). For example, Red Cross processed more than 15,000 volunteers during the 2.5 week period following the September 11, 2001 terrorist attack (Lowe and Fothergill, 2003), and it is estimated that approximately 2,000,000 individuals engaged in volunteer activity during the three-week period following a Mexico City earthquake in 1985 (Tierney et al., 2001). Massive convergence of these sorts can hinder organized relief efforts by overloading transportation and communication systems (e.g., Fritz and Mathewson, 1957; Tierney et al., 2001). In addition, on-the-scene responders are often preoccupied with ad-hoc management of unaffiliated volunteers and are therefore diverted from potentially critical relief tasks (Quarantelli, 1998). Spontaneous volunteers also strain the emergency response infrastructure because they require resources such as food, shelter, and protective equipment (Fernandez et al., 2006b). Furthermore, spontaneous volunteers represent a liability with respect to their own safety as well as the safety of official responders and disaster victims (Fernandez et al., 2006a; Oberijé, 2007). In summary, "It is a paradox - people's willingness to volunteer versus the system's capacity to use them effectively." (Chief Operating Officer and President of UPS, cited in Points of Light Foundation, 2002).

Pros	Cons
Accounts for 75% of search and rescue.	Overload transport and communication networks.
Source of information to official responders.	Divert official responders from duties.
Relieve professionals of menial tasks.	Safety liability.
Eight times return on cost share.	Use resources (food, shelter, protective equipment).

Table 1: Pros and cons of spontaneous volunteer convergence.

In many ways, several of the characteristics associated with volunteer convergence parallel certain aspects of material convergence. Holguín-Veras et al. (2012) present an in depth retrospective analysis of material convergence. Some of the common features of volunteer and material convergence include: both are (i) inevitable occurrences that follow large-scale disaster events; (ii) heavily influenced by media coverage; and (iii) largely the result of citizens who are driven more by impulse than knowledge of actual needs. In addition, volunteer and material convergence are beneficial in that they augment the capacity of the emergency management infrastructure. On the other hand, both also compromise the ability of the formal emergency management system to respond quickly. They cause traffic congestion in affected and surrounding areas due to the influx of people, supplies, and equipment. Volunteer and material convergence also demand the attention of official responders thereby diverting them from activities directly related to meeting the needs of beneficiaries.

The inevitability of volunteer convergence in large-scale disasters is well documented (e.g., Fritz and Mathewson, 1957; Tierney et al., 2001; Fernandez et al., 2006a; Whittaker et al., 2015). Consequently, researchers and practitioners have developed several guidelines for integrating spontaneous volunteers into organized emergency response efforts. Example recommendations include simply planning in advance for volunteer convergence (Oberijé, 2007), training emergency management professionals to work with and manage spontaneous volunteers, creating a central volunteer reception center in a safe location to organize and train convergent volunteers (Fritz and Mathewson, 1957; Points of Light Foundation, 2002), and encouraging affiliation with relief organizations (Oberijé, 2007). However, existing principles and systems for managing volunteer convergence are limited in scale, scope, and operational detail (Fernandez et al., 2006a,b). For example, there is no systematic method for assigning spontaneous volunteers to tasks, which is a particularly difficult undertaking for volunteer managers because of the astronomical number of volunteers associated with convergence as well as uncertainties in volunteer behavior and disaster relief tasks. Furthermore, the effectiveness of the overall disaster relief effort and quality of volunteer experiences are largely driven by how spontaneous volunteers are utilized, highlighting the importance of task assignment decisions.

In order to develop guidelines for volunteer assignment strategies as well as tactical and operational volunteer management decisions in general, it is important to understand the characteristics of volunteer convergence phenomena from a quantitative perspective. The extent of existing quantitative descriptions of convergence are, for the most part, limited to the number of volunteers responding to particular disaster events. Examples include Lowe and Fothergill (2003) who estimate that 15,000 volunteers were processed by Red Cross following the September 11 attacks in 2001, and Pillion (2011) who report 10,000 registered volunteers in response to the Tuscaloosa tornado disaster in 2011. However, assuming that the development of effective volunteer planning and management policies are contingent upon the ability to predict various aspects of spontaneous volunteer behavior, a more comprehensive account of convergence is necessary. For instance, how did the number of volunteers fluctuate during the weeks following the Tuscaloosa tornado? Was there an immediate surge of 10,000 responders that steadily declined, or did the number peak at some other time during the convergence period? How long did the convergence period last? How many hours per day did volunteers work, and how much variability in work hours was there among volunteers? Answers to these and other questions related to spontaneous volunteer behavior would be useful, and perhaps necessary, from the standpoint of helping to inform volunteer planning and scheduling decisions.

The purpose of this study is to quantify volunteer convergence trends in a way that would be useful to help inform volunteer management decisions in practice. Our analysis of volunteer convergence phenomena is based on data collected from a large warehouse during the relief efforts associated with the April 27, 2011 Tuscaloosa, Alabama tornado disaster (e.g. Knupp et al., 2014). For the purposes of this paper, the processes that govern the disaster relief warehouse are represented as a queuing system with stochastic server arrivals and departures. Within this context, volunteer management decisions typically involve dynamic assignment of volunteer servers to relief tasks. Therefore in the spirit of relating volunteer convergence to volunteer management decisions, the focus of this study is quantifying stochastic variables that are relevant to task assignment decisions in a relief warehouse queuing network.

The remainder of the paper proceeds as follows. In the next section, we introduce the relief center warehouse queuing problem. Then in Section 3, relevant studies from the academic literature are discussed. Section 4 provides an overview of the methods used to describe and quantify convergence. The results are presented in Sections 5 and 6 followed by concluding remarks in Section 7.

2 Problem Context

This paper is motivated by the humanitarian relief efforts in Tuscaloosa, Alabama that commenced as a result of the April 27, 2011 tornado outbreak. The effect of volunteer convergence with respect to the response in Tuscaloosa was quite significant (Pillion, 2011). Local officials reacted to the mass influx of volunteers by establishing the Tuscaloosa Area Volunteer Reception Center (TAVRC), which was intended to centralize the processes of registering both affiliated and unaffiliated volunteers, and assigning them to relief activities taking place at various sites throughout the area. In addition to the volunteers handled by TAVRC, there were also several pockets of affiliated volunteers who did not officially register with the TAVRC who were already associated with their respective expanding and extending organizations (e.g., Quarantelli, 1966; Dynes, 1970), most notably, local faith-based organizations. According to the data we retrieved, the TAVRC directed volunteers to official relief activities of the local incident command center, as well as to the decentralized efforts of expanding organizations (e.g., Salvation Army) and extending organizations (e.g., local churches). Nevertheless, the majority of registered volunteers, by far, were assigned to a large relief center that was set up on a temporary basis at an abandoned warehouse.

In this study, volunteer convergence is examined from the perspective of the above-mentioned relief center. In addition to being the site at which most registered volunteers were assigned, this large relief center was also the location where the majority of material donations were received, sorted, stored, retrieved, and distributed. Therefore for the purposes of this study, convergence at the relief center will serve as a a proxy for the convergence experience that followed the 2011 tornado disaster in Tuscaloosa.

Volunteer and material convergence at the relief center are represented in the queuing system shown in Figure 1. Like any queuing system, the relief center in Figure 1 has servers, customers, and waiting lines. Our relief center queuing model features two distinct customer types who wait for service in separate waiting lines: donors who wait in the donor queue, and beneficiaries who wait in the beneficiary queue. For the most part, donors arrive to the relief center in their personal vehicles, although from time to time, high profile donors would show up in large, commercial vehicles. Customers in the donor queue are actually vehicles (i.e., in Figure 1, the circles in the donor queue represent vehicles), and the unloading of material donations from vehicles constitutes the service process. Physically, the donor queue forms in the parking lot outside of the relief center and the public street that leads into the parking lot, oftentimes causing traffic congestion in the surrounding area. Beneficiaries are disaster survivors (or victims) who come to the relief center for food, water, clothing, and other supply items. Unlike the donor queue, the beneficiary queue is comprised of people (not vehicles), and forms inside the relief center. For beneficiaries, service is complete once all necessary items have been retrieved from within the relief center.

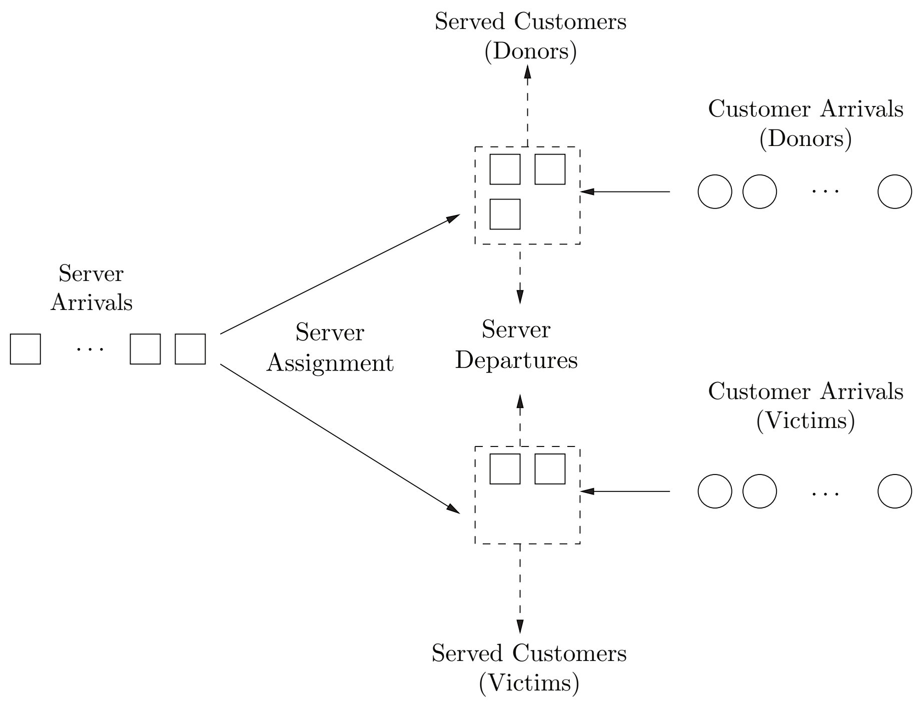

Figure 1: Disaster relief warehouse queuing with server assignment.

Both customer types, donors and beneficiaries, are served by one or more volunteers. Thus volunteers represent the servers in the relief center queuing system shown in Figure 1. However, unlike classical queuing systems, our relief center queuing model is characterized by random server arrivals and departures. In addition, servers are assigned to either the donor queue or beneficiary queue upon arrival or when they reach the front of the server queue. Within this framework, volunteer convergence is represented by the stochastic server arrival process, whereas material convergence is captured by the stochastic arrival process of donors.

One last comment regarding the characteristics of volunteer servers in the relief center context just described: it is not necessary to distinguish volunteers with respect to the skills they bring to the relief effort. Volunteers assigned to the donor queue unload donations (mostly food, water, or clothing) from vehicles, while those assigned to the beneficiary queue use shopping carts to retrieve items for those customers. Both are manual material handling activities that don't require specialized skills. It is therefore reasonable to assume that all volunteers are capable of carrying out both types of service.

There are several advantages to modeling volunteer convergence as a queuing system. Performance measures related to waiting time, system capacity, and congestion can be estimated, all of which are important for quantifying the impact of convergence. In addition, it provides a useful framework for relating a quantitative description of convergence directly to volunteer management decisions, namely how to assign volunteers to tasks as shown in Figure 1. From this perspective, the stochastic variables we are interested quantifying include inter-arrival time, service time, and batch size. Loosely speaking, batch size refers to the number of volunteers who arrive to the relief center at the same time. More detailed definitions of volunteer batch size, interarrival time, and "service" time are given later in this paper in Section 4.1.

Unlike traditional queuing systems that focus on the stochastic processes that govern *customer* arrival and service processes, the queuing system examined in this study concerns the stochastic processes associated with *server* arrivals and departures. Therefore, it is natural to consider the following research questions:

Question 1 *Can server inter-arrival and "service" times be adequately described by an exponential distribution?*

It is well-known that exponentially distributed customer inter-arrival and service times represent a class of queuing models that are analytically tractable (e.g., Winston, 2004). Therefore, it is a desirable property for the stochastic processes governing volunteer arrival and service times as it may lead to closed-form expressions for system capacity and waiting time. Furthermore, given that no previous studies have empirically examined random server arrivals and departures in a queuing context, it would be of interest to ascertain whether or not exponential inter-arrival and "service" times can be justified empirically when it comes to stochastic server behavior.

Question 2 *To what extent, if at all, are batch arrivals relevant?*

Batch arrivals refer to situations in which two or more volunteers arrive at the same time. In the disaster relief context, this is most likely to occur when volunteers are affiliated with the same organization such as Red Cross, a fraternity and sorority, or faith-based organization. However, it is also possible for unaffiliated volunteers to arrive together. This research question is concerned with batch arrivals of unaffiliated volunteers. The nature of arrival and departure processes for affiliated volunteers is addressed in the next question.

Question 3 *How common is it for volunteers who arrive at the same time to also abandon the queuing system at the same time?*

Volunteers who arrive at the same time and later vacate the system at the same time are likely to be affiliated with a group. For the purposes of this paper, we assume that this is the case. That is, if two or more volunteers have the same arrival time t_a and the same departure time $t_d > t_a$, then it is assumed that these two (or more) volunteers are affiliated with the same group. Similarly, it is assumed that unaffiliated volunteers differ in terms of t_a, t_d, or both. From this perspective, Question 3 seeks to determine how relevant affiliated volunteers were in the Tuscaloosa response. Intuitively, the answer is that affiliated volunteers were quite relevant. If this turns out to be the case, then the implications for modeling service capacity of the corresponding queuing system will be important. Therefore, it is of interest to conduct an investigation into the existence of group arrivals and departures, and to determine whether or not the associated stochastic processes are distinct from that of unaffiliated, individual volunteers. It is also interesting to note that while batch arrivals play an important role in traditional queuing systems, batch arrivals in conjunction with batch departures are not particularly relevant as they are in this study.

The final research question is not directly applicable to modeling the relief center queuing system, but would be of interest to tactical capacity planning.

Question 4 *To what extent does the average number of volunteers change over time?*

Capacity changes over time provide a way to quantify the existence and extent of convergence. In particular, the result of answering this question will reveal the rise, peak, decline, and duration of the convergence period.

3 Literature Review

3.1 Volunteer Convergence

Volunteer convergence has received considerable attention from the academic community, primarily in the disaster management and social science literatures. Comprehensive surveys of volunteer convergence research are presented in Whittaker et al. (2015) and Fernandez et al. (2006a). The study of volunteer convergence is also related to the broader topic of *emergent phenomena* as it relates to disaster response. From this more general perspective, both Drabek and McEntire (2003) and Helsloot and Ruitenberg (2004) provide exhaustive accounts of emergent phenomena research. In this section, we briefly highlight trends in the literature as described in the four above-mentioned survey papers.

3.1.1 Early Studies

Perhaps the earliest account of convergence is Prince (1920), who examined post-disaster response to the 1917 Halifax munitions ship explosion (e.g., Drabek and McEntire, 2003; Kendra and Wachtendorf, 2003). Forty years later, a milestone in convergence research was achieved. The pioneering work of Fritz and Mathewson (1957) became the first comprehensive study of material, informational, and personal convergence. By documenting the details of several real-world response efforts, they established convergence as a mainstream, rather than atypical, characteristic of post-disaster phenomena. The work of Fritz and Mathewson (1957) is also widely known for identifying five categories of individuals associated with personal convergence: (i) returnees; (ii) anxious (those concerned about family and friends); (iii) curious; (iv) exploiters; and (v) helpers (i.e., volunteers).

The creation of the Disaster Research Center in 1963 can also be considered a milestone in the evolution of convergence studies. Critical foundations pertaining to convergence from an academic perspective can be attributed to research that came out of the Center (Drabek and McEntire, 2003; Whittaker et al., 2015). In particular, Quarantelli (1966) and Dynes (1970) propose perhaps the most widely accepted typology for individual and organizational responses to disaster. Their organizational theory based typology consists of four organization types as related to disaster response: (i) established, (ii) expanding, (iii) extending, and (iv) emergent. A description of each is presented in Section 1 of this paper.

3.1.2 Survey Papers

According to Fernandez et al. (2006b), the volunteer convergence literature can be partitioned into three categories (see Fernandez et al., 2006b, page 4), each of which is discussed in detail in the Fernandez et al. (2006a) survey paper. These three broad categories are (i) spontaneous volunteer behavior, (ii) disaster volunteer management issues, and (iii) volunteer management systems and plans. Spontaneous volunteer behavior studies address "who volunteers", "why they volunteer", "how they volunteer" (i.e., which tasks they perform), and "under what conditions volunteers respond". The literature also identifies several challenges associated with managing volunteer convergence, some of which are mentioned in Section 1 of this paper. Other challenges include (but are not limited to) matching volunteers to needs, the dynamic nature of needs, and achieving coordination and a common view of the incident among volunteer and professional responders. The third category described in Fernandez et al. (2006b), volunteer management systems and plans, is actually not a stream of academic literature. This category is a compilation of volunteer management guidelines and procedures for practitioners associated with various voluntary organizations as well as federal, state, and local agencies. The results are documented in Fernandez et al. (2006a), who also identify weaknesses of the existing systems. Fernandez et al. (2006b) go on to propose a conceptual model that improves upon these shortcomings.

In the survey paper by Whittaker et al. (2015), definitions of volunteerism are reviewed and a definition of informal volunteerism as related to emergencies and disasters is presented. They define *informal volunteerism* as "*the activities of people who work outside of formal emergency and disaster management arrangements to help others who are at risk or are affected by emergencies and disasters*" (Whittaker et al., 2015, page 361). Their notion of informal volunteerism is slightly more general than spontaneous volunteerism. Informal volunteerism could be "...spontaneous and unplanned, or deliberate and carefully planned" (Whittaker et al., 2015, page 362). Their review of informal volunteerism research is divided into three categories: (i) emergent volunteerism, (ii) extending volunteerism, and (iii) digital volunteerism. *Emergent volunteerism* refers to the post-disaster response of spontaneous volunteers, as well as mitigation and preparedness activities that emerge beforehand. *Extending volunteerism* concerns the activities of existing organizations and groups that extend their modus operandi in response to crisis situations. Examples include sporting clubs, religious groups, or service organizations. Both the emergent and extending modes of disaster volunteerism are based on the well-known typology of citizen response to disaster by Quarantelli (1966) and Dynes (1970), which is described in more detail in Section 1 of this paper. Finally, when individuals or organizations use social media, mapping software, or other communication technologies to participate in disaster response efforts, it is called *digital volunteerism*[1]. The review of emergent, extending, and digital volunteerism presented in Whittaker et al. (2015) primarily consists of papers that describe each type of informal volunteerism based on real-world disaster response experiences. In addition, the literature also highlights characteristics of emergent volunteerism such as improvisation and innovation. Whittaker et al. (2015) conclude that a more comprehensive definition of informal volunteerism is necessary in order to better utilize their capabilities, and that the historically rigid command/control approach to informal volunteer management could be counterproductive.

The Quarantelli (1966) and Dynes (1970) classification system described above actually expands the scope of volunteer convergence research to the broader concept of *emergent phenomena*, which includes not only the convergence of spontaneous volunteers, but also that of organizations and organized groups. Drabek and McEntire (2003) and Helsloot and Ruitenberg (2004) review the literature from this more comprehensive perspective, and they identify several streams of research topics. Many studies systematically discredit misconceptions regarding citizen response to disasters. Common misconceptions, or myths, include that (i) citizens panic, (ii) citizens are helpless, and (iii) looting is pervasive. In fact, the literature suggests quite the opposite: citizen response is often cohesive, innovative, and resilient. On the other hand, the literature also identifies numerous challenges associated with emergent phenomena, many of which are the issues mentioned previously that pertain to spontaneous

[1]Digital volunteerism can actually be emergent or extending. From this perspective, informal volunteering can be physically emergent, digitally emergent, physically extending, or digitally extending.

volunteers. Research topics prevalent in the social sciences domain include (i) clarifying the definition of emergent group; (ii) expanding the number of emergent phenomena categories; (iii) examining emergence during different phases of the disaster management cycle (mitigation, preparedness, response, recovery); (iv) examining emergence in different disaster types; (v) exploring the effects of culture, religion, gender, and ethnicity on emergence; and (iv) comparing emergence across different countries (Drabek and McEntire, 2003). Finally, several studies criticize the rigid command and control culture of formal disaster management organizations.

3.1.3 Quantitative Descriptions of Convergence

Of particular interest to this study from the volunteer behavior perspective is Cottrell (2012), who seems to be the only researcher to present a data analytic account of volunteer convergence phenomena. Cottrell (2012) examined the motivations and expectations of spontaneous volunteers who interacted with the Australian Red Cross in 2009 based on interviews of 16 individuals as well as 237 responses to an online survey. Key findings relevant to our study are related to the timing of spontaneous volunteer participation. In particular, Cottrell (2012) found that (i) a small percentage volunteered within one day (11.8%); an additional 44.9% within the first few days, 21.3% within a week, 9.4% within two weeks, and 12.6% beyond two weeks (this equates to 78% of the surveyed volunteers responding within one week of the disaster event). This response distribution suggests that the volunteer convergence life cycle has warm-up, peak, and equilibrium periods that occur within two weeks of the disaster event. Our study will examine whether or not a similar pattern was present during the volunteer convergence period that followed the 2011 tornado disaster in Tuscaloosa, Alabama.

3.2 Empirical Studies

Although several research papers related to volunteerism are empirical (survey) studies that employ a range of statistical methods, we could only find one that directly informs volunteer assignment decisions. In particular, Willems and Walk (2013) performed canonical correlation analysis to examine the relationship between volunteer motives and task preferences for a youth services organization. They found that there were a core set of tasks that could satisfy all volunteer motives, but that there were also four other sets of variate pairs, each of which was characterized by one type of motive corresponding to one type of task preference. From the purview of volunteer scheduling, having a core set of tasks supports the functional perspective (e.g., Clary and Snyder, 1999) in which a variety of tasks types can be assigned to volunteers with different motives allowing greater flexibility in terms of satisfying volunteer preferences. On the other hand, the four other variate pairs endorse the differentiated perspective (Houle et al., 2005) where task assignments reflect diverse volunteer motives. Consequently, the results presented in Willems and Walk (2013) can be used to make task assignment recommendations based on volunteer motives in such a way that satisfies volunteer preferences, at least within the context of a youth services organization. Another related empirical study is Dekimpe and Degraeve (1997), who investigate volunteer attrition. Although they do not consider volunteer convergence, their study seems to be the only one that empirically characterizes a stochastic process related to volunteer behavior. Using a sample of over 6,000 Red Cross volunteers during a five-year period, the conditional probability of quitting was modeled as the hazard function associated with the exponential probability distribution. Unlike Dekimpe and Degraeve (1997), our study does not assume a specific functional form (such as exponential) for stochastic variables of interest, but rather identifies the best fit probability distribution based on sample data.

Finally, we mention a series of studies that have nothing to do with volunteer convergence. In particular, since the volunteer assignment problem presented in Section 2 is described within the context of a queuing system, the queuing literature is also relevant to this study. Although the queuing literature is quite expansive, only a few papers have a significant empirical orientation, none of which are related to volunteerism. Empirical analyses of queuing systems have been considered within the context of a semiconductor wafer fabrication process (Chen et al., 1988), a computer network environment (Coffman Jr and Wood, 1966), length of stay for hospital patients (Finlayson, 2012), waiting lists for non-urgent hospital treatments (Goddard and Tavakoli, 1998), and automotive manufacturing processes (Inman, 1999). The stochastic variables relevant to most queuing input processes[2] that have been examined from an empirical perspective are interarrival time (Chen et al., 1988; Coffman Jr and Wood, 1966; Inman, 1999) and service time (Chen et al., 1988; Inman, 1999; Finlayson, 2012). Other stochastic variables and relationships of interest that have been studied include time in system (Chen et al., 1988; Finlayson, 2012), waiting time before service (Goddard and Tavakoli, 1998) throughput (Chen et al., 1988), and independence (Finlayson, 2012; Inman, 1999). The above-mentioned papers focus exclusively on stochastic processes related to customers in queuing systems, except for Inman (1999) who also analyzes scenarios involving server reliability. However, our study is the first to examine random server arrival and departure processes in a queuing network and characterize the corresponding stochastic variables empirically.

4 Methodology

The overarching goal of this study is to provide insight into the nature of the stochastic processes associated with volunteer convergence by analyzing data collected from a large-scale disaster relief effort. Convergence data will be examined in an effort to characterize stochastic variables related to the relief warehouse queuing system described in Section 2; namely (i) volunteer inter-arrival time, (ii) volunteer "service" or participation time, and (iii) volunteer batch size. An overview of the methodology to do so is as follows. First, time series plots for each of these variables will be constructed in order to determine whether or not the corresponding stochastic processes are stationary. Next, an algorithm based on the Kruskal-Wallis test (Kruskal and Wallis, 1952) will be applied to assess volunteer arrival and departure processes with respect to homogeneity. The proposed algorithm will partition convergence data into disjoint homogeneous clusters, and the best fit probability distribution for each cluster will be determined by applying standard distribution fitting techniques. The results will also address research questions 1 through 3 introduced in Section 2.

[2]Inman (1999) also examined the appropriateness of the exponential distribution for two other input variables related to reliability queuing models, namely time between failures and time to repair. In addition, Chen et al. (1988) investigated other input variables applicable to the specific semiconductor queuing system considered in their study.

A fourth stochastic variable of interest is the number of volunteers. Times series plots for the average number of volunteers will show how capacity changes over time, and the results will be relevant to Research Question 4.

4.1 Description of Data

Our analysis is based on volunteer data collected during the relief efforts associated with the April 27, 2011 tornado disaster in Tuscaloosa, Alabama. Records of volunteer names, dates of service, locations of relief activities, and arrival and departure times each day were obtained from the Tuscaloosa Area Volunteer Reception Center (TAVRC), a temporary office established by local government to centralize processing and control of volunteer influx. The majority of volunteer activities documented by the TAVRC, most of which spans the four-month period following the tornado (i.e., May - August 2011), includes material handling of donated goods at seven different warehouse locations (two of which were local churches), as well as debris removal at various sites. We restrict our attention to volunteer material handling activities at a single relief warehouse site[3] during the period May 1 - May 31, 2011, resulting in approximately 2,400 data points[4] that will be used in our efforts to quantify volunteer convergence phenomenon. Table 2 provides an example of the data obtained.

ID	Location	Supervisor	Date	Name	In	Out
789	TES	B.S.	5/16/11	E.S.	6:00 AM	11:45 AM
790	TES	B.S.	5/16/11	L.A.	6:00 AM	11:45 AM
791	TES	B.S.	5/16/11	F.C.	7:30 AM	2:00 PM
792	TES	B.S.	5/16/11	B.G.	7:58 AM	6:00 PM
793	TES	B.S.	5/16/11	M.H.	7:59 AM	6:00 PM
794	TES	B.S.	5/16/11	M.H.	7:59 AM	2:00 PM

Table 2: Example data collected from the Tuscaloosa Area Volunteer Reception Center.

[3]The local Red Cross facility was supposed to be the primary location where donations were received, sorted, stored, and distributed. However, this facility was destroyed by the tornado, and a vacant warehouse was instead used for this purpose. Data from this warehouse is the basis of our empirical study.

[4]Electronic records of volunteer data did not exist. The 2,400 data records were entered manually into a database from scanned copies of volunteer time sheets. Data during May 9 - 11 could not be located.

We define *volunteer participation time* as the difference between a volunteer's departure and arrival times (i.e. *out time* − *in time*) on a given work day or work shift, which is analogous to a customer's service time in traditional queuing theory. Similarly, volunteer interarrival time is the server equivalent of customer interarrival time, i.e., *volunteer interarrival time* is the time between consecutive volunteer (server) arrivals on the same day or work shift. For example the interarrival time between volunteers 790 and 791 in Table 2 is 90 minutes. In order to define volunteer batch size, it is necessary to distinguish between group and individual volunteers. If a set of volunteers has the same arrival time and departure time (e.g. volunteers 789 and 790 in Table 2) on a given work day or shift, we refer to each volunteer in this set as a *group volunteer* who together form a unique *volunteer group*. Group volunteers often represent individuals affiliated with relief agencies such as Red Cross, student organizations such as fraternities and sororities, faith-based organizations, or families. Any volunteer that does not belong to a group is referred to as an *individual volunteer*. Note that it is possible for individual volunteers to have identical arrival times (batch arrivals), but their departure times are necessarily different (e.g. volunteers 793 and 794 in Table 2). For group volunteers, *batch size* refers to the number of volunteers belonging to a distinct volunteer group, whereas for individual volunteers, it refers to the number of volunteers with the same arrival time on a given day or work shift.

4.2 Analysis of Volunteer Convergence Trends

In order to address Research Question 4, which was introduced in Section 2, time series plots of the average number of volunteers will be constructed. These time series plots will facilitate the analysis of individual and group volunteer convergence with respect to day of the week as well as the number of weeks past the disaster event. In particular, the presence of convergence phenomena can be detected if the average number of volunteers exhibits an increasing trend or unimodal shape with respect to the number of weeks past the disaster event, or an increasing trend relative to days of the week. One or more of these characteristics would confirm the existence of a ramp-up phase in volunteer participation, which would be consistent with the findings reported in (Cottrell, 2012).

4.3 Analysis of Variables Related to Warehouse Queuing System

Intuitively, it is unlikely that the volunteer convergence data examined in this paper is homogeneous in the sense that relevant stochastic variables associated with each record comes from the same underlying probability distribution. Therefore, we hypothesize that the data sets for each of the four variables of interest (number of volunteers, participation time, interarrival time, and batch size) are heterogeneous and should be distinguished with respect to (i) volunteer type (group or individual), (ii) time of day (morning or afternoon arrival), (iii) day of the week (Sunday - Saturday), and (iv) number of weeks beyond the disaster event (week 1 - week 5). For example, volunteer participation times were probably longer on weekends compared to weekdays. If this turns out to be the case, then the participation time data should be divided into two clusters, namely a weekday cluster and a weekend cluster, and then the best fit probability distribution(s) for each cluster can be determined in order to appropriately describe stochastic participation time processes.

We now describe a hierarchical clustering methodology for partitioning the volunteer data into disjoint homogeneous clusters. Unlike standard hierarchical clustering techniques (e.g. Johnson, 1967; Murtagh, 1983), our implementation is applied to data sets as opposed to individual data values. The basis of the aproach is the Kruskal-Wallis test (Kruskal and Wallis, 1952), which can be used as a nonparametric version of Analysis of Variance (ANOVA) to examine the null hypothesis that all population distribution functions from a collection of data sets are identical (Law and Kelton, 2000; Gibbons and Chakraborti, 2003), or that all population means are equal (Montgomery, 2008). The null hypothesis is accepted if the p-value is greater than the significance level α. Therefore, the p-value serves as the distance measure in our clustering approach. More specifically, the Kruskal-Wallis test will be applied to a collection of $N < \infty$ data sets $\mathcal{D} = \{D_1, \ldots, D_N\}$. Notationally, define $KW : \mathcal{D} \mapsto [0, 1]$, as a function that returns the p-value[5] associated with applying the Kruskal-Wallis test to any finite collection of data sets $\mathcal{D}$. Also, let $\mathcal{C}_i \subset \mathcal{D}$, for $i = 1, \ldots, M$, denote the ith of $M \leq N$ subsets of the original data set $\mathcal{D}, C_i = \bigcup_{D \in \mathcal{C}_i} D$, and $\emptyset$ represent the empty set.

[5] If a confidence level α is selected, then the null hypothesis that all population distribution functions (or means) are identical is rejected if the p-value is less than α.

Hierarchical Clustering Algorithm

0. *(Initialize)* Set $\mathcal{C}_i = \{D_i\}$, $\mathcal{S} = \{\mathcal{C}_1, \ldots, \mathcal{C}_N\}$.

1. $\mathcal{S}^+ = \emptyset, \mathcal{S}^- = \emptyset$. Let $M = |\mathcal{S}|$.

2. For each $i = 1, \ldots M-1$ and $\mathcal{C}_i \notin \mathcal{S}^-$.

   (a) For each $j = i+1, \ldots, M$ and $\mathcal{C}_j \notin \mathcal{S}^-$, compute $KW(\mathcal{C}_i, \mathcal{C}_j)$.
   Let $KW_j^* = \max_{j \in \{i, \ldots, |S/S^-|\}} KW(\mathcal{C}_i, \mathcal{C}_j)$ and $j^* = \operatorname{argmax} KW_j^*$.

   (b) If $KW_i^* > \alpha$, set $\mathcal{C}_{i+M} = C_{j^*} \cup C_i$, $S^+ = S^+ \cup \{C_{i+M}\}, S^- = S^- \cup \{C_i, C_{j^*}\}$.

3. If $S^+ = \emptyset$, STOP. Otherwise,

   (a) $S = S \cup S^+$.

   (b) $S = S/S^-$.

   (c) $M = |S|$.

   (d) Return to step 1.

The output of the above algorithm is a set of clusters $\mathcal{C} = \{C_1, \ldots, C_M\}$ (where $M \leq N$) such that $\bigcup_{i=1}^{M} C_i = \bigcup_{i=1}^{N} D_i$ and $C_i \cap C_{i+1} \cap \cdots \cap C_j = \emptyset$ for each $i = 1, \ldots, j-1$ and $i < j \leq M$. Steps 0 through 4 above are then repeated using $\mathcal{C}$ as input instead of $\mathcal{D}$ resulting in a new set of collectively exhaustive and mutually exclusive clusters $\mathcal{C}'$. This process continues until $KW(C_j, C_{j+1}, \ldots, C_m) \leq \alpha$ for each $j = 1, \ldots, m-1$ and $j < m \leq M$.

Using JMP$^{\text{TM}}$, each clustered dataset $C_i \in \mathcal{C} = \{C_1, \ldots, C_M\}$ is fit to a set of continuous distributions (e.g. exponential, Normal, lognormal) and the goodness-of-fit is evaluated using the Kolmogorov-Smirnov test as described in Law and Kelton (2000). The results of this exercise will enable us to respond to research questions 1, 2, and 3 of Section 2.

5 Volunteer Convergence Trends

As discussed in Section 2, capacity changes over time provide a way to quantify the existence and extent of convergence. The number of volunteers serves as an estimate for volunteer capacity. Figure 2 illustrates the associated times series with respect to day of the week and number of weeks past the disaster event. The results suggest the following volunteer convergence characteristics:

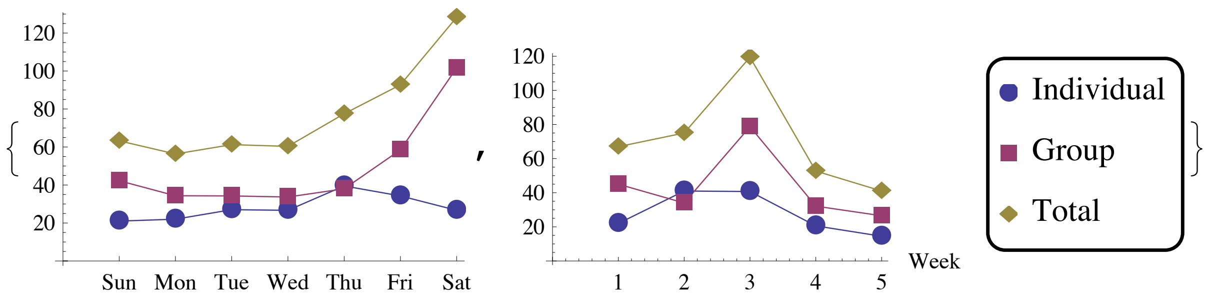

Figure 2: Time series for average number of volunteers by day and by week.

Observation 1 *The average number of participating volunteers (i) increased each day of the week moving toward the weekend, (ii) increased each week following the disaster event until peak participation during week 3, and (iii) decreased each week following week 3.*

The overall average number of volunteers is approximately non-decreasing with respect to day of the week. Specifically, the average number of participating volunteers is relatively stable at the beginning of the week and then starts to increase as the weekend approaches. This is to be expected assuming that the majority of volunteers were preoccupied with work and/or school responsibilities during the week with more available time for volunteer activities during the weekend. However, this perspective does not explain why the average number of Sunday volunteers was comparable to the average number on Monday, Tuesday, and Wednesday as opposed to the average numbers on Thursday, Friday, and Saturday. Parts (ii) and (iii) of Observation 1 suggest that the duration of the volunteer convergence phenomenon associated with the April 2011 tornado disaster in Tuscaloosa, Alabama was approximately three weeks. Lastly, Observation 1 seems to indicate that average number of volunteers is either non-stationary or non-homogeneous from a statistical standpoint with respect to (i) day of the week and (ii) the number of weeks following the disaster event.

Observation 2 *The average number of individual volunteers shows a decreasing trend during the weekend in contrast to a sharp increasing trend in the average number of group volunteers.*

Both the average number of individual and average number of group volunteers seem to exhibit stationary patterns during the weekdays (actually, Sunday through Wednesday), with a consistently larger number of group volunteers. However, the average number of group volunteers during the weekend is clearly non-stationary relative to the weekday averages, whereas the time series is less conclusive concerning the stationarity of individual volunteers during the weekend. For the most part, it does seem necessary from a statistical perspective to distinguish between individuals and groups with respect to the average number of participating volunteers, at least during the weekend.

Note that the algorithm for partitioning the data set into disjoint, homogeneous clusters will not be carried out in this section nor will probability distributions for the number volunteers be determined. These issues will be addressed indirectly in Section 6.3, where clusters and probability distributions for batch size and number of batches will be investigated.

6 Results for Warehouse Queuing System Variables

The properties of the stochastic variables related to the queuing system described in Section 2 are reported in this section. First, results pertaining to volunteer participation time are presented, followed by findings for volunteer interarrival time. The third variable, volunteer batch size, is discussed last. Each of these three variables is analyzed according to the methodology described in Section 4, which includes time series plots, clustering, distribution fitting, and goodness of fit testing.

6.1 Participation Times

In Section 4.1, volunteer participation time is defined as the length of the period between a volunteer's departure and arrival times on a given day. In this section, participation time trends are first analyzed using time series plots. In particular, we examine the average volunteer participation time arranged according to day of the week (Sunday through Saturday) and number of weeks that follow the disaster event (week 1 through week 5). Our attention then shifts towards addressing Research Question 1 presented in Section 2, which has to do with characterizing participation time probability distributions. This will be accomplished by first partitioning the data into clusters using the hierarchical clustering algorithm described in Section 4.3, and then applying standard distribution fitting techniques to each cluster.

The time series graphs and the initial data sets associated with the hierarchical clustering method both distinguish between individual and group volunteers. Recall from Section 4.1 that volunteers with identical arrival and departure times (on the same day) are assumed to belong to the same group, and are therefore referred to as group volunteers. Also recall that in this study, all volunteers are classified as either individual or group volunteers. Thus any volunteer who is not a group volunteer is considered an individual volunteer.

6.1.1 Time Series

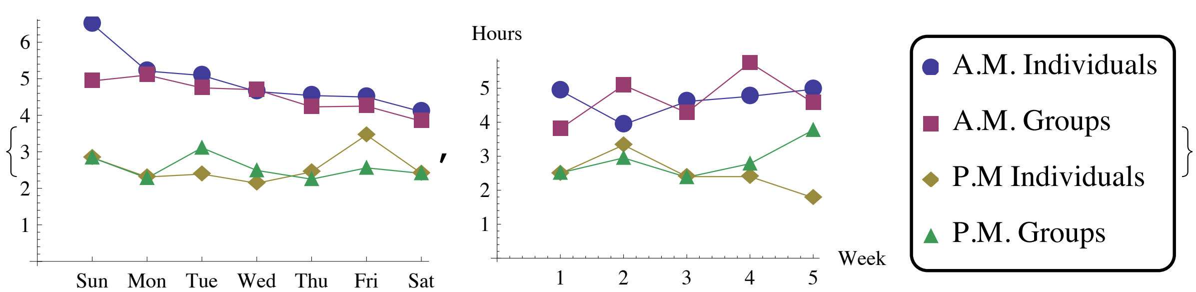

Figure 3: Time series for average participation time hours by day and by week.

Figure 3 shows the average volunteer participation time by day and by week. These time series indicate the following:

Observation 3 *The average participation time of volunteers who arrived in the morning is greater than the average participation time of volunteers who arrived during the afternoon.*

On most days, the latest volunteer departure time was between 5:00 PM and 7:00 PM, although there were instances where the last volunteer departure occurred as early as 2:00 PM and as late as 11:00 PM. Nevertheless, Observation 3 is not surprising since the number of available work hours for volunteers who arrive in the morning is more than that of volunteers who arrive in the afternoon (assuming that the last volunteer departure represents closure of the warehouse on that day).

Observation 4 *The average participation time of volunteers who arrived during the morning exhibits (i) a slight decreasing trend each day as the ensuing weekend approaches and (ii) a slight increasing trend each week following the disaster event.*

These finding are somewhat counterintuitive. As mentioned in the discussion that follows Observation 1, volunteers are more likely to participate on weekends because of work and/or school commitments during weekdays. From this perspective, it would seem that average participation time should increase during the weekend. Figure 3 does show that average participation time is indeed longer on Sunday. However, the shortest average participation times also occur during the weekend, namely on Friday and Saturday. A possible explanation for this phenomenon is as follows. First, recall that the average number of volunteers increases during the weekend (except Sunday) according to Observation 1. So together, observations 1 and 4 (part i) suggest that the average volunteer participation time decreases as the average number of volunteers increases. A likely cause of this inversely proportional relationship between number of volunteers and participation time is that the smaller and more steady number of weekday volunteers may represent a core set of committed volunteers, whereas the sharp increase in the number of volunteers during weekends is likely due to an influx of more casual volunteers. Assuming that the average participation time of committed volunteers is longer than that of casual volunteers, an increase in the number of casual volunteers during weekends will cause the overall average volunteer participation time to decrease.

This theory is weakly supported by Figure 4, which shows how both the average number of volunteers and average participation time fluctuate as a function of the number of weeks past the disaster event [6]. Notice the increase in average participation time that accompanies the sharp decrease in the average number of volunteers during weeks 3, 4, and 5. In this case, the above theory suggests that primarily committed volunteers remain during week 4 and beyond. Also, the increase in the average number of volunteers from week 1 to week 2 is characterized by a slight (nearly negligible) decrease in average participation time. However, there is an increase in both the average number of volunteers and average participation time between weeks 2 and 3, which is contrary to the above-mentioned presumption.

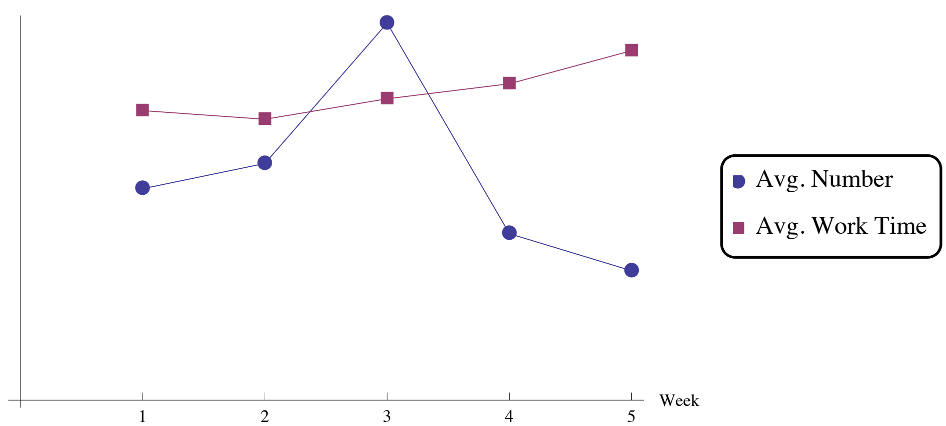

Figure 4: Average volunteer participation by week.

6.1.2 Hierarchical Clustering Results

From the time series shown in Figure 3, it is likely that the volunteer participation time data sets are not homogeneous. In particular, it is obvious that the mean participation time of volunteers who arrived in the morning is greater than the mean participation time of volunteers who arrived in the afternoon (Observation 3), which indicates that the morning and afternoon data sets are not identically distributed. However, it is difficult to make conclusive statements about homogeneity across days of the week based on the time series

[6]The values for "Avg. Number" shown in Figure 4 are the actual (average) number of volunteers divided by 25. Otherwise, the "Avg Work Time" would appear completely flat because of the large differences in the average number of volunteers and average participation times.

graph alone because the trends described in Observation 4 appear to be almost negligible. Therefore, the hierarchical clustering approach described in Section 4.3 is used to partition all of the volunteer participation time data into disjoint clusters where the data in each cluster is homogeneous. The original data is initially partitioned into approximately 140 sets based on day of the week (1 through 7), arrival time (AM or PM), number of weeks past the disaster event (1 through 5), and volunteer type (individual or group)[7]. The hierarchical clustering methodology reduced the initial set of clusters to the minimal set shown in Table 3 based on a significance level $\alpha = 0.10$. JMP™ was used to identify the best-fit probability distribution for each cluster. The last column of Table 3 indicates that the appropriate response to Research Question 1 is the exponential distribution is not appropriate for modeling volunteer participation time.

Cluster	Mean	Standard Deviation	Distribution	p-value	p-value (exponential)
C_1	6.134	2.47	Weibull	0.2500	< 0.01
C_2	2.548	1.05	Johnson	0.5054	< 0.01
C_3	4.476	2.25	Weibull	0.1819	< 0.01
C_4	2.323	1.16	Lognormal	0.1361	< 0.01
C_5	3.379	1.97	Lognormal	0.1070	< 0.01
C_6	1.936	1.18	Johnson	0.6566	< 0.01
C_7	3.925	2.09	Johnson	0.3360	< 0.01
C_8	5.087	2.24	Weibull	0.0156	< 0.01

Table 3: Best fit probability distribution for each participation time cluster.

The average participation time for each cluster during the weeks of May 2011 is shown in Figure 5. As expected, this time series shows clear differences among the eight clusters. However, the average participation time from week to week within each cluster appears to be stationary, except possibly Cluster 5. The results of the hierarchical clustering algorithm verify that participation times are indeed homogeneous from week to week within each cluster (including Cluster 5).

We conclude our analysis of volunteer participation time by illustrating how to determine the conditions in which each of the probability distributions shown in Table 3 is applicable.

[7] The initial number of data sets is then $7 \times 2 \times 5 \times 2 = 140$. However, recall that some of the original data is missing as mentioned in Section 4.1.

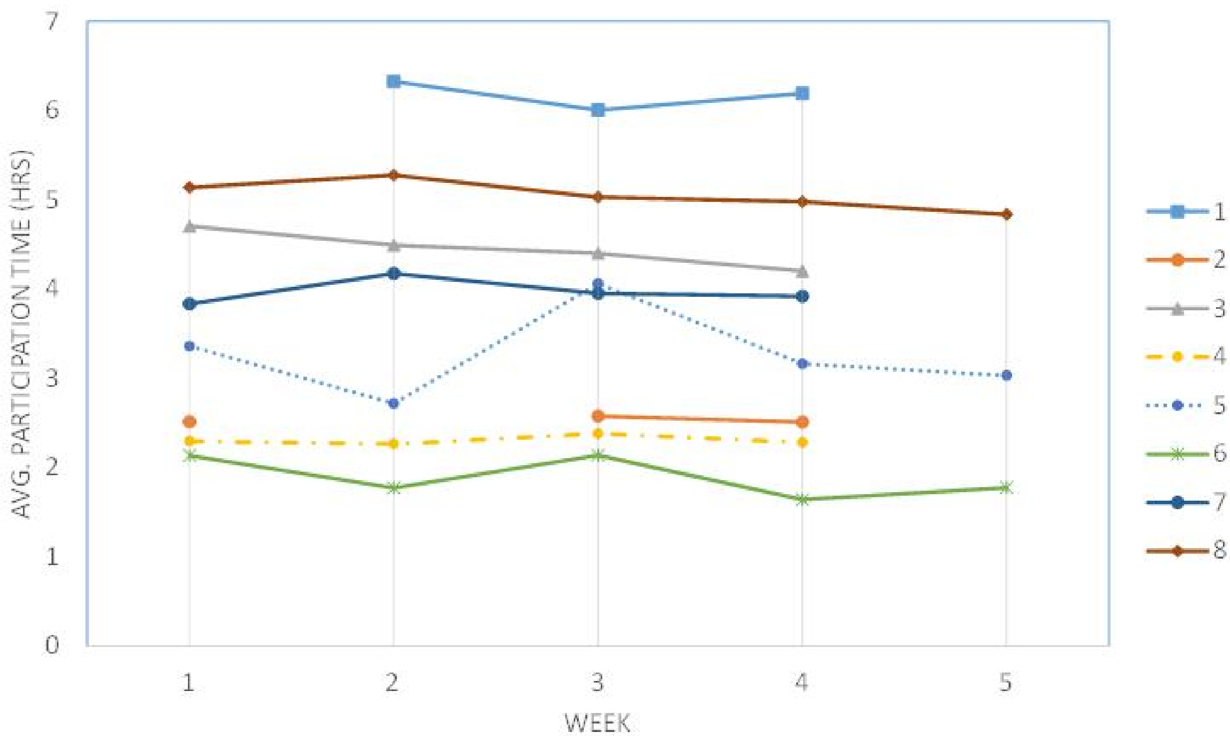

Figure 5: Average participation time by week for each cluster.

Figure 6 shows the composition of Cluster 1 based on attributes of the original 100+ data sets, namely day of the week, time of day (AM/PM), number of weeks past the disaster event, and volunteer type (individual or group). The shaded areas represent the original data sets that were merged to form this cluster. In addition, Figure 6 (along with Table 3) can be interpreted to conclude that a Weibull distribution with mean 6.134 and standard deviation 2.47 can be used to model volunteer participation times on (i) the Sunday two weeks following the disaster event for individual volunteers who show up in the morning; (ii) the Wednesday two weeks after the disaster event, also for individual volunteers who arrive in the morning; etc. Similar diagrams can be constructed for the other participation time clusters as well as the interarrival time clusters derived in Section 6.2.

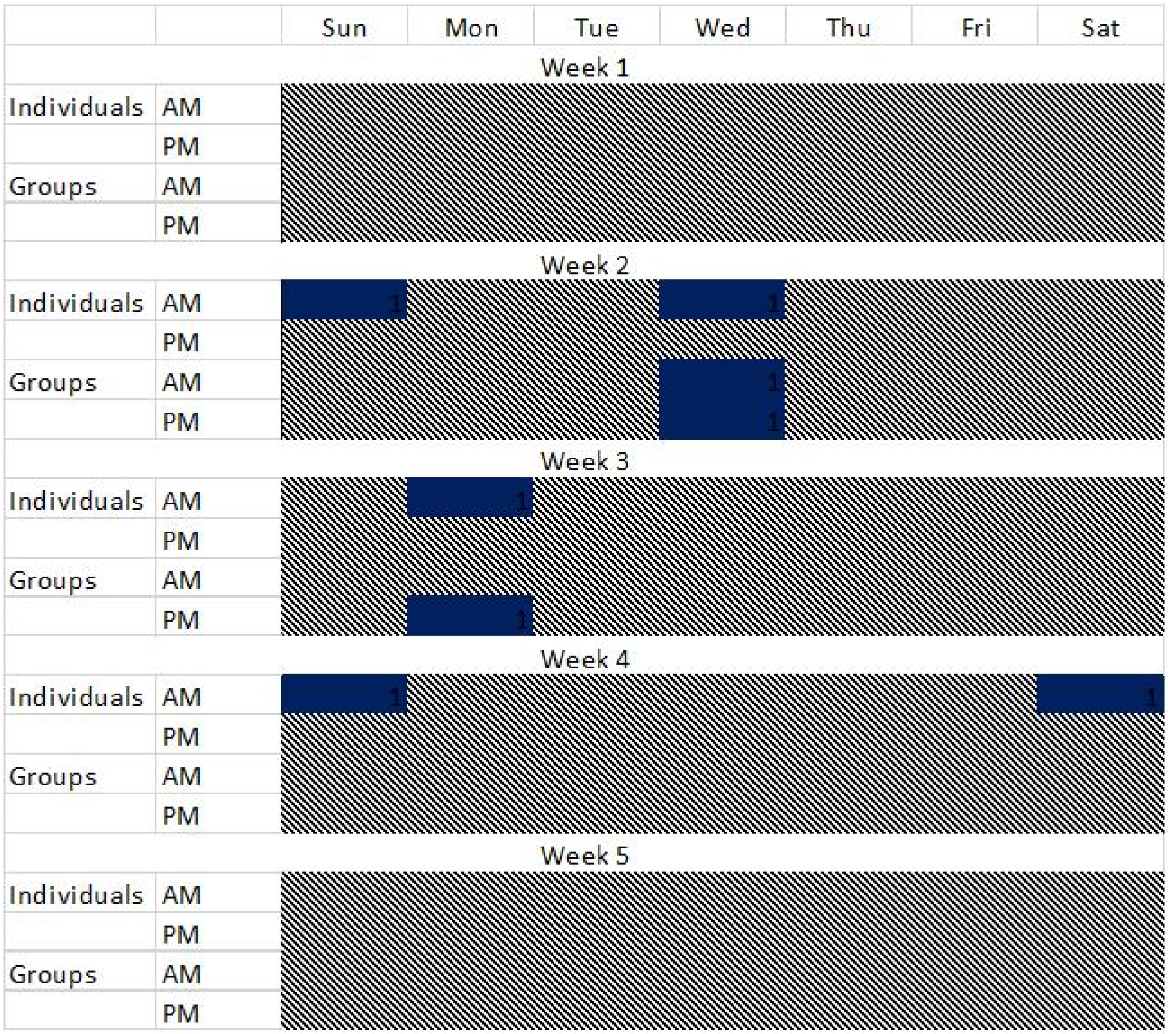

Figure 6: Average participation time by week for each cluster.

6.2 Interarrival Times

Recall from Section 4.1 that volunteer interarrival time refers to the length of time between two consecutive volunteer arrivals on a given day. As in Section 6.1, we first present time series plots to examine interarrival time trends, and then address Research Question 1 posed in Section 2. Research Question 1 has to do with characterizing volunteer interarrival time distributions, which we will accomplish by first partitioning interarrival time data into clusters using the hierarchical clustering algorithm described in Section 4.3, and then applying standard distribution fitting techniques to each cluster.

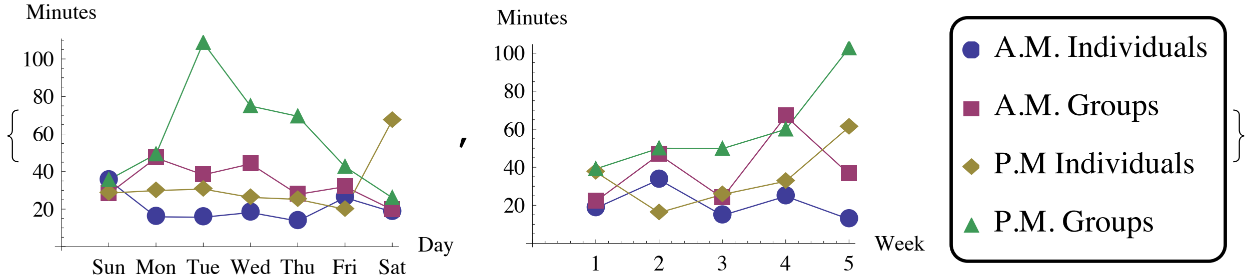

Figure 7: Average volunteer interarrival times by day and by week.

6.2.1 Time Series

Figure 7 shows the average volunteer interarrival time by day and by week. These time series indicate the following:

Observation 5 *The average time between afternoon arrivals was generally greater than the average time between morning arrivals for both individual and group volunteers. Similarly, the average interarrival times of volunteer groups were generally greater than the average interarrival times of individual volunteers for both morning and afternoon arrivals.*

This finding suggests that it necessary to distinguish between morning and afternoon as well as individual and group interarrival times from a statistical perspective.

Observation 6 *The average time between volunteer arrivals during afternoons shows an increasing trend each week following the disaster event.*

Unlike afternoon arrivals, there are no obvious weekly interarrival time trends for individual and group volunteers who arrived during mornings. However, there does seem to be more week-to-week interarrival time variation for groups compared to individuals who arrived during mornings. It is also interesting to note that the average interarrival time for individuals on Saturday afternoons seems to be an outlier, and that the average group interarrival time peaked on Tuesday followed by a sharp decreasing trend through the weekend.

6.2.2 Hierarchical Clustering Results

By applying the methodology in Section 4.3, we obtain the clusters and probability distributions shown in Table 4 for volunteer interarrival times. Note that there is no mainstream probability distribution that fits most of the clusters at the $\alpha = 0.10$ significance level. These results also indicate that there is some evidence (although weak; only 1 out of 7 clusters) that the exponential distribution can be used to model volunteer interarrival times.

Cluster	Mean	Standard Deviation	Distribution	p-value	p-value (exponential)
C_1	1.005	0.753	Exponential	0.1448	0.1448
C_2	0.195	0.261	*	0.0000	< 0.01
C_3	0.194	0.192	*	0.0000	< 0.01
C_4	0.652	0.521	Weibull	0.2023	0.0258
C_5	0.514	0.812	Exponential	0.0372	0.0372
C_6	0.255	0.279	*	0.0000	< 0.01
C_7	0.336	0.296	*	0.0000	< 0.01

Table 4: Best fit probability distribution for each interarrival time cluster.

6.3 Batch Size

Our analysis of batch volunteer arrivals is organized exactly as our analyses of participation times and interarrival times in sections 6.1 and 6.2, respectively (time series plots, hierarchical clustering, distribution fitting). As defined in Section 4.3, batch size refers to the number of individual volunteers that have the same arrival time on a given day, or the number of group volunteers that belong to the same volunteer group.

6.3.1 Time Series

The time series shown in Figure 8 suggest the following:

Observation 7 *The average batch size for individuals appears to be stationary with respect to (i) day of the week and (ii) number of weeks past the disaster event. The average batch size for groups also seems to be stationary by day (except possibly Sunday and Monday mornings), but not by week (see Observation 8).*

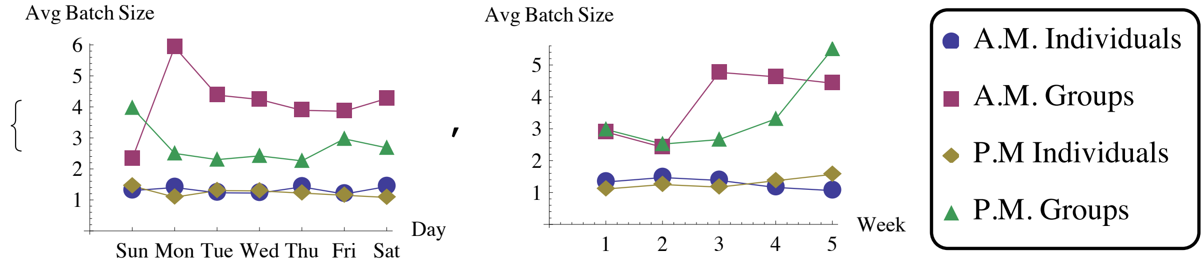

Figure 8: Average batch size of arriving volunteers by-day and by-week.

Observation 8 *The average size of volunteer groups after the peak of the convergence period (week 3) was noticeably greater than the average batch size prior to peak convergence. Furthermore, the average size of volunteer groups who arrived during the afternoon exhibits an increasing trend, particularly following the peak period.*

Recall from Observation 1 that week 3 represents peak participation in terms of the number of volunteers, as well as the end of the volunteer convergence period. Thus it follows from observations 1 and 8 that the average batch size of volunteer groups at the end of convergence and afterwards was larger than the average batch size during the early and middle stages of convergence. Assuming that volunteer groups consisted primarily of affiliated volunteers and the majority of individuals were spontaneous volunteers, one possible explanation for increasingly larger batch sizes is that the number of unaffiliated volunteers decreased over time. Specifically, volunteers may have become affiliated with relief organizations during the latter stages of response and into recovery when the relief efforts became more organized, and a smaller number of the more casual spontaneous volunteers were actually available.

6.3.2 Hierarchical Clustering Results

The methodology presented in Section 4.3 generated the four cluster sets shown in Table 5. Only one cluster matched any known discrete probability distribution at the $\alpha = 0.10$ significance level or better. The Poisson distribution provided the best fit for Cluster 3. It should also be noted that Clusters 1,2, and 3 consisted of only group volunteers.

Cluster	Mean	Standard Deviation
C_1	4.689	5.278
C_2	2.944	2.700
C_3	2.324	0.783
C_4	1.004	0.063

Table 5: Best fit probability distribution for each batch size cluster.

7 Summary

This study investigates volunteer convergence from an operations management perspective by demonstrating the role a quantitative representation of convergence can have with respect to volunteer management decisions following large-scale disasters. Using approximately 2,400 data points collected during the one-month period following the April 2011 tornado disaster in Tuscaloosa, Alabama, probability distributions for selected stochastic variables were characterized empirically. The stochastic variables of interest include volunteer interarrival time, participation time, and batch size upon arrival. Each of these variables is relevant to modeling volunteer convergence within the context of a relief center warehouse as a queuing system with random customer arrival and service processes, as well as random server arrival and departure processes. The convergence data was examined for stationarity using time series plots, and for homogeneity based on a hierarchical clustering heuristic in which the p-value generated by the Kruskal-Wallis test served as the distance metric. Using hierarchical clustering, data pertaining to each of the above-mentioned stochastic variables was partitioned into disjoint homogeneous clusters in terms of volunteer arrival time (morning or afternoon), day of the week (Sunday - Saturday), and number of weeks past the disaster event (week 1 - week 5). Probability distributions for each cluster were then determined using standard distribution fitting methods and statistical software packages.

7.1 Answers to Research Questions

Our findings have the following implications with regard to the questions posed in Section 2:

Question 1 (Volunteer Interarrival and Participation Times): Volunteer interarrival times are highly unpredictable. Of the seven clusters that were formed as a result of the hierarchical clustering procedure, only two match mainstream probability distributions at the 10% significance level or better. However, the participation time distribution for one of these two clusters turned out to be exponential. This result is appealing since exponential interarrival and service times typically lead to mathematically tractable analysis of traditional queuing systems (i.e., queuing systems with a fixed set of servers). Volunteer participation times, on the other hand, are more predictable. Seven of the eight clusters match a mainstream probability distribution at the 10% significance level. Our results also strongly suggest that volunteer participation times are not exponential. The exponential distribution did not meet the goodness of fit test threshold for any of the eight clusters.

Question 2 (Existence of Batch of Arrivals): We established that there are two distinct types of servers: individuals and groups. While batch arrivals of group volunteers are inherent, our study also confirmed the existence of batch arrivals in relation to individuals. Consequently, batch volunteer arrivals should be considered when modeling relief warehouse queuing systems based on the framework presented in Section 2.

Question 3 (Significance of Group Volunteers): Group volunteers played a significant role in the convergence process. In fact, the average number of group volunteers exceeded the average number of individual volunteers during the peak of the convergence period and beyond, as well as on weekends. Moreover, the average batch size of volunteer groups was consistently larger than the average batch size associated with individual volunteers who arrived at the same time. Individual and group volunteers also differed in terms of the best fit participation time distributions for volunteers who arrived in the morning. By contrast, the participation time distributions of individual and group volunteers who arrived during the afternoon turned out to be statistically similar, and the interarrival time distributions of individuals and groups were also homogeneous. Nevertheless, these findings suggest that individual and group volunteer behaviors should generally be modeled as distinct stochastic processes within the context of the relief warehouse queuing system introduced in this paper. In addition, volunteer groups can be modeled as *super servers* who each arrive to and depart from the queuing system at the same time, assuming that members of each group would be assigned to the same workstation for the duration of the event horizon.

Question 4 (Extent of Volunteer Convergence): We examined the number of volunteers over time and found that (i) there were more volunteers during weekends (Friday and Saturday) compared to weekdays, (ii) the number of volunteers on Sunday was more similar to the number of volunteers during weekdays (Monday - Thursday) compared to weekends (Friday and Saturday), and (iii) the duration of the volunteer convergence period was approximately three weeks. The results also confirmed the existence of ramp up, peak, and abatement phases of volunteer convergence following a large-scale disaster event.

7.2 Policy Implications

The results of this study also have several important implications for practitioners. First, the trends we discovered that show fluctuations in the average number of volunteers over time (see conclusions related to Question 4 in Section 7.1) can be used to help emergency managers and authorities make informed capacity planning decisions. For instance, given that volunteers require food, shelter, and equipment (e.g., Fernandez et al., 2006b), the ability to predict the approximate number of volunteers in the system at any point in time will enable emergency managers to coordinate the resources needed to support volunteers well in advance. Similarly, predictive models inspired by historical trends can help authorities (i) anticipate surges in the local population caused by volunteer convergence, (ii) manage these population surges by appropriately scheduling police protection and related services, and (iii) justify the need for additional resources from state and federal governments.

Next, the findings presented in Section 7.1 that address Questions 1, 2, and 3 are most relevant in the context of helping managers of temporary relief center facilities improve their operations. In particular, these results can help facilitate the development of a systematic process for assigning volunteers to tasks, work stations, or sites. Workforce scheduling and task assignment in the disaster volunteer context is more challenging than it is in the commercial sector. The reasons for this are that the availability of spontaneous volunteers is highly unpredictable, and that emergency managers have limited control, at best, when it comes to managing the arrival and departure times of informal volunteers. Furthermore, task requirements during the early stages of disaster response are characterized by a high degree of uncertainty, which means that manpower needs are also highly uncertain. By empirically characterizing selected stochastic variables related to volunteer convergence, this study alleviates some of the unpredictability associated with spontaneous volunteers, which will enable managers to make more informed task assignment decisions. Ultimately, we envision our results being used as input to stochastic models and their corresponding decision support systems that seek to optimize the assignment of spontaneous volunteers

7.3 Limitations and Future Research

One limitation of this study is the data, which consists of approximately 2,400 observations handwritten on sheets of paper. In order to conduct our analysis, each observation was manually entered into a database. This process was not only tedious, but also introduced the potential for data entry mistakes. The data also did not include affiliation information. Consequently, we were not able to definitively distinguish affiliated and unaffiliated volunteers, and were forced to make assumptions regarding this matter. For future studies, the process of recording volunteer arrival and departure times should be automated using notebook computers or other portable information technologies, which would eliminate these concerns. No monotonous data entry by a single individual would be required, which should significantly reduce the likelihood of data entry errors. Instead, each volunteer would be responsible for entering only his or her own information into an automated system. The unreliable and cumbersome task of securing, transporting, and organizing several large boxes of paper on which the handwritten data is recorded can also be avoided if digital technologies are used to record volunteer information. As such, the risk of potentially losing data is reduced. Lastly, facilitating the collection of affiliation information can be easily incorporated into a digitally automated system.

Another limitation is that the scope of this investigation is confined to one relief center and one disaster event. Hence we are unable to definitely conclude that our results are indicative of volunteer convergence patterns in general. However, we would expect some of our findings to be preserved. For instance, it is likely that the progression of volunteer convergence generally consists of ramp-up, peak, and decline phases given that the convergence experiences reported both in Cottrell (2012) and our study seemed to evolve in a similar fashion. On the other hand, the length of the converge period is likely to vary among disaster events. The study by Cottrell (2012) suggests a two-week volunteer convergence period whereas the duration in our study turned out to be three weeks. It is also likely, in general, that a distinction should be made between spontaneous and affiliated volunteers in terms of characterizing participation time distributions. We would expect affiliated volunteers to work longer hours and represent a larger percentage of the overall relief effort compared to spontaneous volunteers. In order to generalize our findings regarding the characteristics of volunteer convergence from a data analytic perspective, future research is needed. In particular, similar studies can be conducted based on past disaster events with sufficient volunteer data, or future events in which data could be collected. Through a series of such studies, an analysis of the similarities and differences compared to ours would reveal general characteristics of volunteer convergences processes.

In closing, the line of inquiry introduced in this paper along with the above-mentioned future research directions will potentially improve our understanding of volunteer convergence, which would in turn be beneficial from the standpoint of developing operational policies for managing spontaneous volunteers.

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