Analytically comparing disaster recovery following the 2012 derecho

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ABSTRACT

This work in progress paper discusses analytically characterizing nonlinear recovery behavior through the context of the derecho windstorm that struck the mid-Atlantic United States in the summer of 2012. The focus is on the recovery efforts of the Appalachian Power Company, and the discussion includes a look at the need for communicating the progress of such recovery efforts to the public. Publicly available recovery data is analyzed and compared with respect to the relative behaviors exhibited by two different nonlinear recovery processes, and some of the implications for understanding the efficiency of different disaster recovery operations are discussed.

Keywords

Disaster recovery, quantitative modeling, recovery behavior, derecho.

INTRODUCTION

Disaster recovery can generally be considered to be associated with the broader concept of disaster resilience, in the sense that a resilient system will ideally have the capacity to recover to a state approximating its pre-disaster condition. Both concepts are relatively difficult to characterize, however, because an extremely disruptive event will impact not only the physical aspects of a community, but also significant elements of its social, economic, and organizational structure (Bruneau et al., 2003; Smith, 2011), and these different elements may recover (or not) to varying extents. These different dimensions of both resilience and recovery have been studied from a number of different angles and by researchers from a number of different disciplines.

One of the issues with analyzing the social dimension of resilience and of recovery, in particular, is the difficulty of quantitatively characterizing an inherently qualitative set of concerns. A significant amount of research has been done on the use of indicator variables to capture different aspects of qualitative factors (Cutter et al., 2003; Birkmann, 2006a, 2006b), and it is an important area of study. Values for such indicator variables tend to be collected on a much larger time scale than that required to analyze the details of disaster recovery operations, however, and thus we focus this initial discussion only on analyzing the physical recovery of a system in the aftermath of a disaster event. The results of this preliminary work will hopefully serve as the basis for expanding the discussion to include consideration of indicator variables in an appropriate context.

The process of recovery for many physical systems can be represented by a time series of distinct observations that occur on a regular, short-term basis. Our discussion is based on two specific examples of this: time series of recovery data associated with restoring electric power to homeowners after a major storm event. Utility companies are among the most recognized service providers to be impacted by large-scale disasters, and the loss of electricity is a very visible indicator that there is a need for resources to be applied towards disaster recovery.

The time series in question represent the disaster recovery process for one particular company, Appalachian Power, in the wake of the derecho windstorm that struck the mid-Atlantic region of the United States in the summer of 2012. The data was specifically provided by the company to keep their customers informed of recovery operations, and we analyze it to provide an initial quantitative assessment of the differences between recovery behaviors in the states of Virginia and West Virginia.

CHARACTERIZING RECOVERY

When attempting to model the recovery of a given system from a disaster event, it is natural to focus first on the two most obvious characteristics of that recovery process: the initial amount of loss from which the system must recover, and the amount of time that it takes to achieve full recovery. With the over-riding significance of these two characteristics in mind, a number of previous efforts to quantitatively model disaster resilience have assumed linear recovery behavior (i.e., a constant rate of recovery), in order to simplify the theoretical description of the entire recovery process and to provide a high-level overview of system behavior (Tierney and Bruneau, 2007; Zobel, 2010). However, actual recovery processes are often best modeled by logistic or exponential curves (either piecewise or continuous in nature), so that they include a period of increasingly rapid progress that eventually slows down as full recovery nears (Cimellaro et al., 2010; Klibi et al., 2012). Our current effort thus focuses on measuring recovery by a nonlinear series of consecutive observations over time, such as in the examples of the post-Katrina recovery processes discussed by Simpson et al. (2010).

It is important to recognize that in the larger context of communicating such recovery behavior to the public, the amount of information that is shared ultimately has an impact on the quality and availability of data for post-disaster analysis of a company's operations. In the case of a business whose operations have been interrupted, providing customers information about the recovery process is important because the long-term reputation of the company can be significantly impacted by customer perceptions about how the incident was handled (FEMA, 2012). In this context, recovery estimates can be provided on different scales (state / county / city / neighborhood, etc.) to identify which portions of a service network are still down, and estimates of recovery dates can be very useful for setting expectations. Too much detail, however, can lead to unrealistic expectations by customers, or to perceptions of bias towards particular groups of individuals.

Because the tail ends of actual recovery processes often tend to be somewhat elongated (Simpson et al., 2010), one tactic that can help improve the perception of efficient recovery is to offer a target threshold of less than 100% recovery. This allows the organization to provide a goal that is quicker and easier to achieve than full recovery, and it provides encouragement to those still without service at that point that recovery is almost complete.

The following case study was chosen to illustrate several quantitative characteristics of nonlinear disaster recovery behavior. We begin with a description of the disaster event and the company's response, and then take a more analytical look at two different recovery trajectories. The discussion ultimately focuses on the nonlinear characteristics of the recovery processes, and introduces some quantitative approaches for using these characteristics to indicate relative recovery behavior.

CASE STUDY: 2012 DERECHO

Nearly 50% of Appalachian Power's customers in Virginia, and almost 65% of their customers in West Virginia, lost power as a result of damage from the straight-line winds of the derecho windstorm that passed through those states on June 29, 2012. Beginning on June 30, Appalachian Power began posting online updates detailing their estimated progress towards restoring power to their customers (https://www.facebook.com/AppalachianPower/). These updates typically provided not only the total number of customers that were still without power as a result of the storm, but also estimates, typically by county, of the date that customers could expect to have their power restored. Although almost all of these postings contained information drawn from official press releases, it was significant that the updates were all posted on the company's Facebook page, thus providing easier access to the information, and even allowing for individuals to respond with their own comments about their perceptions of the recovery process.

On the first day that a recovery estimate was made, July 2nd, approximately 31% of the company's customers were still without power in Virginia as were almost 47% of the customers in West Virginia. As shown in Table 1, updates on the number of customers still without power were posted on Facebook each consecutive day through the 13th of July. Virginia recovered fully on the 11th of July, but the recovery in West Virginia was not complete until July 15th (WV Gazette, 2012). Recovery estimates were given on a county by county basis, and the lengthiest of the initial recovery estimates given on July 2nd implied an expected recovery date of July 7th for Virginia and July 8th for West Virginia.

There were a number of factors that contributed to the difference between these initial recovery time estimates and the actual amount of time that was needed to reach full recovery. These include several additional storms that occurred during the recovery period that caused additional customers to lose power, thus slowing down the existing restoration efforts. It is also important to note that one of the stated goals during the recovery process was to quickly return power to 95% of the company's customers. Although complete recovery wasn't achieved until later, the 95% level was actually reached by July 7th in Virginia and July 10th in West Virginia.

Date	***WV***		***VA***	
	Number	***Percent***	***Number***	***Percent***
30-Jun	323,000	64.60%	234,000	46.80%
2-Jul	234,967	46.99%	155,620	31.12%
3-Jul	192387	38.48%	118881	23.78%
4-Jul	147408	29.48%	96775	19.36%
5-Jul	137480	27.50%	80505	16.10%
6-Jul	108000	21.60%	43000	8.60%
7-Jul	60000	12.00%	19000	3.80%
8-Jul	45000	9.00%	12000	2.40%
9-Jul	38000	7.60%	4600	0.92%
10-Jul	13500	2.70%	700	0.14%
11-Jul	3000	0.60%	0	0.00%
13-Jul	< 250	0.05%	0	0.00%
15-Jul	0	0.00%	0	0.00%

Table 1: Data for West Virginia / Virginia recovery from power loss (https://www.facebook.com/AppalachianPower/)

Figure 1 illustrates the recovery trajectories for both the state of Virginia and the state of West Virginia, as reflected in the data collected in Table 1. In each case, the recovery behavior is distinctly non-linear in nature, with decreasing recovery rates as the processes neared completion. We thus see that each recovery process may be characterized not only by (1) the initial level of loss from which recovery begins and (2) the length of time that elapses until full recovery is achieved, but also by (3) the shape of the recovery curve.

We may calculate the time-varying amount of loss exhibited by each recovery curve by generalizing the work of Zobel and Khansa (2012) to compute the actual area above the curve, from time t=0 to time t=n, at which point full recovery is achieved:

$$A = \sum_{i=0}^{n-1}(t_{i+1} - t_i)(x_{i+1} + x_i)/2 \qquad (1)$$

Recognizing the inherent relationship between recovery and resilience, we then may define a maximum acceptable recovery time, T^*, and calculate the relative resilience of each curve as a percentage of the total amount of loss possible (Zobel and Khansa, 2012):

$$R = (T^* - A)/T^* = 1 - (A/T^*) \qquad (2)$$

Given T^* = 15 days, this gives an overall resilience value for Virginia of 0.88 and an overall resilience value for West Virginia of 0.81, and it provides a normalized means of representing the relative losses suffered in the two areas.

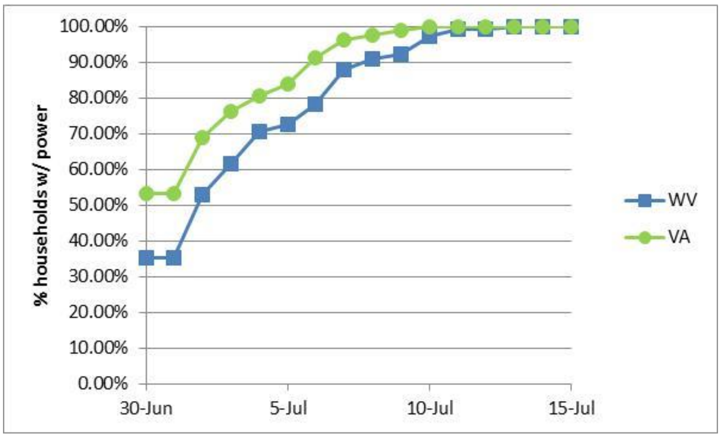

Figure 1: Derecho recovery curves

It is interesting, however, to note that although the total loss suffered by West Virginia was greater than that of its neighboring state, its relative speed of recovery (4.31% / day) was actually somewhat greater than that observed in Virginia (4.25% / day). Thus, even though West Virginia suffered more initial losses and took longer to recover, its recovery process was actually slightly more effective in terms of what it was able to accomplish.

To examine this result a little more closely, we rescaled the loss axis of the two curves to the same interval by calculating the percent that each reported loss amount was of the initial loss on June 30th. We further scaled the Virginia curve up to an equivalent 15 days (from the actual recovery time of 11 days) by adjusting the end point and using linear interpolation to approximate appropriate intermediate observations. If both curves had exhibited linear recovery behavior, this transformation would have resulted in the area above both curves being exactly the same. As illustrated in Figure 2, however, it actually results in the West Virginia curve generating slightly less area than the Virginia curve (only 92% as much area as above the Virginia curve). The West Virginia recovery process thus not only has a slightly faster recovery rate but also it exhibits a slightly more efficient shape, with respect to the length of time that the system spends in a state of significant loss.

It is important to consider that such "efficiency" is relevant only in comparing two recovery curves that have the same actual starting and ending points, or that have been rescaled to a common scale, such as in the example above. The ability to post-process such recovery data supports a deeper analysis of not just total loss and total recovery time, but also the relative progress, per unit time, that is made during recovery.

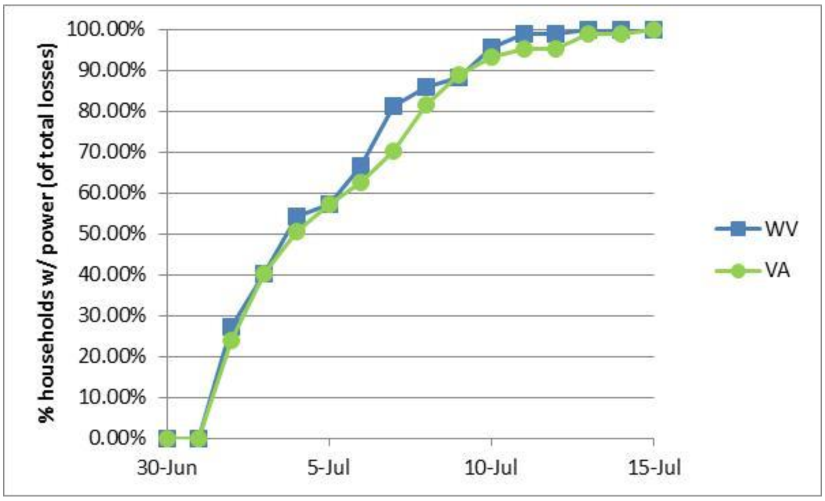

Figure 2: Rescaled derecho recovery curves

CONCLUSIONS

With respect to recovery of Appalachian Power's electric power service after the 2012 derecho, the data shows that the state of Virginia exhibited more resilience than West Virginia because it ultimately had less overall loss, along with a shorter recovery time. Given an assumption of linear recovery behavior, an analytical model of the two recovery processes would have indicated Virginia's greater resilience, but would also have supported the observation that the recovery rate in West Virginia was the better of the two. The actual data, however, shows that the West Virginia recovery process is actually slightly more efficient as well, and recognizing the non-linearity allows us to characterize the relative extent to which this is true.

These results highlight the need for techniques to analytically characterize such nonlinear behavior, in order to better understand its impact both on recovery operations and on the public's perception of those efforts. Greater losses suffered in a given area will typically lead to longer recovery times because there is more work to be done to achieve recovery. The efficiency of the recovery process, however, can have a great impact on how much of that system remains in a state of significant loss and how much of it achieves recovery more quickly. Helping stakeholders recognize that once the initial damage is done, it is *how* recovery is achieved that is important and not just how long it takes to recover, can be a very important part of managing public relations.

This paper defines "loss" in terms of the number (or percentage) of households without electric power at a given point in time. Although this value does provide us a concise indicator of one aspect of the derecho's physical impact, it does not also capture the broader economic, social, or political impacts of the disaster. Because these other types of impacts are also significant in characterizing disaster recovery, however, an important extension to this work is to examine how the fundamental ideas discussed above may also be applied within these other dimensions.

This analysis was conducted almost entirely based upon data provided directly by Appalachian Power. Except for the final recovery date for West Virginia, all information was provided by the company in the form of official Facebook postings or press releases. Although the reliability of the data cannot be confirmed without independent corroboration, the fact that it was the official data provided to the public still gives it practical value in the context of illustrating the differences between two "real-world" nonlinear recovery curves. The use of Facebook to disseminate the information is also valuable in that it provided a platform through which the public stakeholders could directly participate in the risk communication by providing feedback. This is one of the characteristics that helps lead to a successful risk communication effort (EUFIC, 2004).

In considering this particular case study, it is important to note that the two processes being considered are related, since many of the same resources were used in both areas. Decisions about when and where to allocate resources may therefore have had an impact on the relative trajectories that were observed. In order to do a more formal analysis of factors that led to specific behaviors, more information about the decisions that were made during the recovery process would also be needed. Such sensitive information would not typically be available through a publicly available forum such as Facebook, and would require incorporating other sources of more proprietary information.

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