Representing the Multi-Dimensional Nature of Disaster Resilience

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ABSTRACT

Although quantitative analytical information systems are an important resource for supporting decision-making in disaster operations management, not all aspects of a disaster situation can be easily quantified. For example, although the concept of the disaster resilience of a community has a technical dimension within which one can measure the resistance of the infrastructure against, and the speed of its recovery from, a disaster event, it also has social, organizational, and economic dimensions within which these characteristics may be more difficult to measure. This work-in-progress paper introduces a quantitative framework within which the multi-dimensional nature of such disaster resilience can be represented in a concise manner. This can help to improve understanding of the complexities associated with the concept, and thus directly support decision-making in disaster operations planning and management.

Keywords

Community resilience, visualization, social systems, organizational systems, analytical information systems.

INTRODUCTION

Bruneau et al. (2003) introduced the concept of the disaster resilience triangle (see Figure 1), which has primarily been used to measure the resilience of physical infrastructure elements, such as hospitals (Bruneau and Reinhorn, 2007; Cimellaro et al., 2010), in the presence of a natural disaster such as an earthquake.

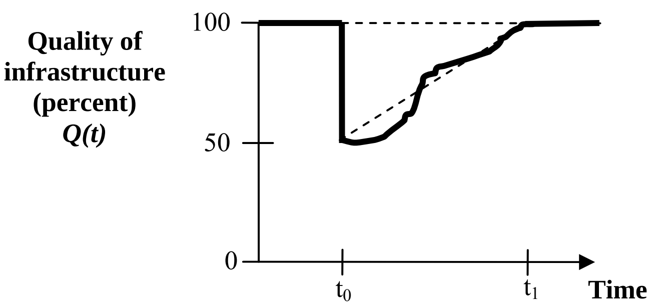

Figure 1 - The original resilience triangle (adapted from (Bruneau et al., 2003))

Disaster resilience as a concept, however, is not traditionally associated just with physical infrastructure. In fact there is significant academic interest, as well as interest from various governmental and relief agencies, in topics such as community resilience, and thus in the ability of social, organizational, or economic systems to protect themselves against and recover from the occurrence of disaster events (Bruneau et al., 2003; Cutter et al., 2008; Adger et al., 2005; Norris et al., 2008; Subcommittee on Disaster Reduction, 2005). The discussion below seeks to apply this idea in the context of the disaster resilience triangle, by providing an approach by which each of the different dimensions of resilience can be simultaneously represented, and thus directly compared and contrasted, using a single graphical representation.

The discussion begins by considering the concept of predicted resilience, and by discussing the nature of the different dimensions of resilience and their relation to this concept. It then provides an approach for standardizing the representation of each dimension and combining the results on a single graph. This leads to a

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brief discussion about comparing (and capturing) the relative value of each dimension to a given decision maker, and finishes with a look at potential issues and opportunities for future research.

DISASTER RESILIENCE

Background

There are a large number of different definitions for disaster resilience within the literature that incorporate the related issues of (1) the impact of a disaster event and (2) the time needed to recover from that event (Cutter et al., 2008; Shinozuka et al., 2004; Tierney and Bruneau, 2007; McDaniels et al., 2008). As discussed above, the relative extent to which each of these characteristics is exhibited in a given system may be visually represented by the *disaster resilience triangle*, which explicitly incorporates the resilience characteristics of *robustness* (resistance to initial loss) and *rapidity* (speed of recovery), as defined by Bruneau et al. (2003). Cimellaro et al. (2010) subsequently developed an approach for using the area under the curve as the basis for an analytic measure of the concept.

Zobel (2010) extended the work of Bruneau et al. (2003) and Cimellaro et al. (2010) by quantifying a new approximation to the concept of the resilience triangle called *predicted resilience*:

$$R(X,T) = \frac{T^* - \frac{XT}{2}}{T^*} = 1 - \frac{XT}{2T^*} \qquad X \in [0,1],\ T \in [0,T^*] \tag{1}$$

where *X* represents the percentage of functionality initially lost due to the impact of the event, *T* represents the time to recovery, and T^* (i.e., $1 \cdot T^*$) is the larger area from which the area of the resilience triangle for *X* and *T* is subtracted. The predicted resilience is thus measured by the percentage of the total area that lies outside the triangle, as in (2010) (See Figure 2).

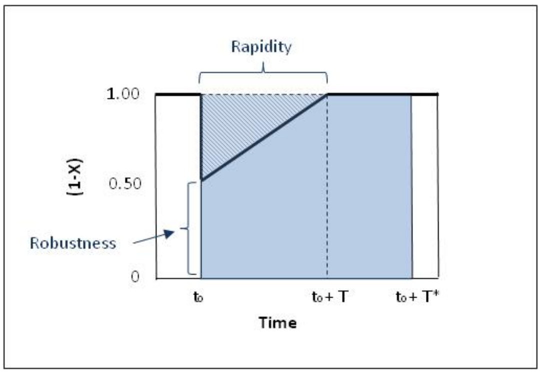

Figure 2 – Predicted resilience as a percent of *T (Zobel, 2010)**

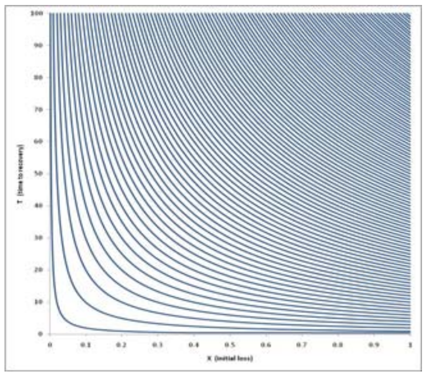

Figure 3 - Predicted resilience curves (Zobel, 2010)

Because different combinations of *X* and *T* may represent very different situations (large impact with quick recovery / small impact with long recovery) but produce triangles with the same areas, there are natural tradeoffs between these two parameters. Recognizing that equation (1) represents a hyperbola for each fixed value of R allows resilience to be represented in a form that makes these tradeoffs easily visible (see Figure 3). All observations on a given resilience curve share the same resilience value, and curves closer to the axes have higher resilience values.

Dimensions of disaster resilience

In addition to defining the properties of a resilient system, Bruneau et al. (2003) discuss what they define to be the four interrelated dimensions of the concept: technical, organizational, social, and economic resilience (TOSE). The *technical* dimension of resilience has to do with the ability of physical systems (and their subsystems or components) to withstand and then recover from the impact of a disaster, whereas the *organizational* dimension refers to the capacity of organizations responsible for managing and implementing disaster-related functions to effectively perform their duties. These two dimensions are relatively straightforward to conceptualize and measure in the context of physical infrastructure systems (Bruneau et al., 2003). The authors further associate the *social* dimension of resilience with the extent to which communities and social systems are able to protect against and then recover from the loss of critical services in a disaster, and the *economic* dimension with the ability to reduce both direct and indirect economic losses in this situation.

These last two dimensions are less straightforward to quantify than the first two, and they tend to be discussed in the broader context of overall community resilience (Bruneau et al., 2003; Cutter et al., 2010).

Considering resilience from the standpoint of these four interrelated dimensions provides an interesting link between two different research communities: the social science community which tends to focus more on the social aspects of disaster resilience, and the engineering or technical community which tends to focus more on the technical, or physical, dimension. The multi-dimensional nature of the concept is well recognized by both communities and although the actual dimensions may vary in their specifics from publication to publication, the underlying recognition of interactions between humans and their environment is a fairly consistent topic across research efforts in both areas (Chang and Shinozuka, 2004; Mileti, 1999; Norris et al., 2008; Shinozuka et al., 2004; Cutter et al., 2008; Cutter et al., 2010).

Because of the complexity of the concept of community resilience, it is an ongoing challenge to define good metrics and standards for measuring it, particularly in the case of the more qualitative social and economic dimensions. The following discussion builds upon previous efforts in this area by suggesting guidelines for developing such measures which may enable the different dimensions of community resilience to be consolidated into a single representation, using the resilience curves discussed above.

CREATING A COMBINED REPRESENTATION

Defining loss and recovery

In the case of the technical dimension of resilience it is relatively straightforward to define and measure the loss of functionality that occurs because of a disaster. One also may easily judge when the associated recovery of a physical system is complete and functionality has been fully restored. This is also true, although perhaps to a lesser extent, with respect to the organizational dimension of resilience. Measurement of the capacity of an organization to perform its duties, particularly when those responsibilities involve clearly defined roles and procedures has been well studied in the business literature (Otley, 1999), and recovery could be judged based on a return to pre-disaster levels of capacity for effectiveness.

With respect to economic resilience, direct economic losses may often be readily measured but indirect economic losses are typically more difficult to quantify. In each case, economists tend to use indicators to represent quantifiable aspects of the overall system behavior. Similarly, because social functionality is not itself directly quantifiable, various indicators have been proposed to capture the nature of the social dimension of resilience. For example, Bruneau et al. (2003) suggest that the number of households with power immediately after an earthquake and the number of injuries treated on the first day are both indicators of the capacity of a community to be socially resilient, because they each have an impact on the ability of social systems to function "normally". In contrast, Cutter et al. (2010) proposes to use such indicators as the percent of the population with a vehicle and the percent of the population that is non-elderly in order to define social resilience.

Part of the difficulty in both of these situations is that social and economic resilience are composite ideas that are made up of a large number of different factors. Particularly in the case of the social dimension of resilience it can be very difficult, if not impossible, to identify a subset of these factors that can be generally agreed upon as being truly representative of the concept. In response to this complexity, Norris (2008) suggests that the condition of recovery, in the sense of social and economic resilience, should be measured as the system having achieved one of many possible desirable states, rather than as having returned to a single pre-designed or pre-determined state.

Resilience curves

In order to apply the concept of the resilience triangle to each of the four dimensions, we propose that (if possible) the initial loss in any given dimension should be measured in terms of a percentage of some baseline amount. In the case of a dimension such as social resilience that is defined by multiple indicators, this loss can simply be expressed as the combined percentage loss of functionality, over all individual indicators. This aligns with the research of authors such as Cutter et al. (2010), whose efforts focus on defining composite indicators.

In theory, adopting this convention would support measuring both the initial loss (X) and the time at which full functionality (or some version of full functionality) has been recovered (T). Resilience could then be defined for each dimension separately, as suggested by Chang et al. (2004) and Bruneau et al. (2007), and a corresponding set of resilience curves (Figure 3) could be generated for all four cases. In any such situation, if the time frame across all four dimensions is consistent, then the resilience values for all the dimensions may instead be plotted on the same set of resilience curves. This would allow all four dimensions of the concept to be compared to one another simultaneously, in order to judge the relative strengths and weaknesses of the system across dimensions.

In reality, however, it is difficult enough to measure the baseline conditions for a dimension such as social resilience, let alone to measure how those conditions have changed after a disaster has occurred. For this reason, it can also be difficult to measure how long it takes to achieve "recovery". Adding to this difficulty is the fact that the current research on quantitative social resilience can tend to focus on the *inherent resilience* of a community, irrespective of a particular disaster event and thus without regard to the amount of recovery time from that event (Cutter, 2008; Cutter et al., 2010). Once this baseline value is established for a particular social system, then theoretically it becomes possible to measure changes in that resilience over time (Cutter et al., 2010). Re-conceptualizing this *inherent resilience* as the "quality" of social infrastructure would then allow it to be considered in the context of Figure 1, with respect to how its level changes in a particular disaster situation and its aftermath. As in the technical dimension, it would then be the extent of this change with respect to time that would characterize the predicted resilience for a given disaster event.

The idea of measuring the inherent resilience of a system, rather than the predicted resilience associated with a particular event, suggests a slightly different use of the resilience curves. Because the inherent resilience of a system is not associated with a particular amount of loss or recovery time, we may instead identify it with an entire resilience curve, irrespective of *X* and *T*. This would provide an additional means for comparing the resilience of the different dimensions, and could provide the opportunity for some interesting analyses of the relationship between the concepts of inherent and predicted resilience.

Normalization

In calculating the resilience for each dimension, it is important to note that, for a given decision maker, 80% resilience in the social dimension may represent an entirely different situation than 80% resilience in the technical dimension, with respect to their actual relative values. By plotting the values for both dimensions on the same set of resilience curves (either as individual points or entire curves), the decision maker is effectively stating that they are equivalent. In order to address this and reflect the perception that they are actually different, it may be necessary to adjust the original resilience values to better reflect their relative contributions.

Zobel (2011) developed an approach to representing a decision maker's preferences that could be used in this situation to determine an appropriate adjustment factor, α, for each individual dimension. The corresponding resilience function (in each dimension) would then become:

$$R_{\alpha_d}(X,T) = 1 - \frac{XT}{2T^*} + \alpha_d\left(\frac{XT}{2T^*}\right) = R(X,T) + \alpha_d\,(1 - R(X,T)). \qquad (2)$$

where $d \in$ {technical (t), organizational (o), social (s), economic (e)}, and α_d is chosen to increase or decrease the resilience of the associated dimension by an appropriate amount, relative to the other dimensions.
Following this transformation, each resulting resilience curve could then be identified and plotted on the same normalized graph, and their relative differences would better reflect the decision maker's perceptions of the different dimensions. If each dimension is instead associated with a specific point of the graph, rather than an entire curve, then each point can simply be translated an appropriate distance along the line passing through the point and the origin, so that the relative ratio between *X* and *T* in each case remains unchanged. Figure 4 provides an illustration of the results of applying this technique.

CONCLUSIONS AND FUTURE WORK

This work-in-progress research effort provides a first attempt at trying to simultaneously represent the relative contributions of the four primary dimensions of disaster resilience. It adopts the convention that resilience can be approximately measured by focusing on the characteristics of robustness and rapidity, as reflected in Zobel (2010), but recognizes the complexity of the concept, particularly with respect to differences in measurement between dimensions. It also recognizes the practical difficulty of collecting information about changes in the underlying characteristics that determine resilience, and thus supports use of an approach to represent the more static concept of inherent resilience. In order to consolidate all dimensions on a single representative graph, it may be necessary to adjust measured (or estimated) values using a decision maker's perceptions. This provides for a concise representation of a very complex concept and establishes a framework within which more effective decision making can be supported.

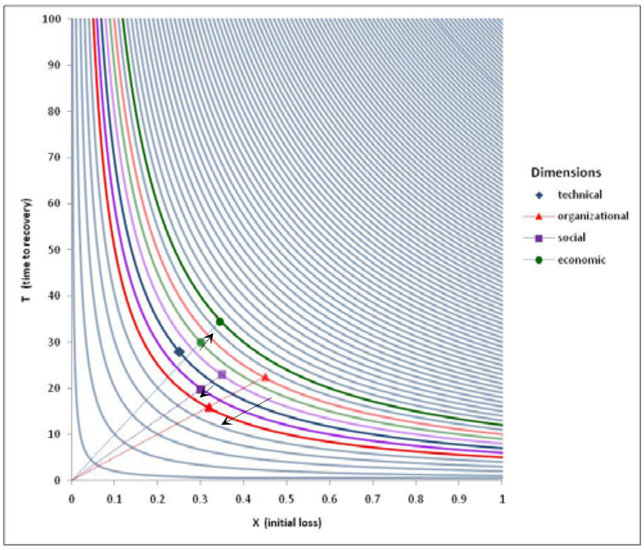

Figure 4 – Example of adjusted resilience curves / values

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