A Novel End-user-oriented Approach to Dynamic Post-disaster Resilience Quantification for Individual Facilities

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ABSTRACT: Community recovery from a disaster is a complex process, in which the importance of different types of infrastructure functionality can change over time. For instance, sheltering facilities can be critical in the immediate post-disaster phase, but play a declining role over the longer-term recovery period. On the other hand, the successful functionality of educational institutions may become important only at the end of any emergency response period. Most of the myriad of metrics available for measuring disaster resilience do not capture the dynamic importance of functionality explicitly, however. This means that very different recovery trajectories of a given infrastructure can correspond to the same resilience value, regardless of variations in its utility over time. While some efforts have been made to integrate features of time dependency into individual facility (i.e., component-level) resilience quantification, the resulting metrics either capture only a limited set of temporal instances throughout the post-disaster response and recovery process or do not offer a way to prioritize time steps in line with variations in the importance of facility functionality. This study proposes a novel yet straightforward metric for component-level post-disaster resilience quantification that overcomes the aforementioned limitations. The metric involves a dynamic weighting component that allows stakeholders to place varying emphasis on different temporal points throughout the recovery process. The end-user-centered approach to resilience quantification facilitated by the metric allows for flexible, context-specific interpretations of infrastructure functionality importance that may vary across different communities. After presenting the metric, we demonstrate it through a hypothetical case study of infrastructure facilities with varying degrees of importance across the post-disaster recovery period, and showcase its versatility relative to a previously well-established measurement of component-level resilience. As the case-study demonstration underlines, the proposed metric has significant potential for use in stakeholder-driven approaches to decision making on critical infrastructure (as well as other types of built environment) recovery and resilience.

1. INTRODUCTION

The need for effective disaster resilience is well established in the literature (Tiernan et al., 2019) and promoted widely across leading international agencies, such as the World Bank and the United Nations (Mochizuki et al., 2018). There is no explicit consensus on the definition of the concept of resilience (Cai et al., 2018), which features across a range of different disciplines including ecology and child psychology (Ayyub, 2014). However, in the context of disasters and communities, the term is broadly captured by the following United Nations Office for Disaster Risk Reduction (UNISDR) explanation: *“ A resilient city is characterized by its capacity to withstand or absorb the impact of a hazard through resistance or adaptation, which enable it to maintain certain basic functions and structures during a crisis, and bounce back or recover from an event ”* (Johnson and Blackburn, 2012).

Implicit in this interpretation of disaster resilience (particularly through the word "certain") is the idea that the importance of post-disaster functionality in a given infrastructure (facility) may change over time. Some facilities, like shelters and hospitals, are critical to the emergency response phase and should be immediately functional for maintaining basic needs (e.g., Hassan and Mahmoud, 2018; Cimellaro et al., 2010; Vecere et al., 2017). On the other hand, other services, such as those related to education, are not required to operate so soon after a disaster; in fact, the re-opening of schools often marks the transition from response to recovery efforts (Scott et al., 2023). In addition, the importance of functionality in different facilities at a certain point in time can vary across neighborhoods (Dong et al., 2021). For instance, immediate operation of food assistance services may be critical for low-income communities, but not necessary for high-income groups that have sufficient pre-existing resources to cope without these facilities for a certain period of time.

Yet, the vast majority of existing metrics for individual facility (i.e., component-level) resilience do not (at least completely) capture the dynamic nature of post-disaster functionality importance (Hosseini et al., 2016). For instance, the resilience triangle measurement proposed by Bruneau et al. (2003), which is perhaps the most well-known and widely used metric in this context, can produce the same resilience result for very different functionality trajectories because each time instant is treated equally. Thus, a hospital that has minimal functionality in the critical emergency phase but recovers quickly thereafter could have identical resilience to a similar facility that has significantly more capacity to deal with emergency casualties but recovers to a fully operational status more slowly. This limitation of the Bruneau et al. (2003) metric was identified and addressed by Zobel (2011); Zobel and Khansa (2014); Chang and Shinozuka (2004), but the resulting approaches only focus on functionality at a finite number of temporal instances (i.e., the beginning and end of recovery processes), such that the importance of performance in intervening periods cannot be accounted for.

While the literature does contain time-dependent component-level metrics that enable disaster-related resilience to be examined and/or distinguished for any temporal instance of interest (e.g., Henry and Ramirez-Marquez, 2012; Rose, 2007), there has been no attempt to explicitly prioritize (weight) time steps in line with the dynamic importance of facility functionality. Time-dependent weighting functions have been introduced in the system resilience domain, reflecting the relative importance of functionality in one type of facility over another (Ghorbani-Renani et al., 2020; Zhang et al., 2021). However, these types of metrics still treat all time steps with equal importance at the component level, and reduce to measurements analogous to that proposed by Bruneau et al. (2003) for a system composed of only one facility.

This study addresses the crucial gap identified in the state-of-the-art, by proposing a novel component-level resilience metric that enables varying emphasis to be placed on different temporal points throughout the recovery process. The dynamic nature of infrastructure functionality importance is specifically captured through a time-dependent weighting component that should be calibrated in consultation with relevant end users. This end-user-oriented feature of the proposed metric has a number of advantages. First, it allows for flexible, context-specific interpretations of recovery importance for different infrastructure, addressing possible inter-community disparities in post-disaster needs. Second, stakeholder participation in the post-disaster planning process can lead to greater awareness of related challenges and higher confidence of being able to address them (Chandrasekhar, 2012) . Ultimately, end-user involvement results in better-informed decision making (e.g., Komendantova et al., 2014), which is the final goal of any resilience assessment.

The rest of the paper is organized as follows. Section 2 introduces the proposed resilience metric, which is then demonstrated for a set of hypothetical infrastructure facilities and stakeholders in Section 3. The paper ends with a discussion on the utility of the metric and its potential application to infrastructure recovery decision making in Section 4.

2. PROPOSED METRIC

The proposed resilience metric provides a weighted average value of normalized functionality $Q(t)$ for an individual facility between two time instances of interest, t_0 (typically the time at which the disaster occurs) and T_{RE} (corresponding to some subsequent point in the post-disaster phase, which may or may not align with the restoration of full operational capacity in the facility and could be disaster-specific). It can be expressed as:

$$R = \frac{\int_{t_0}^{T_{RE}} Q(t)w(t)dt}{\int_{t_0}^{T_{RE}} w(t)dt} \tag{1}$$

where $w(t)$ is a time-dependent weighting, ranging in value from 0 to 1. $w(t)$ is obtained from discussions with relevant facility stakeholders and may be derived directly from recovery goals set in community resilience plans (e.g., Scott et al., 2023; Poland, 2009) . It is a measurement of the relative importance of complete functionality at time t, where $w(t) = 1$ indicates that complete functionality is critical and $w(t) = 0$ is used when functionality is not necessary.

$w(t)$ for a given facility may depend on the severity of a disaster. For instance, the critically important functionality of an emergency shelter may last longer for events that cause substantial residential damage than those that have minimal effect on a region's housing stock. On the other hand, the time at which educational facilities should reach full capacity may be later for high-impact events that require a protracted post-disaster emergency phase. $w(t)$ should also account for any resilience tactics (e.g., Rose and Huyck, 2016) associated with the facility of interest that can be used to supplement or as a substitute for its functionality over a prescribed period of time. For example, $w(t)$ may be zero for an industrial premises during the time period that the associated business can operate with employees working from home (e.g., Cremen et al., 2020).

2.1. *Alignment with existing metrics*

2.1.1. *Component-level metrics*

R is a modified version of the straightforward well-known resilience triangle concept (herein referred to as R^*) proposed by Bruneau et al. (2003) and subsequently updated by Cimellaro et al. (2005). The inclusion of the integral on the denominator of R normalizes the metric, analogous to the $\frac{1}{T_{LC}}$ component of the formulation proposed by Cimellaro et al. (2005), where T_{LC} refers to a specific time period of interest (equivalent to T_{RE} in Eq. 1). R reduces to R^* for $w(t) = C$, where C is some constant between 0 and 1, i.e., the two metrics are equivalent when an equal amount of importance is placed on the full functionality of the facility of interest across the time $\{t_0, T_{RE}\}$. This may arise in the case of some facility that operates at or near full capacity even in "normal" conditions (i.e., when it is not dealing with the aftermath of a disaster), such as a critical bridge in a road network.

2.1.2. *System-level metrics*

The proposed metric assumes a similar functional form to the system-level resilience measurements provided in Eq. (1) of Ghorbani-Renani et al. (2020) and Eq. (8) of Zhang et al. (2021), which also incorporate a dynamic weighting component that accounts for the time-dependent importance of infrastructure functionality. However, a crucial difference between these measurements and the metric proposed in this study is the manner in which relative importance is quantified. The Ghorbani-Renani et al. (2020) and Zhang et al. (2021) approaches measure the importance of functionality in a given infrastructure facility at t relative to that of all other infrastructure facilities within the system or network of interest at the same time (i.e., "inter-infrastructure" or "facility-to-facility" functionality importance; Almoghathawi and Barker, 2019; He and Cha, 2021). These approaches therefore reduce to a time-independent measurement analogous to R^* , if only one individual facility is considered. On the other hand, R measures relative functionality importance in an "intra-infrastructure" sense, i.e., the importance of functionality in a given infrastructure facility at t is measured relative to the importance of the same facility at different times. In other words, the Ghorbani-Renani et al. (2020) and Ghorbani-Renani et al. (2020) approaches are top-down in nature- where the sets of weightings used across different infrastructure reflect the perspectives or rules of one high-level (or generic) decision maker in an autocratic process - whereas the R metric is inherently bottom-up, facilitating bespoke stakeholder priorities for each unique piece of infrastructure it is applied to.

If necessary, R could be integrated explicitly into a system resilience quantification R_{sys}, combining the top-down and bottom-up approaches through a formulation such as (Cimellaro et al., 2014):

$$R_{sys} = \frac{\sum R_n}{N} \tag{2}$$

where N is the number of infrastructure (facilities) within the system of interest. R_n is the resilience of the nth facility in the system that could be expressed as an adapted version of R according to:

$$R_n = \frac{\int_{t_0}^{T_{RE}} Q(t) w_n(t) w_{sys,n}(t) dt}{\int_{t_0}^{T_{RE}} w_n(t) w_{sys,n}(t) dt} \tag{3}$$

where $w_{sys,n}$(t) quantifies the nth facility's inter-infrastructure importance ($0 \leq w_{sys,n}(t) < 1$), $w_n(t)$ is equivalent to $w(t)$ in Eq. (1), and all other variables are as previously defined. To avoid double counting in this case, it is important that $w_n(t)$ is defined independent of the facility's functional interdependencies across the considered system.

3. CASE STUDY DEMONSTRATION

We provide a simple hypothetical case-study demonstration of R for three independent infrastructure facilities of interest: a water supply service, an emergency shelter, and a school. We assume that the time of interest is between $t_0 = 0$ and $T_{RE} = 15$ days after an "expected" disaster (i.e., a disaster that is reasonably expected to occur once during the life of an urban system, which is typically set as a 50-year period; Poland, 2009). Hypothetical $w(t)$ values for the three infrastructure, which are plotted in Figure 1 and provided in Table 1, are quantified assuming that stakeholders and their associated disaster resilience plans would: (1) consider full functionality of the emergency shelter to be critical at first, but this importance to decrease significantly over time to almost nothing at $t = T_{RE}$; (2) deem full functionality of the school to be insignificant at t_0, but increase slowly over time to reach maximum importance at approximately $t = 40$ days; and (3) assign little importance to full functionality of the water supply until $t = 10$ days, which approximately corresponds to the duration of capacity in the backup water system.

We specifically compare the value of R for three contrasting functionality trajectories (see Figure 2) that provide the same value of R^*, i.e.,

$$R* = \frac{\int_0^{15} Q(t)dt}{15} = 0.82 \tag{4}$$

Trajectory #1 linearly increases from 60% functionality at $t = t_0$ to 100% functionality at $t = 13.6$ days. Trajectory #3 involves a steeper functionality increase from a lower initial functionality level than trajectory #1 (5%), but reaches a plateau at only 90% functionality (from $t = 2.8$ days). Trajectory #2 remains constant at 82% functionality, independent of time. The R values for each recovery trajectory ($R_{\#1}$ to $R_{\#3}$) and each facility are included in Table 1.

Functionality trajectory #1 produces the highest R value for the water supply service. This result is explained by the fact that the trajectory provides the largest functionality (across the three examined trajectories) at the most important time for the water supply service to be operational (i.e., $t \geq 10$ days).

Functionality trajectory #2 produces identical values of $R = R^*$ for each infrastructure facility, since it does not change dynamically. It leads to the highest R value for the emergency shelter and the lowest R value for the water supply service. This is because it provides adequate functionality in the period immediately after the disaster when the shelter is most required, but its functionality is outperformed by that of #1 and #3 when a fully functional water supply service is critical at a later stage.

Functionality trajectory #3 provides the highest value of R for the school, since the trajectory aligns well with the increasing importance of school functionality over time. However, the trajectory produces the lowest R value for the emergency shelter, since it provides very little functionality in the immediate post-disaster period. Trajectory #3 results in identical R^* values for both the water supply service and the school, which both have increasing functionality requirements over time. Finally, it is interesting to note that the value of R can change considerably between trajectories for the same infrastructure facility. For instance in the case of the emergency shelter, the R value for trajectory #2 is 26% larger than that for trajectory #3.

In summary, the results indicate that the proposed resilience metric R can distinguish the best functionality trajectory for bespoke infrastructure stakeholder needs, among a set that produces the same level of resilience according to traditional measurements. It is important to note that the results are specific to the considered time period. For example, functionality trajectory #1 provides a higher R value for the school (=0.94) than trajectory #3 ($R_{\#3} = 0.89$) if $T_{RE} = 30$ days, given the superior functionality performance of trajectory #1 across the extended time period considered.

Table 1: $w(t)$ and resulting R values associated with the hypothetical case-study water supply service, emergency shelter, and school, computed for the three hypothetical $Q(t)$.The best R value for each facility is denoted in bold.

facility	$w(t)$	$R_{\#1}$	$R_{\#2}$	$R_{\#3}$
water	$\begin{cases} 0.1, & \text{if } t \leq 10 \\ 1, & \text{otherwise} \end{cases}$	**0.93**	0.82	0.88
shelter	$e^{-t/4}$	0.71	**0.82**	0.65
school	$1-e^{-t/4}$	0.86	0.82	**0.88**

4. CONCLUSIONS

This study has proposed a new metric for measuring post-disaster resilience that explicitly accounts for dynamic fluctuations in the criticality of infrastructure functionality across the post-disaster period. The time-dependency of functionality importance is reflected in a dynamic weighting function that can be calibrated through relevant stakeholder feedback, facilitating an end-user oriented approach to flexible, context-specific resilience assessment. The metric is specifically designed for component-level applications, but could be easily extended to a system-level context using some sort of weighted aggregation approach, as discussed in the text.

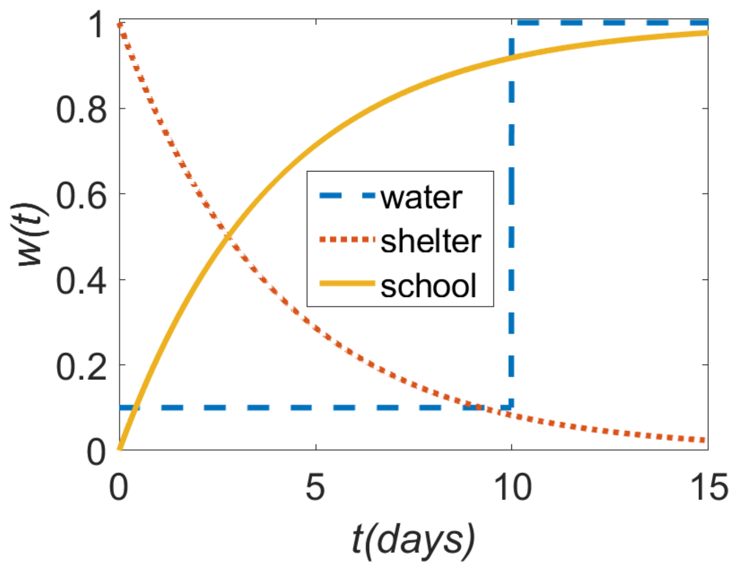

Figure 1: Hypothetical $w(t)$ for a water supply service, an emergency shelter, and a school.

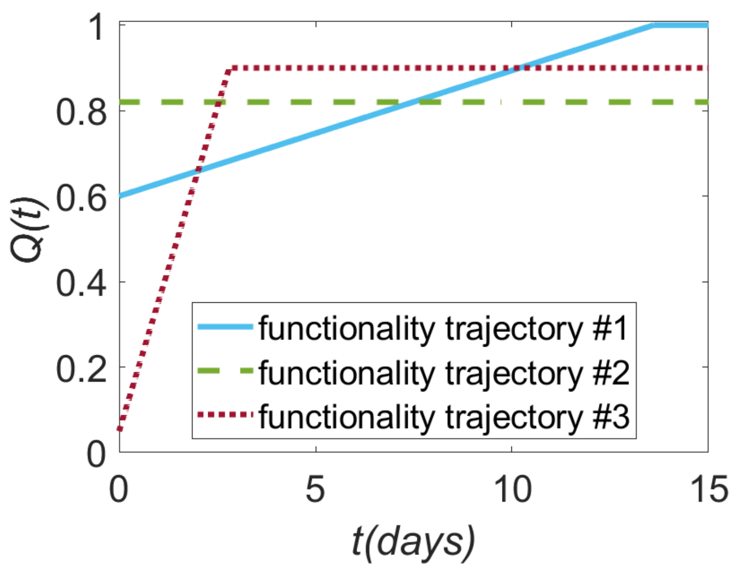

Figure 2: Three hypothetical functionality trajectories $Q(t)$ with identical R^* values .

We have demonstrated the metric using three hypothetical infrastructure components and associated stakeholder input on functionality importance, to identify the best (most resilient) functionality trajectory for each case, among a synthetic set of three. Each of the investigated functionality trajectories yield the same resilience value computed according to the traditional trianglular-based metric first introduced by Bruneau et al. (2003), despite having significantly different shapes. On the contrary, the proposed metric provides reasonably different values for the trajectories, in line with stakeholder functionality requirements. For instance, the highest resilience value is assigned to the trajectory with the most initial post-disaster capacity if stakeholders prioritize emergency-phase functionality (i.e., in the case of an emergency shelter), whereas trajectories with maximum functionality later on in the recovery process produce the highest resilience values if stakeholders do not perceive immediate functionality to be essential (i.e., in the case of a school or a water supply for which there are temporary backup resources).

The case study demonstration clearly indicates the ability of the metric to naturally distinguish diverse optimum recovery trajectories for different infrastructure, based on bottom-up underlying stakeholder needs rather than (at least exclusively) relying on top-down autocratic comparisons of functionality importance across different types of infrastructure. This is a useful feature of the proposed metric that could be leveraged to effectively coordinate the post-disaster recovery process across different types of infrastructure and various relevant stakeholders (e.g., civic agencies, utility infrastructure operators, and nongovernmental organizations) in a given urban system, in the face of limited recovery resources, investment, and time (e.g., Olshansky et al., 2012; Choi et al., 2019; Pant et al., 2014). This type of coordination process would first involve designing a series of bespoke recovery trajectories that account for unavoidable constraints (e.g., construction worker shortages) across time. The proposed metric could then be used to appropriately assign each trajectory to a corresponding infrastructure facility, in accordance with the dynamic importance of its functionality.

To conclude, the proposed metric for post-disaster resilience quantification across individual facilities possesses promising potential as an effective tool for facilitating informed stakeholder-oriented decision making on post-disaster infrastructure recovery. Future work will focus on applying the metric to more realistic case studies and exploring its expansion to a more explicit consideration of system-level resilience.

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