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Post-disaster infrastructure restoration: A comparison of events for future planning

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ABSTRACT

The restoration of lifeline infrastructures following a major disruptive disaster is a complex task. Along with the implementation of mitigation measures, pre-event recovery planning can be of great assistance to this process. This paper seeks to inform such planning discussions by suggesting likely paths of recovery over time, and in turn computing indicative estimates of expected restoration times. While current methods can require significant amounts of data and are calibrated to few events, the presented approach analyses and combines 63 electricity, water, gas, and telecommunications post-disaster infrastructure recoveries from across the world. Recoveries are compared across disaster types with global median recovery curves produced to inform likely restoration rates for future disasters. Models based on initial outages or seismic shaking intensity directly provide estimates of expected recovery times back to 90% operability of the initial disruption. An application of the presented methodology is presented as a case study for the Wellington Region of New Zealand with recovery estimates comparing favorably with those presented in the literature.

1. Introduction

Following a natural disaster, the repair of infrastructures back to comparable pre-disaster levels are of major importance for both the livelihood of citizens [47] and maintaining economic activity across a city or region [58,59]. While infrastructure component damage is typically estimated for a given event intensity through fragility curves [56,62], the prediction of system level recovery can prove difficult due to specific network properties, the nature of disruption, and dependencies on other infrastructures during recovery efforts.

In defining the restoration of infrastructure functionality over time, modeling approaches typically take the form of statistical curve fitting or through simulations, such as resource constrained models [35,9], Markov processes [34,41,77], or detailed network models [5,51]. In modeling the restoration process, the deterministic resource constraint approach estimates recovery times based on empirical or assumed repair rates and available resources. Similarly, a Markov Process approach can model the distribution of limited resources, however, the state of each system at any time are considered to follow a random process, hence the ability to model uncertainty explicitly. Network models typically comprise high resolution supply and demand nodes connected by links to simulate the repair and propagation of infrastructure operability allowing spatial and temporal recovery. While such methodologies can optimize restoration scheduling priorities, input data requirements are significant with results typically location specific and limited in transferability to other areas without developing new models. This is where the advantage of using statistical approaches is realized.

Such approaches derive restoration curves based on empirical data, where the specific restoration process is not modeled directly, with earthquake shaking intensity typically used to define the overall system outage level, ultimately producing a single recovery curve. The fitting of curves to empirical data using an assumed functional form enables comparisons between recovery efforts of alternate disasters [56,8].

For discrete-event scenarios, Chang et al. [8] estimate restoration times and curves for water and electricity networks based solely on the 1971 San Fernando Earthquake and the 1994 Northridge Earthquake's respectively. Similarly, though calibration to the 1995 Hyogoken-Nanbu Earthquake, Nojima and Kato [53] predict outage durations and affected populations for Japanese earthquakes based on shaking intensity, lifeline service penetration, and population density predictors.

With more calibration data, Liu et al. [46] take a different approach and apply statistical models to estimate electricity outages across fourteen wind based events. While Nateghi et al. [49] and Guikema et al. [29] follow a similar approach, both estimating

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outages as a function of climatic, topographical, land cover, human and material resources, and population densities amongst others. Ultimately these approaches require a significant amount of potentially difficult to obtain input data which can be limited in accuracy – if accessible at all. For this reason, alternate methods utilizing expert opinions in modeling restoration over time have been proposed for specific geographies [1,2], however, with a number of significant disasters since publication, empirical data is of interest to this study.

While a range of approaches have been taken to predict the expected recovery from a disruptive event over time, challenges are presented for practitioners in the requirement of significant amounts of input data and the inherent methodological and computational complexities that arise in such modeling efforts. This study seeks to contribute to the existing literature through the provision of a scalable and spatially transferable approach to estimate restoration times based on a specific outage level – ultimately minimizing the required input data while widening the predictive capacity. The aim of the presented approach is to provide indicative predictions of restoration times for pre-event planning purposes through combining empirical infrastructure recovery data from a range of geographies and types of natural disasters. As such datasets have not been observed in the literature, conclusions drawn can shape recommendations for future studies in the field.

The paper begins by defining the properties of restoration curves to establish terminology used in the paper (Section 2). This is followed by the construction of dimensionless global median restoration curves with comparisons across the disruptive event categories and the selected electricity, water, gas, and telecommunications infrastructures (Section 3). Models for scaling these restoration curves are developed in Section 4, and are then applied as a case study for the Wellington Region of New Zealand with comparisons to the current literature surrounding this major earthquake scenario in Section 5. The paper concludes with a discussion surrounding the limitations of the models and future use.

2. Characterising restoration curve properties

The restoration of an infrastructure is typically represented by plotting the functionality of the ith infrastructure $Q_i(t)$ over time t, following a disruptive event at t_0 (Fig. 1).

The term functionality can represent a wide range of variables such as; the population without service [53], connections not receiving service [17,38,68], or the percentage of operable nodes/links [2] amongst others. Depending on the spatial and temporal resolution of collected data, variations in population densities can provide a range of functionality estimates. For simplicity, this study assumes that reported functionality parameters are sufficiently similar and hence comparable between disasters, however, only a single one of these variables is accepted in each functionality dataset.

At the time of disruption, t_0, the resulting functionality $Q_i(t_0=0)$ is an indication of infrastructure robustness (Fig. 1), or the ability for an infrastructure to resist the impacts of an event, where a reduced value indicates low robustness and a high value suggests little damage is evident i.e. a highly robust infrastructure. As shaded in Fig. 1, integrating below the curve across a specific time period represents the resilience of the ith infrastructure, R_i [11]. This provides an index appropriate for comparisons of community performance [4] or infrastructure performance across events [79].

For further comparisons between events, the temporal variable can be separated into four stages; pre-event, reaction, response, and recovery phases (Fig. 1). Although an oversimplification of the typically dynamic and complex infrastructure rebuild process, each of these stages are usually evident with varying lengths. Following a disruption at t_0, the reaction phase is initiated and is defined as having no positive infrastructure recovery taking place in the given time step. The first time step showing positive restoration is denoted t_s to represent the time to start recovery. While this period may be insignificant ($t_s \rightarrow 0$), delays in the restoration of infrastructures are often apparent. For example, following a significant earthquake event, gas distribution networks can be automatically shut down in part [33,68] or voluntarily fully shut down for risk of leaks and acting as a propellant [22,26,28,40,64,8].

The following phase represents the response to the event, otherwise referred to as the emergency period [30]. During such time, normal social and economic activity is still disrupted, however, lifeline restoration is expected to commence. Fig. 1 indicates an initial rapid restoration across this period, such that dQ_i/dt is at a maximum in the initial stages of the response phase. Such may be indicative of readily available stored inventories, resources, and planned alternative service methods. With sufficient knowledge of the network damage, the response phase begins to represent a more informed and coordinated response over time, allowing reinstatement of functionality to the infrastructure through repair or additional redundancies. Over time, the longer-term recovery

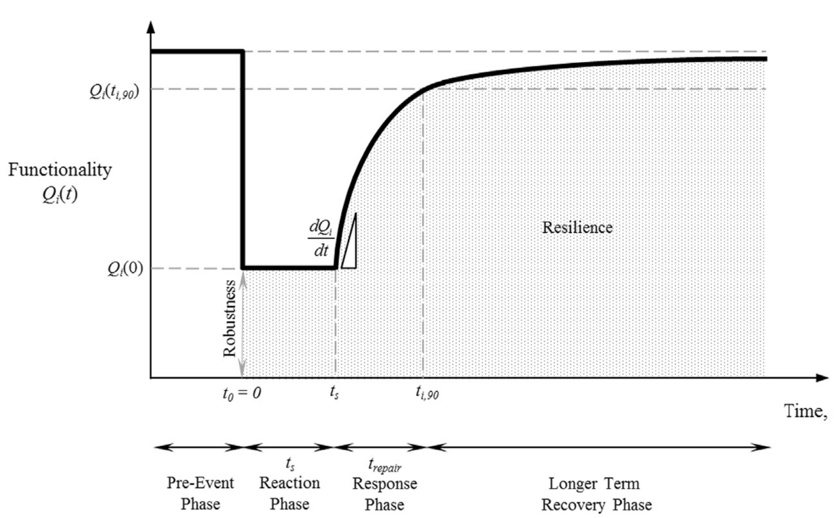

Fig. 1. Example recovery process of a system back to pre-event functionality.