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# Near-optimal planning using approximate dynamic programming to enhance post-hazard community resilience management

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ABSTRACT

The lack of a comprehensive decision-making approach at the community level is an important problem that warrants immediate attention. Network-level decision-making algorithms need to solve large-scale optimization problems that pose computational challenges. The complexity of the optimization problems increases when various sources of uncertainty are considered. This research introduces a sequential discrete optimization approach, as a decision-making framework at the community level for recovery management. The proposed mathematical approach leverages approximate dynamic programming along with heuristics for the determination of recovery actions. Our methodology overcomes the curse of dimensionality and manages multi-state, large-scale infrastructure systems following disasters. We also provide computational results showing that our methodology not only incorporates recovery policies of responsible public and private entities within the community but also substantially enhances the performance of their underlying strategies with limited resources. The methodology can be implemented efficiently to identify near-optimal recovery decisions following a severe earthquake based on multiple objectives for an electrical power network of a testbed community coarsely modeled after Gilroy, California, United States. The proposed optimization method supports risk-informed community decision makers within chaotic post-hazard circumstances.

## 1. Introduction

In the modern era, the functionality of infrastructure systems is of significant importance in providing continuous services to communities and in supporting their public health and safety. Natural and anthropogenic hazards pose significant challenges to infrastructure systems and cause undesirable system malfunctions and consequences. Past experiences show that these malfunctions are not always inevitable despite design strategies like increasing system redundancy and reliability [1]. Therefore, a sequential rational decision-making framework should enable malfunctioned systems to be restored in a timely manner after the hazards. Further, post-event stressors and chaotic circumstances, time limitations, budget and resource constraints, and complexities in the community recovery process, which are twinned with catastrophe, highlight the necessity for a comprehensive risk-informed decision-making framework for recovery management at the community level. A comprehensive decision-making framework must take into account indirect and delayed consequences of decisions (also called the post-effect property of decisions), which requires foresight or planning. Such a comprehensive decision-making system must also be able to handle large-scale scheduling problems that encompass large combinatorial decision spaces to make the most rational plans at the community level.

Developing efficient computational methodologies for sequential decision-making problems has been a subject of significant interest [2–5]. In the context of civil engineering, several studies have utilized the framework of dynamic programming for management of bridges and pavement maintenance [6–10]. Typical methodological formulations employ principles of dynamic programming that utilize state-action pairs. In this study, we develop a powerful and relatively unexplored methodological framework of formulating large infrastructure problems as *string-actions*, which will be described in Section 5.2. Our

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formulation does not require an explicit state-space model; therefore, it is shielded against the common problem of state explosion when such methodologies are employed. The sequential decision-making methodology presented here not only manages network-level infrastructure but also considers the interconnectedness and cascading effects in the entire recovery process that have not been addressed in the past studies.

Dynamic programming formulations frequently suffer from the *curse of dimensionality*. This problem is further aggravated when we have to deal with large combinatorial decision spaces characteristic of community recovery. Therefore, using approximation techniques in conjunction with the dynamic programming formalism is essential. There are several approximation techniques available in the literature [11–14]. Here, we use a promising class of approximation techniques called *rollout* algorithms. We show how rollout algorithms blend naturally with our string-action formulation. Together, they form a robust tool to overcome some of the limitations faced in the application of dynamic programming techniques to massive real-world problems. The proposed approach is able to handle the curse of dimensionality in its analysis and management of multi-state, large-scale infrastructure systems and data sources. The proposed methodology is also able to consider and improve the current recovery policies of responsible public and private entities within the community.

Among infrastructure systems, electrical power networks (EPNs) are particularly critical insofar as the functionality of most other networks, and critical facilities depend on EPN functionality and management. Hence, the method is illustrated in an application to recovery management of the modeled EPN in Gilroy, California following a severe earthquake. The illustrative example shows how the proposed approach can be implemented efficiently to identify near-optimal recovery decisions. The computed near-optimal decisions restored the EPN of Gilroy in a timely manner, for residential buildings as well as main food retailers, as an example of critical facilities that need electricity to support public health in the aftermath of hazards.

The remainder of this study is structured as follows. In Section 2, we introduce the background of system resilience and the system modeling used in this study. In Section 3, we introduce the case study used in this paper. In Section 4, we describe the earthquake modeling, fragility, and restoration assessments. In Section 5, we provide a mathematical formulation of our optimization problem. In Section 6, we describe the solution method to solve the optimization problem. In Section 7, we demonstrate the performance of the rollout algorithm with the string-action formulation through multiple simulations. In Section 8, we present a brief conclusion of this research.

## 2. System resilience

The term *resilience* is defined in a variety of ways. Generally speaking, resilience can be defined as "the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions [15]". Hence, resilience of a community (or a system) is usually delineated with the measure of community functionality, shown by the vertical axis of Fig. 1 and four attributes of *robustness, rapidity, redundancy*, and *resourcefulness* [16]. Fig. 1 illustrates the concept of functionality, which can be defined as the ability of a system to support its planned mission, for example, by providing electricity to people and facilities. The understanding of interdependencies among the components of a system is essential to quantify system functionality and resilience. These interdependencies produce cascading failures where a large-scale cascade may be triggered by the malfunction of a single or few components [17]. Further, they contribute to the recovery rate and difficulty of the entire recovery process of a system. Different factors affect the recovery rate of a system, among which modification before disruptive events (ex-ante mitigations), different recovery policies (ex-post actions), and nature of the disruption are prominent [18]. Fig. 1 also highlights different sources of uncertainty that are associated with community functionality assessment and have remarkable impacts in

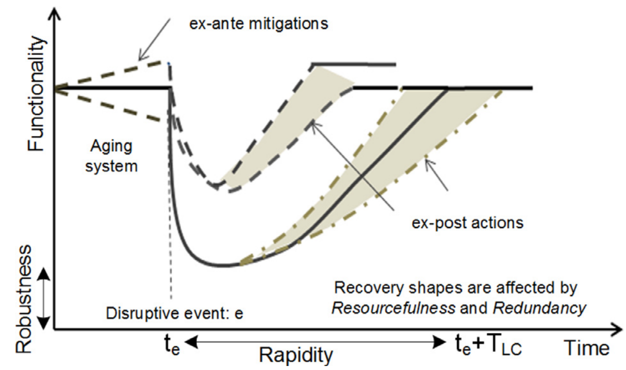


**Fig. 1.** Schematic representation of resilience concept (adopted from [16,20]).

different stages from prior to the event to the end of the recovery process. Therefore, any employed model to assess the recovery process should be able to consider the impacts of the influencing parameters.

In this study, the dependency of networks is modeled through an adjacency matrix $\mathbf{A} = [x_{ij}]$, where $x_{ij} \in [0, 1]$ indicates the magnitude of dependency between components $i$ and $j$ [19]. In this general form, the adjacency matrix $\mathbf{A}$ can be a time-dependent stochastic matrix to capture the uncertainties in the dependencies and probable time-dependent variations.

According to the literature, the resilience index $\mathfrak{R}$ for each system is defined by the following equation [16,21]:

$$\mathfrak{R} = \int_{t_e}^{t_e+T_{LC}} \frac{Q(t)}{T_{LC}} dt. \tag{1}$$

where $Q(t)$ is the functionality of a system at time $t$, $T_{LC}$ is the control time of the system, and $t_e$ is the time of occurrence of event $e$, as shown in Fig. 1. We use this resilience index to define one of the objective functions.

## 3. Description of case study

In the case study of this paper, the community in Gilroy, California, USA is used as an example to illustrate the proposed approach. Gilroy is located approximately 50 km south of the city of San Jose with a population of 48,821 at the time of the 2010 census (see Fig. 2) [22]. The study area is divided into 36 gridded rectangles to define the community and encompasses 41.9 km$^2$ area of Gilroy. In this study, we do not cover all the characteristics of Gilroy; however, the adopted model has a resolution that is sufficient to study the methodology at the community level under hazard events.

Gilroy contains six main food retailers, each of which has more than

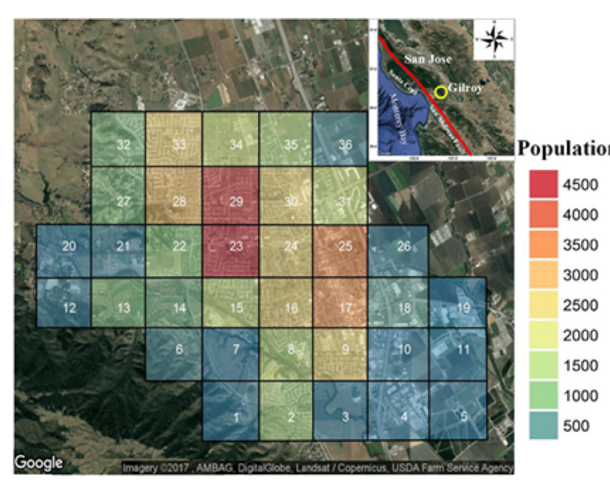


**Fig. 2.** Map of Gilroy's population over the defined grids.