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A PROBABILISTIC FRAMEWORK FOR POST-DISASTER RECOVERY MODELLING OF BUILDINGS IN DEVELOPING COUNTRIES

Eyitayo OPABOLA[1], Carmine GALASSO[2]

Abstract: *This study introduces a probabilistic framework for modelling the post-disaster recovery of buildings in developing countries. The proposed framework combines a building-level assessment of individual assets to evaluate the post-disaster functionality state of a building portfolio. As part of the framework, a stochastic network analysis approach is proposed to estimate the recovery time of damaged buildings while accounting for technical, environmental, socioeconomic, political, and cultural factors, quantified using data gathered from past events in developing countries. The framework recognises the importance of inclusive recovery and the need for intervention prioritisation for some building classes by including a multicriteria decisionmaking module for intervention prioritisation. A case study is presented to illustrate the application of the proposed framework to model the post-earthquake recovery of a synthetic low-income residential community. The analysis showed that negative technical, environmental, socioeconomic, political, and cultural factors could amplify the reconstruction time of damaged buildings by a factor of almost three. The proposed framework can support decision-makers in disaster planning and management strategies for vulnerable low-income communities.*

Introduction

Recent catastrophic events worldwide have emphasised the challenges to achieve rapid postdisaster recovery, particularly in Global South contexts. For example, the majority of the occupants of the over 500,000 buildings demolished after the 2015 Gorkha earthquake continued to live in temporary shelters for over 18 months after the disaster (The Asia Foundation, 2016). About 65,000 displaced people were still homeless five years after the 2010 Haiti earthquake (IOM, 2015).

The delayed recovery process in some of these countries is often influenced by various technical, environmental, socioeconomic, political, and cultural aspects (e.g., the presence of political conflicts or war, availability of stable governance, land disputes, and lack of technical know-how, among many other factors). For example, Sharma et al. (2018) reported that the absence of local government resulted in several months of delays before reaching out to specific regions affected by the 2015 Gorkha earthquake. Furthermore, resolving fundamental issues (e.g., tender process, building permits, and land acquisition) took at least four times the required time. Data presented by Weerakoon et al. (2007) show that the recovery rate of buildings in Sri Lanka following the 2004 Indian Ocean tsunami was eight times larger in conflict zones compared to zones outside the conflict region. Furthermore, reports (e.g., Gharaati and Davidson 2008; Kennedy et al. 2008) have highlighted that poor management skills can lead to construction delays, rejection by beneficiaries, rework, and demolition of newly constructed buildings. Delays associated with poor management skills reportedly impeded recovery time by a factor of up to three.

It is essential for local authorities and other stakeholders in disaster-prone regions to have access to efficient computational tools that can help forecasting and plan/shape recovery trajectories while explicitly considering the various technical, socioeconomic, political, environmental, and cultural factors in their communities.

[1] Senior Research Fellow, University College London, London, United Kingdom, e.opabola@ucl.ac.uk [2] Professor, University College London, London, United Kingdom

Recovery modelling frameworks available in the literature are either building-specific or community-level. Regarding building-level post-disaster recovery modelling, various studies (e.g., Almufti and Willford 2013) have been developed to evaluate the downtime and recovery trajectory of damaged buildings. However, these studies focus mainly on repair downtime modelling.

Therefore, they may be unable to capture long-term recovery facets of low-income countries typically dominated by reconstruction and not repair. Furthermore, these studies do not consider the diversity in disaster resilience between countries due to various geographic, technical, environmental, socioeconomic, political, and cultural factors. As such, some of the existing frameworks may not be easily extrapolated to regions outside of the United States, for instance. Similar conclusions can be reached for most community-level recovery modelling studies (Lin and Wang, 2017b) focusing on developed nations. It is noted that studies (e.g., Burton et al. 2017) have developed post-disaster housing frameworks that implicitly consider socioeconomic factors. However, existing methodologies lack a harmonised framework to adequately account for the previously mentioned factors that strongly influence recovery processes in developing countries. This is a research gap that needs to be filled.

Based on these remarks, the current study proposes a framework for post-disaster recovery modelling of disaster-struck marginalised communities. The proposed framework combines a building-level assessment of the structural and non-structural seismic performance of each building to estimate the post-disaster functionality state. Recognising the importance of inclusive recovery and the need for intervention prioritisation for some building classes, the proposed framework includes a multicriteria decision-making module for intervention prioritisation at the community-level. A stochastic network analysis (SNA) approach is then used to probabilistically estimate the recovery time of damaged buildings, accounting for intervention prioritisation hierarchy. The SNA accounts for technical, socioeconomic, political, environmental, and cultural factors influencing a community's recovery trajectory at a system and building level, demonstrating the influence of such factors on post-disaster reconstruction projects. Finally, a case study is presented to demonstrate the applicability of the proposed framework to model the post-earthquake recovery of a residential community. The proposed framework can serve as a tool to inform decision-makers on disaster planning and management strategies. For example, local authorities can use information from recovery trajectories to manage short-term and longterm shelter needs, among other issues.

Proposed framework

Overview

The proposed methodology combines five distinct modules to evaluate the probabilistic postdisaster recovery trajectory of buildings (Figure 1). The subsequent subsections provide a summary of each module.

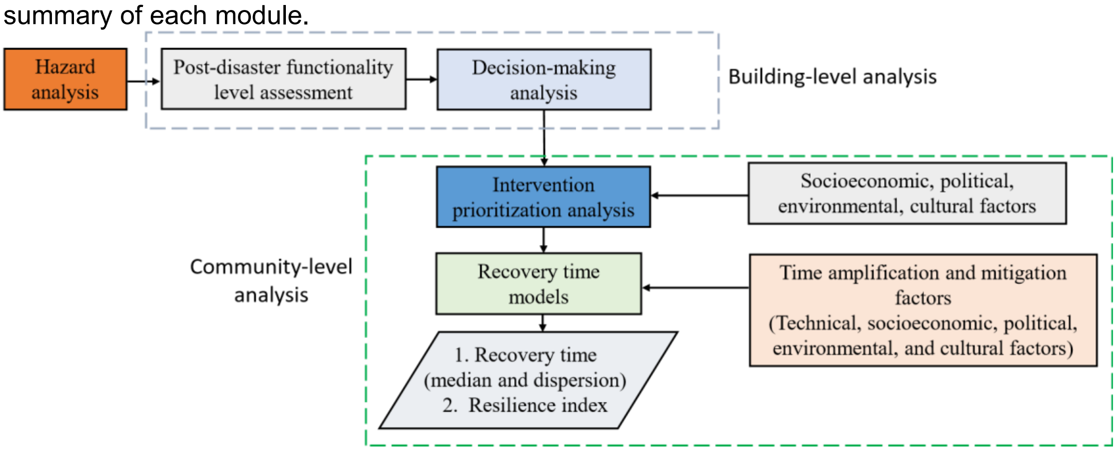

Figure 1 – Proposed framework

Hazard analysis

The hazard analysis simulates the local hazard intensity measures (IMs; e.g., earthquake-induced ground shaking, flood-induced water depth, typhoon-induced wind speeds) at each building location for a particular event scenario. The hazard analysis adequately accounts for the spatial distribution of the intensities throughout the region of interest (Markhvida, Ceferino and Baker, 2018).

Post-disaster functionality assessment

The functionality level assessment implemented in this study builds on the work by Lin and Wang (2017b) to classify a damaged building into four functionality levels (FL0, FL1, FL2, and FL3) based on the damage states of the structural and non-structural components and utility service availability (See Figure 2 for a description of each functionality level). Post-disaster damage assessment of structural and non-structural systems is performed by relating hazard-induced IMs (e.g., peak ground accelerations and spectral accelerations in the case of earthquake hazard) and/or hazard-induced engineering demand parameters (EDP) (e.g., interstory drifts and peak floor accelerations) to building-level and/or component-level damage and loss estimates. This is done through fragility models expressing the probability of various building-level damage levels as a function of a hazard IM (e.g., Gautam et al. 2021; Martins and Silva 2021) or the probability of various component-level damage levels as a function of an EDP (e.g., FEMA 2012) for both structural and non-structural components/systems within a building.

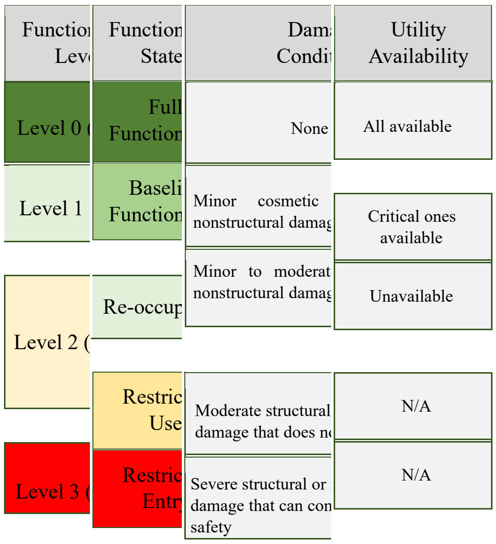

Figure 2 – Post-disaster functionality assessment

Decision-making on intervention

Once the functionality level is determined, a decision is made on the appropriate intervention strategy. A decision-making flowchart is presented in Figure 3. The flowchart assumes that buildings in FL1 and FL0 are in a repairable state, and any minor damage to the systems will not compromise the response of the building in an aftershock. However, it is also assumed that repairs that are not safety-critical can be done while the building is in continued use. An FL3 building requires partial or total replacement, and relocation may be necessary in some instances (e.g., buildings located in liquefiable soil).

A decision-making analysis is required to decide whether an FL2 building would be decommissioned. Such analysis could be done by comparing the mean loss ratio (i.e., the ratio of the repair cost to the total replacement cost of the building) to a predetermined threshold (e.g., FEMA 2012), a cost-benefit analysis, or a multicriteria decision-making analysis. The choice of the analysis type is dependent on the decision-makers.

Intervention prioritisation at the community level

To achieve an inclusive recovery process in government (or any centrally)-managed intervention projects, it is crucial to adopt an intervention prioritisation model incorporating all socioeconomic, political, and cultural factors. Furthermore, community-level intervention requires substantial resources – including workforce, time, funding, and material. Therefore, appropriate resource allocation is essential to mitigate the adverse socioeconomic impacts of a prolonged recovery process.

The intervention prioritisation analysis is needed for developing an intervention prioritisation list for damaged buildings at the community level. The intervention prioritisation list was developed using the *technique for order of preference by similarity to ideal solution* (TOPSIS) (Hwang and Yoon, 1981) – a multicriteria decision-making method. For the sake of brevity, the calculation steps are not shown here. The inputs for the TOPSIS method are the performance measures and criteria weights. The considered criteria include the political importance of buildings requiring intervention, social vulnerability indicators of people in affected buildings, and the historical and cultural significance of the affected buildings (see Figure 4). The criteria weights can either be defined based on expert judgment or using the Analytical Hierarchy Process (AHP) (Saaty, 1980). More information on TOPSIS and AHP can be found in Hwang and Yoon (1981) and Saaty (1980).

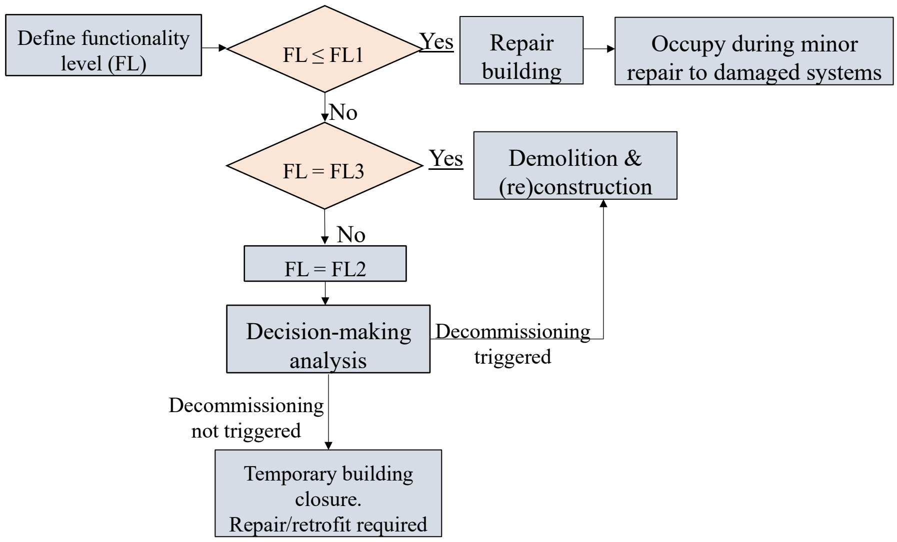

Figure 3 – Intervention decision-making flowchart

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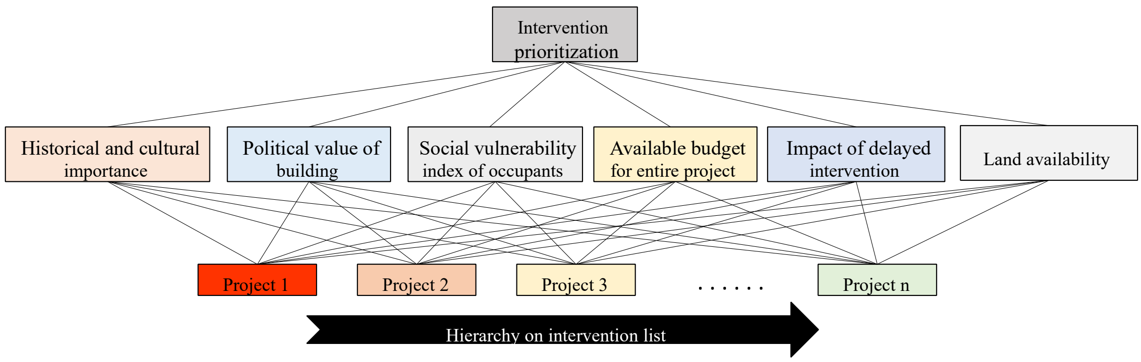


Figure 4 – Multicriteria decision-making method for Intervention prioritisation

Recovery time modelling using stochastic network analysis

This study uses an SNA technique to model buildings' recovery time. In this SNA, the probabilistic distribution of the recovery time is developed through critical path analysis using Monte Carlo sampling (MCS). The critical path indicates the required minimum timeframe to complete a given project.

The recovery time R_t to attain a given functionality level $Q(t)$ is defined as a function of the mobilisation time M_t and the intervention time I_t and can be expressed as:

$$R_t\,(Y) = f\,[M_t\,(Y),\ I_t\,(Y), Q(0), Q(t)] \tag{1}$$

where Y is a set of variables characterising the selected intervention strategy for the building (i.e., repair, retrofit, replacement, or relocation), and $Q(0)$ is the initial post-disaster functionality level.

Each task in the intervention and mobilisation phases is characterised by three durations – the optimistic duration (a), the most likely duration (m), and the pessimistic duration (b) (see Figure 5). The three duration parameters for each task are defined from the average time (w) to complete a task in an ideal (typically pre-disaster) scenario using recovery time amplification and mitigation factors which have been quantified from field data (Opabola and Galasso, 2023) (See Table 1).

The optimistic duration (a) for task i can be estimated using Equation (2).

p

$$a(t_i) = \prod_{l=1}^{p} MF(t_{li}) \times w_i \quad (2)$$

In Equation (2), *w* is the average time to complete a task in an ideal pre-disaster situation, *l* is the number of mitigation factors (MF) (*l* = 1, 2, .., *p*) influencing task *i*. As previously mentioned, mitigation factors may be time-dependent, which must be accounted for when calculating *a*.

The pessimistic duration (*b*) is the maximum time to complete a task assuming all the time amplification factors are activated, and there are no time mitigation factors. The pessimistic duration (*b*) can be estimated using Equation (3).

$$b(t_i) = \prod_{n=1}^{q} AF(t_{ni}) \times w_i \quad (3)$$

Parameter	Factor
Time amplification factors	
Land dispute resolution	1.25 – 2
Pandemic	1.5 – 3
Delay in material procurement	1.2 – 2.5
Hostile political conditions	1.5 – 5
Poor management skills	1.5 – 3
Funds disbursement	1.25 – 3
Technical delays	1.2 – 2.5
Time mitigation factor	
Voluntary mobilisation	0.5 – 0.9

Table 1 – Parameters for modelling recovery times

The most likely duration (*m*) captures the highest likelihood of completing the task in a given timeframe. *m* is defined to be closer to *a* if there is a higher likelihood that the mitigation factors would be more prevalent than the amplification factor or closer to *b* otherwise. When uncertain, *m* can be defined as 0.5(*a*+*b*).

The defined duration parameters (i.e., *a*, *m*, and *b*) are then used to generate a PERT distribution for each task duration. The defined probabilistic duration parameters for each task are then used to carry out MCS. This entails conducting critical path analyses (for a chosen number of iterations) using randomly chosen task durations in each iteration. The expected critical path and critical path duration (i.e., expected recovery time) are evaluated for each iteration. Once the iterations are completed, it is then possible to evaluate the recovery time distribution required to attain the functionality level (*Q(t)*) after each intervention task is completed (Figure 5) – the analysis output.

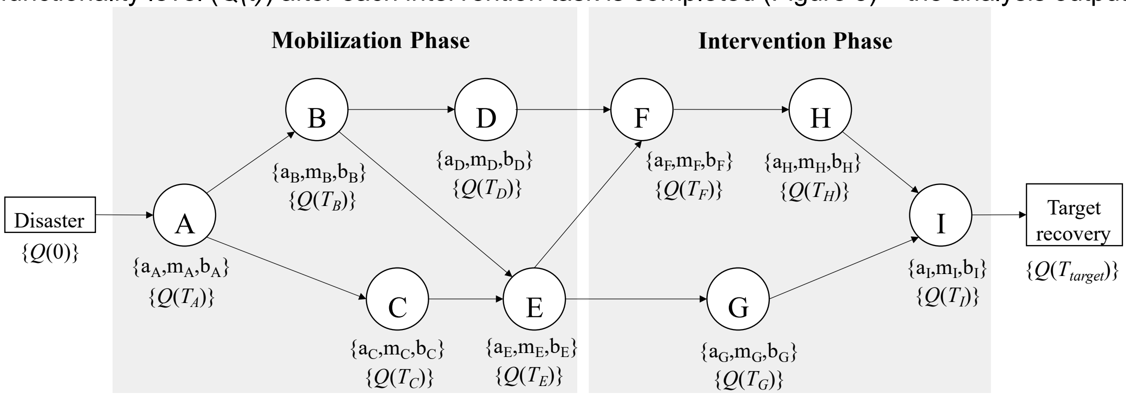


Figure 5 – Stochastic network analysis for recovery trajectory modelling

Application

Overview

The proposed framework is illustrated through two case studies (and multiple scenarios for each case study) to model the post-earthquake recovery of a synthetic small-scale residential community with a population of 22,500 people (Figure 6). Each case study intends to demonstrate how local authorities can adopt the proposed framework as a disaster risk management tool for specific objectives.

The synthetic residential community consists of a building stock of 450 reinforced concrete (RC) frame buildings comprising 150 two- and 300 four-story frames. Most buildings in the residential community (90%) are assumed not designed to modern seismic codes and are susceptible to non-ductile behaviour. The remaining 10% of the building stock is code-conforming.

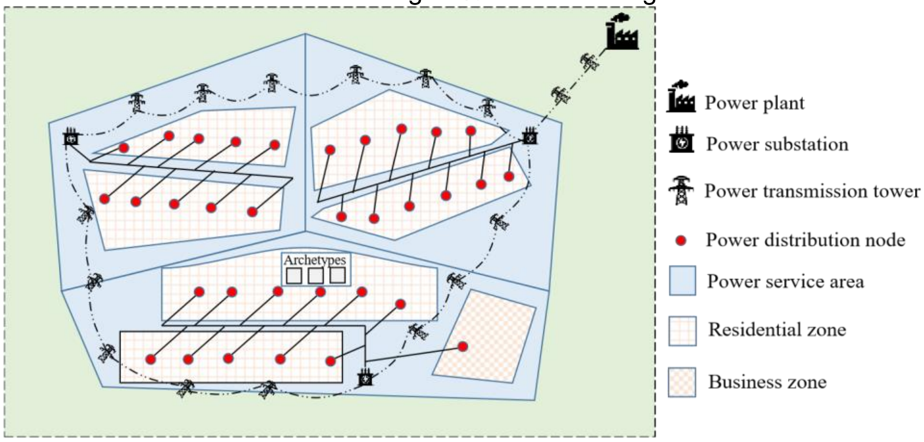


Figure 6 – Case study community

Hazard analysis

The recovery modelling of the community is carried out for a moment magnitude 7 scenario occurring from a normal fault situated about 20km from the community. A V_{s30} of 360m/s is assumed for the community as a whole. The hazard analysis uses the Campbell and Bozorgnia (2014) ground-motion model to derive spectral accelerations at the building locations, substation sites, and distribution nodes. Furthermore, the Markhvida et al. (2018) approach generates 1,000 realisations of spatially cross-correlated spectral intensities at the building locations, substation sites, and distribution nodes using Principle Component Analysis.

Case study 1: Impact of socioeconomic factors on long-term community-level recovery

This case study demonstrates how the proposed methodology can capture the influence of socioeconomic factors on long-term community-level recovery, specifically rehousing of displaced people. Three scenarios are considered – scenario 1-1 is an ideal scenario with no recoveryimpeding factors on reconstruction projects. Scenario 1-2 simulates a scenario where community conflicts and bureaucratic delays influence post-disaster reconstruction; scenario 1-3 represents a scenario with material procurement, construction worker skills, and funds issues. A similar workforce (i.e., 80 crews) is assumed for all scenarios.

The probable functionality level of each building is estimated by combining the fragility functions for the structural and non-structural systems with the IMs (spectral acceleration at 1s) at the building site. The seismic fragility models of the structural systems and non-structural components are based on Villar-Vega et al. (2017) and FEMA (2022), respectively. For each of the thousand realisations of spatially correlated spectral accelerations that were simulated, the post-disaster functionality level of each building is evaluated as described in the methodology section.

Given that the case study looks at long-term recovery, the recovery analysis focuses on reconstructing buildings recommended for reconstruction. The calculation assumes that all displaced households are in temporary shelters until permanent buildings are reconstructed. A key assumption in this analysis is that no life was lost during the disaster, and each displaced household is provided with a new one-story single-family residential house.

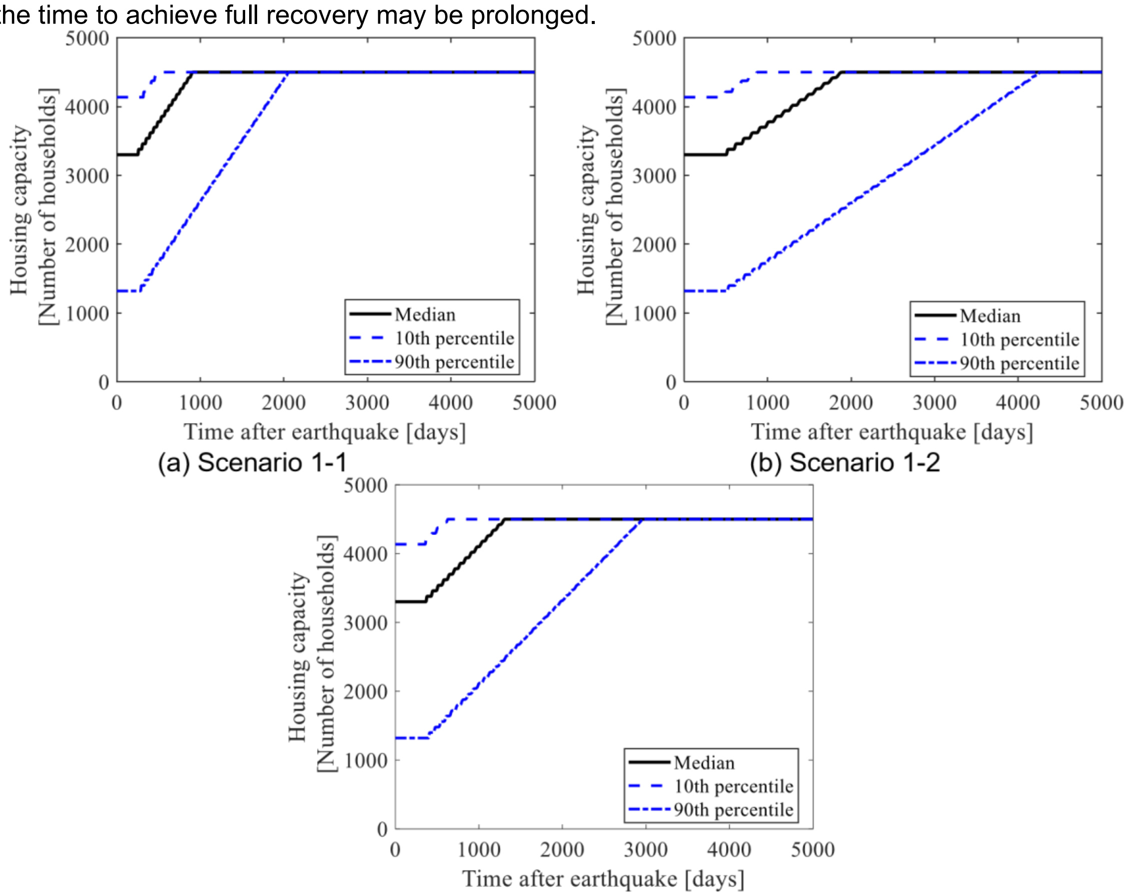
The intervention sequence of the reconstruction process entails sourcing for reconstruction funds, planning, and building design, securing relevant permits, tender process and contracting engineers and builders, site clearing, site mobilisation, and construction. The average time to complete each task in an ideal pre-disaster situation (w), adopted in Equations (2) and (3), for the reconstruction projects are based on information derived from actual construction projects of onestory single-family residential houses in Palu, Indonesia. The time amplification factors considered for each task and each scenario (to estimate the pessimistic time *b*) are based on the maximum of the range presented in Table 1. A unity factor is used to estimate the optimistic time (*a*). The most likely time is assumed to be 0.5(*a*+*b*).

Figure 7 compares the recovery curves of the three considered scenarios. As shown in the figure, accounting for socioeconomic factors significantly increases the time required for several families to return to permanent housing.

According to the case study, community conflicts and bureaucratic delays increased communitylevel recovery time to more than five years (twice the period required in scenario 1-1).

Decision-makers could use such information to develop appropriate mechanisms that can ensure full recovery in communities susceptible to communal conflicts, especially in cases where postdisaster conditions could escalate such conflicts.

Delays associated with material procurement, construction worker skills, and funds issues (scenario 1-3) could result in less downtime than in scenario 1-2. This is attributed to the fact that funds issues may be present during the initial phases of the project (the case assumed in the analysis). However, if funds-related issues are prevalent in each phase of the recovery project, the time to achieve full recovery may be prolonged.



(a) Scenario 1-1

(b) Scenario 1-2

(c) Scenario 1-3

Figure 7 - Community-level housing capacity restoration for (a) Scenarios 1-1; (b) 1-2; and (c) 13.

Case study 2: Impact of structural retrofit policies on long-term community-level recovery

This case study demonstrates how the proposed methodology can capture the influence of retrofit policies on community resilience. This study assumed a similar social vulnerability index for the entire community. Hence, the selection of low-code buildings for retrofit is based mainly on distance from the fault (i.e., low-code buildings closer to the fault are considered for retrofit). This assumption is adopted because the same fragility functions were adopted for the buildings (but different sets of fragility functions for different building heights). The fragility functions for the retrofitted buildings are based on Opabola et al. (2021).

Four scenarios are considered. Scenario 2-1 assumes no retrofit (i.e., 90% of the entire building stock remains non-ductile). Scenario 2-2 considers retrofit of 25% of the total low-code buildings closest to the fault (irrespective of the number of stories) – a total of 101 buildings are retrofitted. Scenario 2-3 considers retrofit of 50% of total low-code buildings closest to the fault. Scenario 24 assumes retrofit of 75% of the total low-code buildings closest to the fault. Finally, scenario 2-5 considers retrofit of all low-code buildings.

Regarding recovery-impeding factors, only delays due to material procurement are considered. A similar workforce (i.e., 80 construction crews) is assumed for all scenarios.

Figure 8 compares the normalised median post-earthquake housing capacity (defined as the ratio of the number of non-displaced households to the total number of households), the median time to achieve full community recovery (i.e., construct all new permanent houses), and the proportion of retrofitted low-code buildings. For example, as shown in the figure, retrofitting 50% of the lowcode buildings increases the normalised median post-earthquake housing capacity to 90% (from 70%) and reduces the median full recovery time by 40%.

Case study 2 is relevant in cases where local authorities want to identify buildings that need to be prioritised for retrofit because retrofitting such buildings significantly enhances community-level recovery.

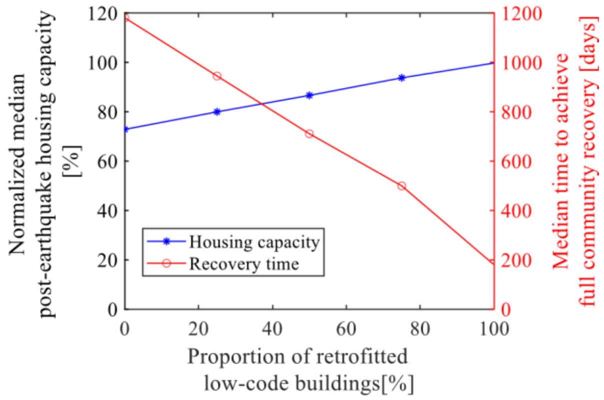


Figure 8: Relationship between normalised median post-earthquake housing capacity (defined as the ratio of the number of non-displaced households to the total number of households), the median time to achieve full community recovery (i.e., construct all new permanent houses), and the proportion of retrofitted low-code buildings

Conclusions

Local authorities and decision-makers need to access efficient and reliable disaster planning and management tools to achieve desirable levels of community resilience. This study proposes a probabilistic framework for modelling the post-disaster recovery pathway of a community while accounting for technical, socioeconomic, political, environmental, and cultural factors that can impede or speed up post-disaster recovery. The output of the proposed framework is the probabilistic distribution of recovery times and various resilience indicators (e.g., the proportion of displaced households).

The proposed framework is demonstrated using a hypothetical community subjected to an earthquake scenario. The case study is used to capture the influence of various technical, environmental, socioeconomic, political, and cultural factors on post-disaster housing reconstruction. The analysis shows that, due to negative socioeconomic, political, and cultural factors, internally displaced people might remain homeless for up to five years after the disaster. The analysis also shows how community-level building retrofit policies can be designed by accounting for the quantified benefits of the retrofit to improve community resilience.

Based on the outcome of the case study, it is recommended that local authorities invest in policies that ensure the considered factors (i.e., consider the influence of conflicts within the community, bureaucratic delays, lack of community participation, and poor onsite construction management) are mitigated.

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