Quantification of economic benefits of functional recovery-based design: a stepwise review of the methodology

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ABSTRACT

Most building codes and seismic design standards in many earthquake-prone countries, such as New Zealand, are life-safety-focused. However, learnings from past major events and recent research direction have called for recovery-based design that considers both life safety and functionality of buildings post-hazard to aim for higher community resilience. Accordingly, functional recovery has been introduced as a link between building-level and community-level resilience objectives. However, functional recovery-based design still requires a firm rational foundation in terms of its benefits relative to the additional cost it incurs compared to the current life-safety-centred design philosophy. Drawing upon available frameworks, this paper aims to provide a step-by-step review of the existing methodology for quantification of the economic benefits of implementing explicit functional recovery targets in seismic design standards. The methodology consists of four steps: 1. seismic risk assessment to quantify direct losses and determine the robustness, 2. estimation of the pre-repair timeframe to account for the time it takes to conduct actions required before the restoration can begin, e.g. financing and repair mobilization, 3. estimation of the duration of utility infrastructure disruption, which would inhibit the restoration of functionality to individual buildings, and 4. economic recovery simulation to quantify the indirect economic losses and rapidity of the recovery process. A review of the existing models and available analytical approaches required within each step is conducted, strengths and shortcomings are discussed, and gaps are identified for future research.

1 INTRODUCTION

Building design standards have evolved throughout the years to ensure life-safety by enforcing minimum requirements at component-level design (Mahmoudkalayeh and Mahsuli 2021). Where properly calibrated and enforced, these standards have been able to achieve a target risk in terms of life-safety in past earthquakes (NIBS 2019). However, the life-safety-centred philosophy behind these standards does not explicitly aim for continued functionality or mitigation of downtime post-hazard (Li et al. 2023). In fact, even communities with buildings built according to the leading codes have been unable to avoid long restoration periods after disastrous events. This has been observed in the 2010-2011 Canterbury Earthquake Sequence in Christchurch, New Zealand (NZ), where over 60% of multi-storey reinforced concrete buildings in the Central Business District were replaced (Marquis et al. 2017), and more than ten years later, restoration is still underway (Li et al. 2023). Indeed, such a long restoration timeframe has signified a considerable mismatch between the target performance objectives of building standards and society's expectations of how buildings should perform in a seismic event (Horspool et al. 2023).

In wake of the recent events raising awareness about the need for a "better than code" design (Li et al. 2023), and the technical and scientific advancements making it possible to gain greater resilience at the expense of reasonable investments (Almufti and Willford 2013), the concept of Resilience-based Design has been proposed. Resilience refers to the ability of a community to withstand a disruption and recover from it within a desirable timeframe (FEMA-NIST 2021). As such, resilience aims for two objectives: Robustness and Rapidity. Robustness refers to the strength of the system to withstand a given level of demand and remain functional after the disruption and is indicated by the remaining performance of the system. Rapidity, on the other hand, refers to the speed with which the performance is restored and is indicated by the slope of the recovery curve, which is a curve depicting how performance of the system changes throughout the recovery period (Bruneau et al. 2003). Improving community resilience is a complicated and long-term objective that requires a wide range of mitigation plans, one of which is to explicitly design new buildings for such an objective. However, building standards prescribe minimum requirements on a building-level, which does not directly translate to resilience on a community-level. As such, there is a need to properly link community resilience objectives to design targets for individual buildings. Two concepts have been proposed in the literature to serve as this link: *reoccupancy* and *functional recovery*. Reoccupancy is the state at which the building is safe to enter and be used as shelter. Functional recovery is a step beyond reoccupancy, in which buildings can safely and adequately provide their "basic intended functions" following a disaster. The ability of a building to support its basic intended functions is defined as a performance state in-between full pre-disaster functionality and what would be deemed enough for reoccupancy (FEMA-NIST 2021). As such, functional recovery necessitates not only the building itself to be functional, but also such utility infrastructure networks as water distribution and power supply network, which provide various services to the occupants, to be serviceable (Almufti and Willford 2013). Finally, full functionality follows functional recovery, where pre-disaster functionality is fully restored (FEMA-NIST 2021).

As functional recovery is a relatively novel concept, design criteria for functional recovery-based design do not yet exist (NIST 2022) to determine the explicit changes to current design and construction practices needed to realize a desirable recovery timeframe post-hazard. However, two concepts have been developed in the literature in response: 1. Low-damage design and 2. Repairability-based design. Low-damage components and design techniques help to mitigate the sustained damage due to a disaster. Examples of low-damage designs are the use of low-damage structural and non-structural components, supplemental energy-dissipating systems, or base-isolation technologies (Almufti and Willford 2013). Repairability-based design proposes more stringent component-level strain and deformation limits or higher minimum building-level strength and/or stiffness requirements within building standards to provide a higher probability of repairability post-hazard. This, in turn, enhances the robustness and promotes a more rapid recovery. However, low-damage components, novel design techniques, and more stringent design criteria often lead to an increase in demand for material, equipment, and labour from construction industry as well as a need for higher-performance materials, all of which incur a higher initial construction cost. Experience indicates significant opposition among those stakeholders who bear the upfront additional costs against changes to the code that bring up even the slightest of cost increases. As such, a change towards functional recovery-based design needs a firm rational foundation in terms of its benefits relative to the additional cost it incurs (FEMA-NIST 2021). The benefits comprise a wide range including direct and indirect economic, social, and environmental benefits (Habibi et al. 2023) and are distributed across various stakeholders (NIST 2022). Direct economic benefits are monetary savings in terms of lower repair costs, while indirect economic benefits are expressed as mitigation of loss of economic activity or as reduced business interruption, displacement costs, and rental expenses. Social benefits are lives saved, injuries prevented, and less tangible benefits, such as mitigation of loss of cultural heritage and social connectedness. Environmental benefits are reduced environmental impacts caused by the restoration process in terms of carbon emission and used embodied energy (FEMA 2018a; NIST 2022). This paper provides a step-by-step review of the existing frameworks for quantification of the economic benefits of a functional recovery-based design and the available models and analytical approaches required for such a quantification in the literature. Strengths and limitations of each approach are discussed, and gaps are identified for future research.

2 THE METHODOLOGY

Drawing upon existing literature, the method by which to quantify the economic benefits of a functional recovery-based design consists of four steps: 1. seismic risk assessment, 2. estimation of the pre-repair timeframe, 3. estimation of the duration of infrastructure disruption, and 4. economic recovery simulation. These steps and how they are linked to each other are shown in Figure 1. In the following subsections, several existing frameworks and available approaches in the literature for each step are discussed respectively.

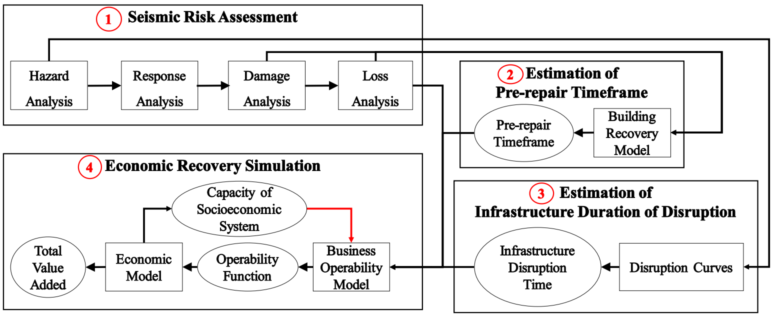

Figure 1: General framework for quantification of the economic benefit.

2.1 Seismic Risk Assessment

A seismic risk assessment quantifies the level of damage to buildings and the subsequent probability distribution function (PDF) of losses due to an earthquake. Multiple frameworks, such as FEMA P-58 (FEMA 2018a) and FEMA-NIBS (2012), which have been developed by the Federal Emergency Management Agency (FEMA) and the National Institute of Building Sciences (NIBS) in the United States (US), exist to fulfil such a purpose. The former framework has been applied in the Performance Assessment Calculation Tool (PACT) (FEMA 2018b) and SP3 software tool (Haselton Baker Risk Group 2024) and the latter in the Hazards-United States (HAZUS) software (FEMA-NIBS 2012). These frameworks are based on the framing equation proposed by the Pacific Earthquake Engineering Research (PEER) centre as follows:

$$\lambda(DV > dv) = \iiint G(dv|dm) \cdot \mathrm{d}G(dm|edp) \cdot \mathrm{d}G(edp|im) \cdot |\mathrm{d}\lambda(im)| \quad (1)$$

where λ represents the annual exceedance rate, $G(.)$ is the complementary cumulative distribution function, DV is the decision variable, DM is the damage measure, EDP is the engineering demand parameter, and IM is the intensity measure (Cornell and Krawinkler 2000). As such, this framework requires four levels of analysis: hazard, response, damage, and loss analysis. These are explained further in the following.

The main output of a hazard analysis is the hazard curve, which shows the exceedance probabilities of the intensity measure, e.g. peak ground acceleration, at the building site. There are both deterministic and probabilistic approaches to conduct a seismic hazard analysis. The former considers an earthquake scenario with a specific magnitude and a fixed location and calculates the intensity measure using attenuation relations (Abrahamson 2006). In the latter, all the sources of aleatory and epistemic uncertainties are to be considered.

This requires probabilistic models including occurrence, magnitude, rupture location, and ground shaking intensity models (Mahsuli et al. 2019; GNS Science 2022), where all the local seismic sources are considered. The conventional method for a probabilistic seismic hazard analysis is based on the theorem of total probability, which requires identification of all the local major sources of seismicity and their characteristics, definition of the PDF of magnitude and distance for each source, and the use of attenuation relations to establish the exceedance probability of the intensity measure from any target value. Reliability and scenario sampling methods have also been implemented to conduct probabilistic seismic hazard analyses in the literature. In reliability methods, the exceedance probability of the intensity measure from any target value is assessed by integrating the joint PDF of a set of random variables over the area in which the intensity measure exceeds the target value. Scenario sampling method is based on Monte Carlo sampling, in which the probability distribution of the maximum intensity measure over the lifespan of the building is obtained by simulating enough samples using various probabilistic models (Mahsuli et al. 2019; Rahimi and Mahsuli 2019).

Thereafter, the response analysis determines the PDF of building response given the intensity measure and capacity of the structure. This demands a response model, which can adequately represent the behaviour of all the structural elements contributing to the strength and stiffness of the building. Different types of response modelling approaches can be classified under three major categories: 1. Lumped-plasticity models, 2. Fibre element models, and 3. Continuum finite element models. In lumped-plasticity models, structural elements are modelled to behave elastically, and the nonlinearity in response is captured by rotational springs located at points where plastic hinges are expected to be formed (Lignos and Krawinkler 2011). A moment-rotation diagram is assigned to these springs based on the geometrical and material properties of the element as well as its loading conditions and how its pre- and post-yield stiffness/strength capacity, deformation capacity, and deterioration behaviour depend on these characteristics (Lignos et al. 2019). On the other hand, fibre element models consider several fibres along each dimension of the element and assign a stress-strain diagram to each fibre, which accounts for material properties of the element and its potential failure modes (Karamanci and Lignos 2014). Finally, continuum finite element models divide each structural/non-structural component into several nodes and elements with corresponding material properties. These models are not common for modelling the seismic performance of buildings but are rather used to model complex behaviour of a single component with more detail. After modelling, building response is analysed under a given loading protocol. There are two types of response analysis methods commonly used to determine the response in a seismic risk assessment: 1. Static pushover analysis (SPA) and 2. Dynamic time-history analysis (THA). In an SPA, the building is pushed under a specific loading protocol, e.g. story shears in the dominant mode of vibration, until a target roof drift is met. The outcome of an SPA is a pushover or capacity curve, which plots the building lateral resistance versus its lateral displacement (FEMA-NIBS 2012). In a THA, the structure is analysed under a set of ground motions recorded during a past event. As a simplified approach, HAZUS (FEMA-NIBS 2012) proposes the capacity spectrum method, which gives an estimate of the response based on a single degree of freedom simplification as a performance point where demand and capacity spectra meet.

Given the building response to seismic excitations, the damage analysis then determines the damage state of all the components within the building. This requires damage fragility curves, which specify the probability of exceeding the onset of multiple discrete damage states given the response. Each damage state corresponds to a detailed description of the damage to the component requiring a specific set of repair actions. FEMA P-58 (FEMA 2018b) provides such component-level fragility curves for many structural and non-structural components. Recently, the Applied Technology Council (ATC) has provided an extension to the FEMA P-58 framework as ATC-138 (ATC 2021; Cook et al. 2022), in which the ability of the building to meet reoccupancy and functional recovery, given the damage state of its components, is evaluated using a series of fault trees. On the other hand, the FEMA-NIBS framework provides global-level fragility curves for three general categories of structural, non-structural drift-sensitive, and non-structural acceleration-sensitive components.

The advantage of the latter framework is its lower computational demand as the response is estimated at a uniform value across the height, whereas FEMA P-58 requires quantification of the response at each story.

Finally, the loss analysis determines the PDF of various loss types, given the damage measure, using consequence functions. Consequence functions determine the median and corresponding variability of losses at each damage state. FEMA P-58 (FEMA 2018b) provides component-level consequence functions for all the considered structural and non-structural components. The loss types considered in this framework are direct economic losses due to repair/replacement costs, indirect economic losses due to repair time, social losses due to fatalities and serious injuries requiring hospitalization, and environmental impacts due to emission of carbon dioxide and use of embodied energy to repair/replace the building. Similarly, the FEMA-NIBS framework (FEMA-NIBS 2012) provides repair cost consequence functions for structural, non-structural drift-sensitive, non-structural acceleration-sensitive, and content components based on their damage measure and building occupancy class. It also provides casualty, repair time, and downtime consequence functions at the building-level as a function of the building occupancy class and its structural damage state.

2.2 Estimation of the Pre-repair Timeframe

After the damage to the building and the associated losses are quantified, the recovery trajectory is simulated. However, for the recovery to begin, there are several pre-requisite measures to be taken beforehand. These include an inspection of the damage, conducting clean up and temporary repairs, gathering the required financial resources for the repair, mobilizing a team of engineers to redesign the building or its components if required, mobilizing contractors to do the repairs, and acquiring required permits for the restoration project (ATC 2021; Cook et al. 2022). These are called impeding factors as they impede the onset of repair, and the longest time it takes to deal with all these impeding factors is the pre-repair timeframe. Impeding factors have the potential to significantly delay the restoration of functionality (Almufti and Willford 2013; Marquis et al. 2017). ATC-138 (ATC 2021; Cook et al. 2022) provides truncated lognormal probability distributions with suggested median values and lognormal standard deviations for the effects of the impeding factors on delaying the onset of restoration given the sustained damage, incurred repair cost, and estimated repair time. Although pre-earthquake contingency plans, such as having pre-arranged resources on retainer, can reduce the effects of the impeding factors, the most reliable method to limit the pre-repair timeframe is by inhibiting the sustained damage in the first place (Almufti and Willford 2013). As such, functional recovery-based design has the potential to significantly shorten the duration of pre-repair timeframe through achieving a higher robustness.

2.3 Estimation of the Duration of Infrastructure Disruption

Functional recovery means regaining comfort and liveable condition as well as resumption of the basic intended functions, e.g. business activity within an office. This necessitates restoration of power, water, lighting, elevator operation, heating, ventilation, air-conditioning, cooling, and fire extinguisher systems (Almufti and Willford 2013), which in part depends on the serviceability of utility infrastructure systems. As such, to quantify functional recovery timeframe, there is a need to estimate the expected time during which infrastructure systems would be disrupted after a given earthquake. In fact, the recovery timeframe of infrastructure systems may have a predominant effect on the recovery curve (Cardwell 2022) and subsequently, on the overall economic benefit of a functional recovery-based design. One area for future research is to closely examine this effect to see at which point, functional recovery-based design of individual buildings loses its advantage because of inability of infrastructure systems to provide the intended services due to their sustained damage. However, quantification of infrastructure disruption time involves several complexities due to interdependencies and redundancies within and in-between systems as well as their scattered geographical distribution throughout a region. Nevertheless, there are some research studies on the estimation of the duration of infrastructure disruption following an earthquake. Such estimations are provided as infrastructure disruption curves. The vertical axis of these curves represents the probability that services could be restored within the corresponding time on the horizontal axis, given the intensity measure. HAZUS provided such curves for utility and lifeline infrastructure systems based on the data from the ATC-13 project (ATC 1985). The considered utility infrastructure systems comprise potable water, wastewater, oil distribution, natural gas, electrical power, and communication networks. Several components are considered for each utility infrastructure system, and a damage fragility curve is introduced for each component. Each damage state is then attributed to a median restoration time and a corresponding dispersion within a lognormal probability distribution. More recently and as part of the Resilience-based Earthquake Design Initiative for the Next Generation of Buildings (REDi) project, Almufti and Willford (2013) provided such disruption curves for several categories of infrastructure services due to a design-level earthquake. The considered infrastructure systems comprise electrical power network, water distribution, wastewater, natural gas, and telecommunication systems. Among them, electrical power, water, and natural gas networks were found to control the total disruption time of infrastructure systems.

2.4 Economic Recovery Simulation

The last step is to simulate the economic activity following the shocks generated by the earthquake to evaluate the overall disaster-induced economic impact across the whole economy. This step requires two models: 1. Business operability model and 2. Economic model. The former calculates business operability functions, given the outputs of steps 1 to 3 for all the individual buildings and utility infrastructure systems within the community, i.e. loss values, delays due to the impeding factors, and infrastructure disruption time. Operability shows the ability of a business to meet its demand after a disruptive event as a percentage of the normal output (Cardwell 2022). Operability values then enter the economic model to derive actual production of businesses and subsequently, their economic activity in terms of the annual value-added, during the recovery period. In the following, different types of available business operability and economic models in the literature as well as how they are linked to each other are discussed.

There are various economic models available for an economic recovery simulation, some of which are Input-Output (I-O), Computable General Equilibrium (CGE), and Dynamic Equilibrium-Seeking (DES) models. I-O models describe the final demands in any sector of the economy based on the relationships between suppliers and producers within the economy with an emphasis on the interdependencies between different branches. In other words, I-O models assess the flow-on impacts of changes in the production of one sector on any other dependent sector through supply chain mechanisms (Miller and Blair 2009). The original formulation of I-O modelling is demand-driven, in which final demands by end consumers are exogenously determined, and total production output has a linear relationship with the final demand. This linear relationship is defined through the introduction of a technical coefficients matrix, which determines how total outputs depend on inter-industry transactions (Galbusera and Giannopoulos 2018). An issue with the use of I-O models for assessing the impacts of natural disasters is that the impacts may be double counted as the losses of a firm that is directly impacted by the disaster may also be included in the indirect supply chain impacts of other firms that depend on it (McDonald et al. 2017). Another issue is the inability of I-O models to account for inherent flexibilities within the economy, e.g. consumers/producers using alternative suppliers not affected or less affected by the disruptive event to make up for the supply shortages in the aftermath (Hallegatte 2008). Due to this rigidity and the linear relationship within I-O models, their results are often regarded as an upper-bound for the economic impacts of a disaster (NIBS 2019; Botzen et al. 2019).

CGE models equilibrate quantities supplied and quantities demanded through price change mechanisms in every time step of the economic simulation. Multiple agents are considered in CGE models, the most typical of which are households, firms, industrial sectors, local and national governments, factors, e.g. capital and labour, investment and savings account, direct tax on income, indirect tax on production, imposed tariffs on imports, and an external sector to account for imports, exports, and account deficits. In short, CGE models solve a system of simultaneous equations, in which consumption agents, such as households, try to optimize their utility subject to budget constraints, while production agents, such as firms, try to optimize their profit subject to technology and production constraints. Simultaneously, the market clearing conditions must hold, i.e. the supply and the demand must match for both the quantities and the factors (Hosoe et al. 2010). To account for flexibilities within an economic system, CGE models rely heavily on substitution between imported and domestic goods by consumers through the constant elasticity of substitution (CES) function as well as transformation between the domestic and the foreign market (exports) by producers through the constant elasticity of transformation (CET) function (Hosoe et al. 2010; Smith et al. 2016). The extent to which this transformation can happen depends on the elasticity parameter of the CET function, which indicates the sensitivity of the supply ratio between the domestic and export markets to a change in the relative price. The same goes for the CES function (Hosoe et al. 2010). The use of the CES and CET functions in a CGE model substantially moderates the impacts of any shock to the economy. Accordingly, the economic impacts assessed through a CGE model are often regarded as a lower-bound due to the generous elasticity parameters often used (Rose and Liao 2005; NIBS 2019; Botzen et al. 2019). Nonetheless, CGE models have several advantages over I-O models, such as the whole-of-economy coverage, more flexibility in household utility and firms' production functions, definition of resource constraints, modelling consumers' behaviour, and provisions of price information in equilibrium (Tatano and Tsuchiya 2008). Furthermore, unlike I-O models, CGE models are nonlinear and thus, better reflect actual conditions, such as economies of scale (Rose and Liao 2005). However, the effectiveness of CGE models for disaster risk and recovery analyses is limited as they have several shortcomings in their capability to simulate the dynamic post-hazard behaviour of economic agents (McDonald et al. 2018; Cardwell 2022). This is because CGE models are based on optimal decision making of economic agents, which leads to immediate return to equilibrium after any shock to the economy (Tatano and Tsuchiya 2008). That is, CGE models force equilibrium in every time step of the economic simulation, which is in sharp contrast to a realistic situation after a disaster, as for much of the recovery period, prices are expected to be out-of-equilibrium (Cardwell 2022). Moreover, CGE models are of a static nature, which does not allow the dynamic features of a recovery process to be properly captured (Hosoe et al. 2010).

Finally, DES models, introduced by McDonald and McDonald (2020), replicate the main features of a CGE model in a system dynamics framework. Like basic CGE models, DES models repeatedly rely on nested CES and CET functions to account for different alternatives for demand and supply options (Smith et al. 2016). However, unlike basic CGE models, DES models can account for out-of-equilibrium dynamics during and after a disruptive event (Cardwell 2022). DES model variables change in time dynamically and are equilibrium-seeking, but they do not force an equilibrium in every time step as is the case with CGE models (McDonald and McDonald 2020; Cardwell 2022). Moreover, unlike basic CGE models, which provide no information about the causal relationships and transition pathways of the variables of systems between equilibrium states, DES models provide insights into emergent behavioural changes, adaptations during the disruption period, and transition pathways using equilibrium-seeking causal dynamics (McDonald et al. 2018; McDonald and McDonald 2020). As such, DES models can effectively capture the dynamic temporal features of the recovery trajectory of an economy following a disruptive event. A DES-type model is incorporated in the Measuring the Economics of Resilient Infrastructure Tool (MERIT). MERIT is an analytical tool developed by Market Economics in the Economics of Resilient Infrastructure (ERI) research program (Smith et al. 2016), which quantifies economic impacts of disruptive events and evaluates effectiveness of strategies to enhance resilience.

As Figure 1 illustrates, quantification of the economic benefits requires a business operability model in addition to an economic model. In I-O economic models, business operability reduction due to a disruptive event is endogenously incorporated. For instance, a commonly used category of I-O models for disaster-induced impact assessments is Inoperability Input-Output Model (IIM). The output of an IIM is the inoperability vector of all the industries given a perturbation to one element of the economic system. Inoperability is the complementary of operability and shows the inability of a system to provide its as-planned production. An IIM uses a transformation of the technical coefficients matrix called an interdependency matrix

(NIBS 2019), which shows how much additional inoperability is caused by a damaged industry to other industries that depend on it through ripple effects within an interdependent economic system (NIBS 2019). In CGE modelling, on the other hand, the parameters of the CES production functions are calibrated based on the information on changes to sectoral outputs due to input supply disruptions. Accordingly, shocks to such factors of production as capital, labour, and land are first determined using the direct impacts of the disaster. Then, adjustment factors are used to calibrate input variables of production functions. Examples of such inputs are substitution, factor productivity, and land availability (Rose and Liao 2005; Pauw et al. 2011; Kajitani and Tatano 2018). Production functions determine actual production following the disruption and are used to derive operability values in the aftermath. Lastly, in MERIT, operability functions are exogenous to the DES economic model. As such, MERIT consists of two parts: 1. The Business Behaviour Module (BBM) to calculate the operability function of all the industries within the economy, and 2. The Dynamic Economic Model (DEM) to simulate the economic activity using a DES-type modelling approach.

The BBM takes information and data about a hazard scenario as inputs and calculates business operability as a function of the overall disruption to infrastructure and non-infrastructure systems with respect to time. The infrastructure systems considered in the BBM are water distribution, sewerage, electricity, phone, data, gas, road, rail, port, airport, and fuel supply networks (Brown et al. 2015). The experienced disruption to each of these infrastructure systems is calculated as a linear regression model of the duration of disruption based on the survey data from the 2010-2011 Canterbury Earthquake Sequence (Seville et al. 2014). As for the non-infrastructure systems, the experienced disruption to the premises, neighbourhood, and staff is currently considered as a function of the hazard intensity at the building site (Brown et al. 2015; Cardwell 2022). Premises refer to the building, its components, inventory, and equipment, while neighbourhood disruption refers to the damage to adjacent buildings and pavement or access difficulties. Staff disruption reflects impacts of the disaster on the well-being and availability of staff (Brown et al. 2015). Finally, the overall disruption can be measured as the average of the maximum experienced disruptions of the infrastructure and the non-infrastructure systems. After the BBM calculates the operability, this value is given as an input to the DEM alongside the quantity of the damaged built capital and population projections. Finally, the DEM generates economic variables and outputs, e.g. the annual value-added by each industry and prices of all commodities and services (Cardwell 2022).

However, such a linear relationship between the business operability model and the economic model disregards the fact that the recovery trajectory depends not only on the sustained damage and demanded restoration actions post-hazard, but also on the capacity of the socioeconomic system to supply the restoration process with the required resources, e.g. labour and capital. For instance, it is important to see how much repair can be conducted as time elapses based on the availability of staff and equipment/material in the construction industry considering price hikes due to the large demand and limited supply following an earthquake (Hallegatte 2008). This requires a feedback link from the economic model to the business operability model, e.g. from the DEM to the BBM within MERIT, as shown with a red arrow in Figure 1. The feedback link must redefine the operability of businesses as a function of the capacity of the socioeconomic system to supply the required resources for restoration. This, in turn, requires a redefinition of the experienced disruption of infrastructure and non-infrastructure systems as functions of the incurred damage and loss, as shown in Figure 1. Such a mechanism has generally been ignored in the literature; accordingly, there is currently no feedback between the DEM and the BBM in MERIT (Cardwell 2022). A major area of improvement to be investigated by future studies is to add this feedback structure to MERIT. Note that doing so would endogenize the operability function into the DEM.

Finally, to assess the economic benefit of a functional recovery-based design, there is a need to apply the methodology of Figure 1 to two scenarios. In one scenario, buildings are designed and constructed to achieve functional recovery objectives, while in the other baseline scenario, building regulations stay as they are. Figure 2 shows a representative recovery curve for an economy following a disaster in case of both scenarios.

As illustrated in this figure, a functional recovery-based design is expected to lead to a lower decline in the economic activity, i.e. a higher robustness, a shorter pre-repair timeframe due to the impeding factors as discussed, and a faster recovery, i.e. higher rapidity. Aggregating these advantageous effects gives the overall economic benefit per the framing equation proposed by Cimellaro et al. (2010) as follows:

$$B = \frac{\int_t (Q_2(t) - Q_1(t)) \cdot \mathrm{d}t}{\Delta T} \tag{2}$$

where B is the overall economic benefit in terms of value-added in monetary units, $Q_1(t)$ is the economic activity in the current state of the building standard, i.e. status quo, $Q_2(t)$ is the economic activity in the functional recovery-based design scenario, and ΔT is the simulation time. The numerator in Eq. (2) is defined by the area between the dashed blackline and the solid black line in Figure 2. To summarize, Table 1 shows the existing frameworks and available analytical approaches in the literature that are reviewed in this paper. This table is not comprehensive but categorizes the most common methods and state-of-the-art models used to conduct each of the four steps of the basic methodology of Figure 1 in the literature as discussed above.

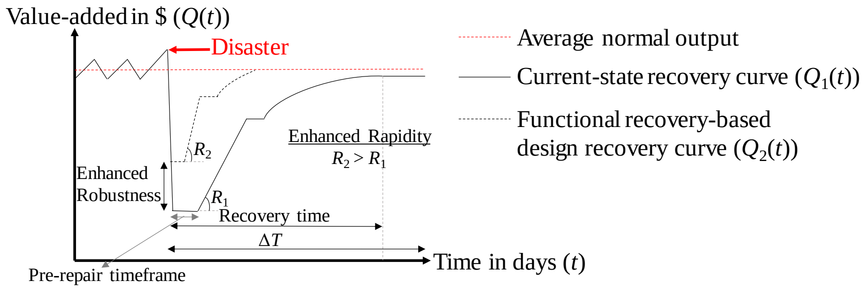

Figure 2: Representative recovery curve for an economic system following a disaster; R is the rapidity.

Table 1: Existing frameworks for quantification of the overall economic benefit that are reviewed herein.

Step	Analytical Sub-step	Existing Approaches/Frameworks Reviewed in This Paper
1. Seismic Risk Assessment	1.1. Hazard Analysis	a. Deterministic methods b. Probabilistic conventional method (total probability) c. Probabilistic reliability methods d. Probabilistic scenario sampling method
	1.2.1. Response Modelling	a. Lumped-plasticity models b. Fibre element models c. Continuum finite element models
	1.2.2. Response Analysis	a. Static pushover analysis b. Dynamic time-history analysis
	1.3. Damage Analysis	HAZUS/FEMA P-58 damage fragility curves
	1.4. Loss Analysis	HAZUS/FEMA P-58 consequence functions
2. Estimation of the Pre-repair Timeframe	No sub-step	ATC-138 building recovery models
3. Estimation of the Duration of Infrastructure Disruption	No sub-step	HAZUS/REDi disruption curves
4. Economic Recovery Simulation	4.1. Business Operability Modelling	a. Interdependency matrix in an IIO model b. Calibration of production function parameters in a CGE model c. Exogenous functions as in MERIT
	4.2. Economic Modelling	a. Input-Output (I-O) models b. Computable General Equilibrium (CGE) models c. Dynamic Equilibrium-Seeking (DES) models

3 CONCLUSION

Recent experiences of long restoration periods following major earthquakes worldwide have pronounced a gap between seismic performance of code-conforming buildings and society's expectations from how they should perform. This alongside the technical and scientific advancements in engineering and construction herald a better seismic design standard that goes beyond life-safety and ensures a desirable recovery timeframe post-hazard as well. Functional recovery-based design has been proposed as a response to this demand as it can provide a greater robustness through low-damage components and design techniques and a higher chance of repairability post-hazard through preventing significant deterioration of structural capacity. However, such a change in the underlying philosophy of design standards incurs a higher initial construction cost, against which significant oppositions may exist. As such, there is still a need to quantify the benefits of functional recovery-based design and to determine whether such benefits can outweigh the associated higher upfront costs. The benefits comprise a wide range from direct and indirect economic savings to mitigation of disaster-induced social and environmental losses. Distribution of these benefits among relevant stakeholders and their relative impact on the decision whether to adopt functional recovery-based design depend on the building occupancy type and importance level among other parameters. This paper presents a stepwise review of the existing methodology to quantify the economic benefits of a functional recovery-based design. The methodology consists of four steps: 1. Seismic risk assessment to quantify direct earthquake-induced losses, 2. Estimation of the time it takes to deal with the factors impeding the onset of repair, 3. Estimation of the time during which utility infrastructure systems are inoperable, and 4. Economic recovery simulation to quantify the economic activity during the recovery period. Several available frameworks and analytical approaches in the literature for each step are enumerated, their strengths and limitations are discussed, gaps are identified, and potential solutions to fill the gaps are introduced.

ACKNOWLEDGEMENT

This project was supported by Te Hiranga Rū QuakeCoRE, an Aotearoa New Zealand Tertiary Education Commission-funded Centre. The QuakeCoRE publication number is 930.

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