A Stochastic Formulation to Assess the Environmental Impact of the Life-Cycle of Engineering Systems

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Abstract

This paper proposes a Stochastic Life-Cycle Assessment (LCA) as a general stochastic formulation to quantify the environmental impact of an engineering system. The assessment is performed in terms of embodied energy, energy consumption, and carbon footprint during the service life of the system. At the same time, its ability to resist a hazard is considered. The proposed formulation is general and takes into account the effects of shocks (robustness) and gradual deterioration (durability), assessing the GHG emissions due to repair or reconstruction after an undesired event. The formulation is used in an example of four-story reinforced concrete (RC) office building, whose construction site is relevantly seismic. Two different seismic design levels are compared.

1 Introduction

Over the last few years, governments around the world have been trying to reduce emissions for limiting global warming. Many governments aim to go beyond the Kyoto targets Protocol (Ochsendorf 2012). The building sector accounts for 30-40 % of all the primary energy consumption and is responsible for 40-50 % of GHG emissions across the world (Ramesh et al.

2010; Luo et al. 2016). As a result, in recent years there has been a great growth of green building rating systems such as the well-known LEED protocol (Leadership in Energy and Environmental Design by U.S. Green Building Council).

The Intergovernmental Panel on Climate Change (IPCC) suggests reducing emissions from buildings by limiting energy consumption, easing renewable energy, and monitoring non-CO_2 emissions (like methane, nitrous oxide, and fluorinated greenhouse gases) (IPCC 2007a). Therefore, the environmental impacts of different design techniques should be carefully considered. At the same time, a general formulation is needed to evaluate the environmental impact considering the entire service-life of engineering systems. Different processes in each stage of the life cycle cause GHG emissions, from the manufacturing and transport of materials to the construction of the system, and from the usage stage to the demolition stage. Even though the greater contribution of emissions is typically due to the use stage, GHG emissions due to the materials and energy production, in addition to the construction stage, play a significant role in the emission reduction (Ochsendorf 2012; Yeo and Potra 2015). Some recent studies focused on the assessment and the optimization of engineering systems (especially for buildings) by minimizing their GHG emissions by performing a Life Cycle Assessment (LCA) in terms of their environmental impact. In this sense, optimizations strategies have been also proposed (Norman et al. 2006; Kumar and Gardoni 2013). The purpose of these studies is to promote the reduction of GHG focusing on emissions at each stage (Seo and Hwang 2001) or identify the phases causing the most significant emissions and the most affecting materials (Welsh-Huggins and Liel 2017; Fay et al. 2000).

However, aspects of sustainability and hazard resistance are often considered separately (Gardoni 2019). Therefore there is a need to base the modern designs of the engineering systems on multidisciplinary considerations balancing sustainability and reliability (Gardoni et al. 2016; Alibrandi and Mosalam 2017; Gardoni 2017; Murphy et al. 2018). In addition, existing sustainability studies typically do not consider the deterioration of engineering systems over time, which might lead to an increase of GHG emissions in the usage stage and well as new emissions due to needed repairs.

Only a few studies have proposed improvements to LCA by considering stages associated with hazard damage and deterioration in the life cycle of the engineering systems (e.g., Padgett and Tapia 2013; Hossain and Gencturk 2014; Welsh-Huggins and Liel 2017) and provided attempts to integrated sustainability and resilience (e.g., Menna et al. 2013; Feese et al. 2015; Alirezaei et al. 2016; Belleri and Marini 2016; Calvi et al. 2016; Dong and Frangopol 2016; Padgett and Li 2016; Wei et al. 2016; Chhabra et al. 2017; Simonen et al. 2018; Liel and Welsh-Huggins 2019; Yang and Frangopol 2019; Faber et al. 2020; Giresini et al. 2020). However, there is still a need for a general stochastic formulation to assess the environmental impact of the life-cycle of engineering systems.

This paper defines a general formulation to predict the environmental impact over time of an engineering system. The assessment is performed in terms of embodied energy, energy consumption, and carbon footprint during the service life of the system (which could be longer than the lifespan of the system if the system needs to be rebuilt). The formulation considers the possible repairs or reconstruction needed due to gradual and/or shock deterioration.

As an example, the proposed formulation is illustrated by computing the environmental impact of a four-story building in Los Angeles, California. The formulation is useful for selecting the most environmentally friendly design and construction activity to reduce greenhouse gas emissions, considering the deterioration and hazard resistance of the engineering system.

The next section reviews previous studies and methods used to develop the proposed formulation. The third section presents the proposed Stochastic Life-Cycle Assessment. In the fourth section, the paper analyzes the example building.

2 Literature review

2.1 Life-Cycle Assessment

The U.S. Environmental Protection Agency defines the well-known Life-Cycle Assessment (LCA) as a "cradle-to-grave" approach (EPA 2008). LCA is the evaluation of environmental emissions during a product's entire lifespan. It analyzes the inflow of material and energy processes and outflow of environmental impacts during the entire lifespan (Welsh-Huggins and Liel 2017). LCA quantifies the consumption of materials, energy, and emissions into the environment and evaluates their impacts and possible solutions to reduce it. There are four steps in LCA (EPA 2008): 1) Goal and scope definition; 2) Life-Cycle Inventory (LCI) or inventory analysis, which includes data collection and calculations to quantify the material and energy transactions of the system; 3) Life-Cycle Impact Assessment (LCIA), which includes evaluation of potential environmental impacts based on the LCI; 4) Interpretation of results, which is the evaluation of the results of the inventory analysis and the impact assessment.

Recent studies include the optimization of systems by minimizing GHG emissions by performing an LCA in terms of environmental impact (e.g., Seo and Hwang 2001; Park et al. 2013; Biswas 2014; Luo et al. 2016). The main goal is to find measures to reduce GHG focusing on 1) construction materials for infrastructure, 2) building operations, and 3) material transportation.

2.2 Life-Cycle Energy Analysis

The Life-Cycle Energy Analysis (LCEA) allows the consideration of all the energy inputs to a system in its life-cycle (Ramesh et al. 2010). The analysis typically includes the following phases: manufacturing, usage, and demolition. Each stage of the life-cycle of an engineering system is associated with energy use. Considering the life cycle of the building allows making long-term considerations. Life-cycle energy use can be distinguished as embodied energy, operating energy, and demolition energy (Ramesh et al. 2010; Fay et al. 2000).

Embodied energy, as well known, includes the acquisition of the sources of energy for all construction stages, including the renovation of the system. It consists of two parts: initial (i.e. the energy incurred for the first construction of the system) and recurring embodied energy (i.e. that for some regular maintenance and replacements).

Operating energy is the part required to ensure prescribed comfort features. For a building, it is the energy for HVAC (heating, ventilation, and air conditioning), domestic hot water, lighting, and running appliances.

Demolition energy takes into account the demolition stage of the construction including the transportation of the waste to landfill sites and/or recycling plants (Ramesh et al. 2010).

Many studies show the differences between the embodied energies of different systems and evaluate strategies for optimizing the energy requirements (Cole and Kernan 1996; Fay et al. 2000). Several studies reported that operating energy has the biggest contribution (80-90%) in the life-cycle energy use of buildings followed by embodied energy (10-20%), whereas demolition energy has a very small share (Cole and Kernan 1996; Ramesh et al. 2010). Even though the greater contribution is due to the operating energy, embodied energy plays a relevant role in emission reduction (Gardoni et al. 2003). In particular, embodied energy assessment allows the evaluation of the performance in terms of energy efficiency, which combines both the costs and the environmental impacts. Embodied and operating energy can be reduced by acting on construction techniques or the choice of materials. As an example, adopting materials that require less energy during manufacturing or locally available or re-using materials and components. However, materials used for the reduction of the embodied energy might have a greater impact on the use phase (Ramesh et al. 2010). Similarly, optimal thermal insulation can reduce operating energy over time but it may have a greater contribution to the embodied energy. The environmental impacts of different life-cycle stages are strongly interdependent, as one stage may affect one or more of the others. The goals should be to reach a balance between Embodied and Operating energy (Fay et al. 2000). Such balance can be reached by looking at the entire building's life.

LCEA can be useful when considering strategies to reduce primary energy use and emissions control. Primary energy includes all-natural sources (all energy products not transformed), it is the energy needed to produce the energy used by the consumer. The energy consumed by the customers is called end-use energy or delivered energy (Fay et al. 2000); Ramesh et al. 2010). For assessing the environmental impact, considering primary energy is recommended. However, energy is only a part of the environmental impact assessment and Life-Cycle Assessment of buildings is needed for a more complete environmental impact analysis.

2.3 Life-Cycle Analysis of engineering systems

Engineering systems are subject to gradual and shock deteriorations (Chanter and Swallow 2007; Choe et al. 2008; Kumar et al. 2009; Kumar and Gardoni 2012; Kumar and Gardoni 2013; Kumar and Gardoni 2014a; Kumar and Gardoni 2014b). Jia et al. (2017) proposed a stochastic formulation, called Stochastic Life-Cycle Analysis (SLCA), which integrates the models of the state-dependent deterioration (Jia and Gardoni 2018a,b) and the state-dependent recovery and resilience analysis (Sharma et al. 2017). SLCA defines the life-cycle performance of a deteriorating system in terms of an indicator or performance measure $Q(t)$, as a function of time t (e.g., the reliability or functionality of the system).

Deterioration models (e.g., Jia and Gardoni 2018a,b) predict the system state as a function of the values of the state variables $\boldsymbol{X}(t)$ that typically change with time due to multiple deterioration events. The deterioration of the system is affected by external conditions/variables at time t, defined as $\boldsymbol{Z}(t) = [\boldsymbol{E}(t), \boldsymbol{S}(t)]$, where $\boldsymbol{E}(t)$ denotes environmental conditions/variables and $\boldsymbol{S}(t)$ indicates shocks/hazards intensity measures. The vector $\boldsymbol{X}(t) = \left[X_1(t) \cdots X_j(t) \cdots X_{n_x}(t)\right]^T$ signifies the state of variables of the system at time t. The set of basic variables included in this vector are material properties, member dimensions, imposed boundary conditions, etc. (Gardoni et al. 2002, 2003). The initial state variables at time $t = 0$ is $\boldsymbol{X}_0 = \boldsymbol{X}(t = 0)$. The system state changes from $\boldsymbol{X}_0$ to $\boldsymbol{X}(t)$ at time t due to multiple deterioration processes.

Sharma et al. (2017) proposed a stochastic recovery model for deteriorated (or damaged) systems. The recovery model is based on modeling the time of the recovery steps and of the occurrence time of possible disrupting shocks (e.g., seismic loads). A work plan can be developed for every recovery process, containing all the required recovery activities. By the combination of deterioration (Jia and Gardoni 2018a,b) and recovery models (Sharma et al. 2017), we can compute $\boldsymbol{X}(t)$ at every time t during the service life of a system. Once the time-variant state variables $\boldsymbol{X}(t)$ are determined, the capacity of the system and the demand that a shock imposes on the system can be defined. Following Gardoni et al. (2002), the capacity of the system can be expressed as

$$C(t) = C[\boldsymbol{X}(t), \boldsymbol{\Theta}_C] \quad (1)$$

where $C[\boldsymbol{X}(t), \boldsymbol{\Theta}_C]$ is the predicted capacity at time t, and $\boldsymbol{\Theta}_C$ is the vector of parameters of the capacity model. The demand due to a shock, with intensity measures $\boldsymbol{S}(t)$ can be written as (Jia et al. 2017; Sharma et al. 2017; Jia and Gardoni 2018a,b)

$$D(t) = D[\boldsymbol{X}(t), \boldsymbol{S}(t), \boldsymbol{\Theta}_D] \quad (2)$$

where $D[\boldsymbol{X}(t), \boldsymbol{S}(t), \boldsymbol{\Theta}_D]$ is the predicted demand at time t, and $\boldsymbol{\Theta}_D$ is the vector of parameters of the demand model. The capacity and demand models can predict the time-variant system performances, measured in terms of $Q(t)$ expressed as

$$Q(t) = Q[C(t), D(t)] \quad (3)$$

For example as in Jia et al. (2017), Sharma et al. (2017), and Jia and Gardoni (2018a,b), $Q(t)$ could be the conditional failure probability, or fragility, at time t given the occurrence of a shock with a given intensity measure or the reliability index of the system (Ditlevsen and Madsen 1996; Gardoni 2017) given the limit-state function $g(t) = C(t) - D(t)$.

2.4 Probabilistic assessment of structural damage

The paper considers earthquakes as the main hazards. If an earthquake occurs, a repair might be needed, which has a corresponding environmental impact. Therefore, a probabilistic assessment of the possible structural damage is needed to then account for the contribution to the environmental impact of the occurrence of a hazard and the post-hazard functionality.

Bai et al. (2009) proposed a probabilistic approach to compute the conditional probability of having specified structural damage (or being in a certain damage state) for a given seismic intensity. Their study proposes a damage state classification developed from the Applied Technology Council (ATC-13) damage factors, the ATC-38 damage state classifications, and the ATC-38 database of building damage. Considering d damage states, the special case of Bai et al. (2009) considers $d = 4$. Table 1 provides the description of each damage state according to Bai et al. (2009).

The probabilistic approach proposed by Bai et al. (2009) is based on the relationship between the performance levels used to define fragility curves (i.e., each performance level P_L is introduced in the definition of the limit state function that defines a fragility curve) and damage states. Damage factors L_k are assigned to each damage state k to quantify the structural damage as a percentage of the portion of the structure that needs to be replaced. To capture the variability in L_k for a given damage state, L_k is assumed to be a random variable with a beta distribution. Once the damage factor is defined, we obtain the total damage factor for a given intensity measure $L_k|IM$. Figure 1 shows the relationship between fragility curves and damage states. The figure shows that the damage states are bounded by the fragility curves.

The constitutional probability of being in each damage state $P_{k|IM}$ can be calculated as the difference between the conditional probabilities of the bounding fragility curves P_{L1}, P_{L2} and

P_{L3} for a given IM. Following Bai et al. (2009), $L|IM$ is assumed to have a Beta distribution as L_k. Considering d damage states, the conditional mean and the variance can be calculated as

$$E[L|IM] = \mu_{L|IM} = \sum_{k=1}^{d} \left(L_k \cdot P_{k|IM}\right) \tag{4}$$

$$Var[L|IM] = \sigma^2{}_{L|IM} = \sum_{k=1}^{d} \left[\left(L_k - \mu_{L|IM}\right)^2 \cdot P_{k|IM}\right] \tag{5}$$

where $\mu_{L|IM}$ is the conditional mean of the total damage factor for a given IM and $\sigma^2{}_{L|IM}$ is the conditional variance of the total damage factor for a given IM.

3 Proposed Stochastic Life Cycle Assessment

3.1 Overall formulation

We propose a general stochastic formulation for assessing the environmental performance over time of an engineering system in terms of its carbon footprint, embodied energy, and energy consumption. The proposed stochastic life-cycle assessment can consider shock and gradual deteriorations in the sustainability analysis and estimation of the GHG emissions throughout the lifespan of a system. The life cycle of engineering systems includes several stages, each stage is associated with energy consumption and GHG emissions. During its life cycle, the system is subject to various hazards and it is likely to need repair after a certain level of deterioration or damage, such repair provides a further contribution of energy. The analysis considers the following phases in a life cycle: construction, usage, demolition, and recovery, where the energy uses are the embodied energy, operating energy, demolition energy, and recovery energy.

Figure 2 presents the flow of the basic steps in the proposed formulation. The formulation starts with the input data that define the characteristics of the engineering system and the external conditions. As we defined in Section 2.3, the initial state variables at time $t = 0$ are expressed by the vector $\boldsymbol{X}_0$; this vector includes variables such as material properties, the geometry of the system, and imposed boundary conditions. The vector of the external conditions/variables at time $\boldsymbol{Z}(t) = [\boldsymbol{E}(t), \boldsymbol{S}(t)]$ is composed of the environmental conditions/variables, $\boldsymbol{E}(t)$ and shocks/hazards intensity measures,$\boldsymbol{S}(t)$. In the System Modeling step, we model the deterioration and recovery/repair cycles of an engineering system throughout its lifespan according to the SLCA proposed by Jia et al. (2017), Jia and Gardoni (2018a,b), and Sharma et al. (2017). The state variables and the capacity and demand models are used to predict the time-variant system performance measures $Q(t)$. Finally, in the Environmental Impact Analysis, we compute the energy use and related emissions at each stage.

3.2 System modeling

Engineering systems alternate phases of being in use or down and are subject to gradual and shock deterioration. We model the system under the deterioration and repair/recovery cycles using the Stochastic Life-Cycle Analysis proposed by Jia et al. (2017), Sharma et al. (2017), and Jia and Gardoni (2018a,b). Taking into account the gradual and shock deteriorations, we define the state variables of the structural system $\boldsymbol{X}(t)$ considering environmental conditions/variables as well as shocks/hazards models. Once the state variables are defined at every time t by combining the deterioration and recovery models, we can compute the capacity of the system using Eq. (1) and the demand that the shock imposes on the system using Eq. (2). In general, all models of capacity and demand that assume the state variables as input can be adopted in the formulation. We model the state variables and calculate the corresponding capacity and demand to predict the system state at each time t, measured in terms of $Q(t)$, which can be, for example, a measure of functionality, reliability, or efficiency. In particular, once the limit-state function, $g(t) = C(t) - D(t)$ is defined, we can calculate the time-variant probability of failure of the system, given the occurrence of a shock with a given intensity measure. At each time t, we can obtain a set of fragility curves by considering different performance levels (or capacities) that define different limit states.

For shock deterioration, we model the occurrence times and intensities of possible shocks that can affect $Q(t)$. Specifically, considering earthquakes as shocks, we model the random occurrence of shocks as a Poisson process, which in general could be either homogeneous (i.e., with constant occurrence rate) or non-homogeneous (i.e., with time-varying occurrence rate). More generally, any random process that can give the probability of occurrence of an event can be adopted. Given the occurrence of a shock, the intensity of the shock can be modeled using commonly used distributions for the specific intensity measure, which are typically site-dependent. Any earthquake intensity measure can be adopted in the proposed formulation. The earthquake intensity is here assumed to follow the distribution calculated using the second-order logarithmic formulation for hazard curves according to Kumar and Gardoni (2013)

$$\ln\{P[S > s]\} = a_1 + a_2 \left[\ln\left(\frac{s}{S_{min}}\right)\right]^2 \qquad s \geq S_{min} \tag{6}$$

where $\ln(\cdot)$ is the natural logarithm, and $a_1 < 0$, $a_2 < 0$ and S_{min} are regional constants that depend on the interpolated site-dependent data. The expression in Eq. (6) is a concave parabola with the vertex at $(\ln(S_{min}), a_1)$. We use only the part of parabola where $s \geq S_{min}$ (i.e., the right portion) in which the hazard curve is monotonically decreasing. Using Eq. (6), we obtain the hazard curve with the annual rate of exceedance, that, considering a short time span (like one year) can be confused with the annual probability of exceedance. Then, considering the time span of the building we obtain the distribution used in our simulation.

3.3 Environmental impact analysis

Carbon Footprint, in terms of "carbon dioxide equivalent" or CO_2e, is a common metric to account for the global warming impact (GWP) of the different GHG. CO_2e quantifies, as well known, the equivalent amount of CO_2 emitted from the different GHGs and is commonly measured in tonnes of carbon dioxide equivalents (tCO_2e).

3.3.1 Computation of emissions

Once the scope is defined and the impact categories which need to be evaluated are decided upon, we can compute the total amount of the CO_2e emissions at each stage, as functions of time and the system state. This formulation is different from existing ones because CO_2e emissions depend on time. The total amount of the CO_2e emissions ($\mathrm{tCO_2e}$) when the engineering system is in use is

$$CO_{2,USE}\left(\left[t_0, t_f\right]\right) = \sum_{i=0}^{n-1} \Delta CO_{2,USE}(t_i, t_{i+1}) \tag{7}$$

where t_0 is the initial time of the usage stage, t_f is the final time of the usage stage that corresponds to the lifespan of the building, n is the index of the last time step, and

$$\Delta CO_{2,USE}(t_i, t_{i+1}) = \left[OE(t_{i+1} - t_i) + EE_d\left(Q([t_i, t_{i+1}])\right)\right] \cdot CF \tag{8}$$

in which OE is the operating energy (kWh), EE_d (kWh) is the recurring embodied energy computed in the time interval Δt needed when the engineering system is in use for maintenance and replacements (this term depends primarily on gradual deterioration), and CF $\left(\frac{\mathrm{tCO_2e}}{\mathrm{kWh}}\right)$ is the conversion factor which corresponds to the equivalency factors. Since EE_d is unknown, it is treated as a random variable in the proposed formulation.

The Operating energy evaluated in the interval Δt is expressed as

$$OE(t) = \int_{t_i}^{t_{i+1}} E_P(t)dt \tag{9}$$

where $E_P = \frac{E_C}{\eta}$, E_C is the energy consumption (a result of the energy simulation), and η is the efficiency of the power plant producing the energy. With η we take into account the percentage of power loss of the power plant. We have to consider the loss to compute the emissions in terms of primary energy. The two quantities E_C and E_P refer to energy consumption (end-use energy or delivered energy) and energy production, respectively. For assessing the environmental impact, it is recommended to consider primary energy.

CO_2e emissions in the recovery stage are functions of the conditional probabilities of being in each damage state. The expected amount of CO_2e emissions (tCO_2e) in the recovery stage $CO_{2,R}$ at any time t, when a hazard occurs, can be expressed as

$$CO_{2,RE} = E\left[CO_{2,RE}|(IM, \boldsymbol{X}(t))\right] \tag{10}$$

where $E\left[CO_{2,RE}|IM\right]$ is the expected value of CO_2e for a given intensity measure.

Construction and recovery phases are evaluated in the same way (i.e., the recovery phase from the state of complete damage is the same as the construction phase plus a demolition phase). Therefore, the total amount of CO_2e emissions (tCO_2e) in the construction stage ($CO_{2,CS}$) can also be expressed by Eq. (10).

The total amount of CO_2e emissions (tCO_2e) in the Demolition Stage ($CO_{2,DS}$) is

$$CO_{2,DS} = \sum_{i=1}^{m} q_i \cdot I_i \tag{11}$$

where m is the number of materials/processes, q_i (kg) is the quantity of engineering system material/process; I_i ($kgCO_2e$) is the impact indicator of the material/process per unit. All the terms of this equation needed to calculate the CO_2e emissions are included in the Demolition Energy. After finding the different amount of CO_2e emissions during the whole life cycle of the engineering system, we can obtain the total carbon footprint during the life-cycle of the engineering system $CO_{2,life-cycle}$ by adding all of the contributions calculated from Eqs. (7), (10) and (11)

$$CO_{2,life-cycle} = CO_{2,CS} + CO_{2,USE} + CO_{2,DS} + CO_{2,RE} \tag{12}$$

3.3.2 Life cycle inventory and energy simulation

After determining the materials and energy processes needed for the system, we convert them into their related emissions. Conversion factors provide information on the amount of pollutants discharged into the atmosphere by a process, fuel, equipment, or specific source. In this analysis, the factor is expressed in tons of CO_2e per tons of material/process/energy.

We make an estimation of the list of activities for each stage of the system. To conduct the inventory analysis in this formulation, we use the Work Breakdown Structure (WBS) to make a list of all the activities. WBS is a decomposition of the project into various hierarchies depending on different levels of detail (California Energy Commissions 2016). Task definition can be determined through the WBS and the activity list. The activity list presents the tasks required for a project. Each activity is a single work task that takes some amount of time and has an identifiable start and finish times. Figure 3 illustrates the first level of a simplified WBS, the entire level consists of mobilization and site preparation, substructure, superstructure, and finishing. Within these levels, there may be further divisions and, finally, a list of activities is obtained.

WBS is the starting point to estimate GHG emission and energy consumption during the stage of the supply of construction materials, as well as the construction, recovery, and demolition stages. Once the activity list is defined, we determine the amount and sources of different construction materials, equipment (work hours and energy consumption), and transport of materials. Then, we can determine the energy use and CO_2e emission required for each task. Once we know the quantities of materials for each activity, we can estimate the emissions from production and transport.

The structural damage is evaluated as a percentage of structural portion replacement of the system for each damage state and related emissions. The CO_2e emissions associated with each damage k, $CO_{2,k}$, are determined to estimate the total amount of emissions during the recovery stage $CO_{2,RE}(t)$, where $CO_{2,RE}(t)$ is calculated based on the data of the Life-Cycle Inventory. The term $CO_{2,k}$ for each damage state can be expressed with the following expression:

$$CO_{2,k} = \sum_{i=1}^{m} q_i \cdot I_i + E_C \cdot CF, \tag{13}$$

where m is the number of materials/energy/processes, q_i (ton) is the quantity of engineering system material/process, I_i $\left(\frac{\mathrm{tCO_2e}}{ton}\right)$ is the impact indicator of material/process per unit, E_C (kWh) is the energy for the construction stage; CF $\left(\frac{\mathrm{tCO_2e}}{\mathrm{kWh}}\right)$ is the conversion factor. All the terms are included in the definition of Embodied energy. The impact indicator I_i provides information on the global warming impact of each component. It includes emissions due to the production and manufacture of materials. The embodied energy and CO_2 emissions are defined deterministically; however, the input variables in Eq. (13) could be modeled as random variables. The energy in the usage stage is given by software like Energy-Plus, VisualDOE, e-Quest, DesignBuilder, Ecotect, or by available data (Ramesh et al. 2010). The Operating energy of a building is given by electricity and fuels for heating, sanitary water, lighting, and appliances.

3.3.3 Modeling of the Damage State

After modeling the system, as mentioned in Section 3.2, the system state at any time t is represented in terms of the performance indicator $Q(t)$, which changes with time due to gradual and shock deteriorations. A recovery operation is needed when the indicator deteriorates beyond a specified (or desired) limit (Jia et al. 2017; Sharma et al. 2017; Jia and Gardoni 2018a,b). We describe the damage of the system at a given time t using the Probability Mass Function (PMF) of $Q(t)$, which gives the probability that $Q(t)$ takes a specific value within a set of possible values. We define different recovery strategies corresponding to each damage state. We also account for the emissions from the energy and materials consumed by deterioration and consequent recovery.

For the k^{th} damage state, we define the mean value of the emissions and a corresponding confidence interval. We then calculate the probabilistic GHG emissions corresponding to each recovery strategy. We assume a Beta distribution for the emissions associated with each damage state and we draw samples from these distributions, $CO_{2,k}$. The expected value of the emissions, $CO_{2,RE}$, for a given intensity measure at time *t*, considering the k^{th} damage state, to account the emissions for the recovery stage $CO_{2,RE}$ is expressed as

$$E\left[CO_{2,RE}|IM\right] = \sum_{k=1}^{s} CO_{2,k} \cdot P_{k|IM}, \tag{14}$$

where $E\left[CO_{2,RE}|IM\right]$ is the expected value of CO_2e for a given intensity measure at time *t*, s is the number of damage states, $CO_{2,k}$ is the emissions associated with each damage state. Eq. (14) is needed for computing the amount of CO_2e emission in the recovery stage.

4 Example

The proposed formulation is illustrated in this section considering a hypothetical four-story office building made in reinforced concrete and located in Los Angeles, California. We apply the general formulation described earlier to calculate the total carbon footprint during the life cycle of the building. This example includes the energy use of construction, usage, demolition, and recovery. Accordingly, the energy uses for each phase are embodied energy, operating energy, demolition energy, and recovery energy.

4.1 Input data and building modeling

The space frame has a floor area of 120 by 180 ft with six frame lines resisting lateral loads in each direction, located in seismic design Category D. So the total amount of slabs for the four floors is 86.400 ft^2 (which means 8,026 m^2). In this example, we compare the environmental impact of the life-cycle of a seismically designed (with the current design standards, Haselton et al. 2008) building and a non-seismically designed building, consisting of only a vertical load resisting system (Williams et al. 2009).

The service life of the buildings is assumed to be 100 years. We assume to only consider shock deterioration due to earthquakes. Because of this, the operating energy is constant for each Δt when the building is in use, and we do not consider recurring embodied energy. Also, we assume that the system state goes back to the undamaged state at the end of the recovery activities and that the building is repaired quickly with respect to the frequency of earthquakes (i.e., each repair is short with respect to the time between consecutive earthquakes.)

The fragility curves are on three different performance levels: P_{L1}, P_{L2} P_{L3} (Hazus Technical Manual 2019). Table 2 reports the parameters mean, μ and standard deviation, σ for each performance level of the fragility curves used for the two different seismic design levels.

The occurrence of earthquakes (considered only in terms of mainshocks) is given by a homogeneous Poisson process, with a constant occurrence rate (Kumar and Gardoni 2012). The earthquake intensity Peak Ground Acceleration (PGA) is calculated with the second-order logarithmic formulation for hazard curves according to Kumar and Gardoni (2013) expressed by Eq. (6). For Los Angeles, the values of a_1, a_2 and S_{min} are found to be -1.949, -0.2688 and 0.005, respectively.

4.2 Environmental impact analysis

The environmental impact analysis is performed by considering first an inventory analysis and then the probabilistic assessment of structural damage. The carbon footprint is expressed in terms of tonnes of carbon dioxide equivalents (tCO_2e).

4.2.1 Inventory Analysis

Before calculating the CO_2e, we conduct the inventory analysis described in Section 3.3.2. The first step is to define the Work Breakdown Structure (WBS) for the construction stage. The WBS is defined using data and activities from the RSMeans database (RS Means Company 2008). Consequently, we can determine energy and CO_2e for each task. CO_2e emissions are evaluated with the impact indicator associated with each material/process and with the conversion factor for the energy contribution. The processes include the acquisition of natural resources, manufacturing of materials, and fuel combustion due to the transport of materials to the construction site. Distances are assumed by considering the suppliers/retailers available near the construction site. The impact indicators of material/process per unit are evaluated with SimaPro LCA Code (SimaPro), not reported here for the sake of brevity and available in Lanza (2017).

Once the WBS is defined for the construction stage, we define a work breakdown structure for each damage state to account for a mean value of emissions (estimating the energy use, the materials required for each level of damage). We consider four different damage states: insignificant, moderate, heavy, and complete. To define WBS for insignificant, moderate, heavy, and complete damage state we take into account a percentage of the material/process/activity of the WBS for the construction phase and following the WBS of the damage considered. Figure 4 shows a schematic Work Breakdown Structure for each damage state. The $CO_{2,k}$ and CO_2e emissions associated with the construction stage are computed using Eq. (13). Table 3 shows the parameters of the beta distribution associated with each damage state.

The building materials inventory was conducted following the design drawings. We estimate the energy consumption in the usage stage by performing an energy simulation following the requirements of the U.S. and the State of California (Alibrandi and Mosalam 2017; California Energy Commissions 2016). The usage stage includes the GHG emissions associated with appliances, lighting, computing, office, air conditioning, lifts, fans, heating, etc. All these aspects are taken into account by eQuest, Quick Energy Simulation Tool (Hirsch 2010) which provides the energy consumption $\mathrm{E_C}$ required for maintaining comfort conditions.

4.2.2 Probabilistic assessment of structural damage

The damage state is modeled by using the probabilistic assessment of structural damage explained in Section 2.4. Figure 5 shows the probability mass function (PMF) of the performance indicator $Q(t)$ that gives the probability of being in the four different damage states (insignificant, moderate, heavy, and complete) as a function of time t.

The conditional probability of being in each damage state for a given IM is the difference between the fragility curves in Table 2. Figure 6 shows the probabilities of each damage state depending on PGA. The seismically designed building is characterized by Insignificant damage for $PGA < 0.3\,g$, Moderate damage for $0.3\,g < PGA < 0.6\,g$ and Complete Damage for $PGA > 1.5\,g$. For the non-seismically designed building, the Insignificant and Moderate damage ends up to $PGA \sim 0.3\,g$, Heavy and Complete damage for $PGA > 0.3\,g$. We can now compute the environmental impacts due to the needed repairs after the damage caused by an earthquake. The expected value of emissions for a given IM for the recovery stage $CO_{2,RE}$ can be calculated using Eq. (14).

4.2.3 Computation of emissions at each stage

We consider the conversion factor (CF) from *The Emissions & Generation Resource Integrated Database (eGRID).* Since the State of California's annual CO_2 equivalent total output emission rate is 555.400 lb/MWh, the same CF is considered for the two buildings.

The total amount of the CO_2e is obtained from Eq. (7) and is assumed to be the same for both buildings. For the case study, the comparison is just among different seismic design levels of the two buildings. Figure 7 shows the annual GHG emissions in the usage stage for the seismically and the non-seismically designed building.

The Operating energy consumption can be calculated with Eq. (9), and it is assumed to be constant in (t_i, t_{i+1}). The time interval is taken to be one year. The energy production to compute the emissions is $E_P = \frac{E_C}{\eta}$. The efficiency coefficient η takes into account the percentage of power losses of the power plant, considering the characteristics of the California power plants, where the percentage power losses of the power plant are calculated based on

EIA data by the total net generation and estimated losses, as in U.S. Energy Information Administration technical documents (2012 and 2014).

CO_2e emissions in the construction ($CO_{2,CS}$), the recovery stage $\left(CO_{2,R}\right)$, the Demolition Stage ($CO_{2,DS}$) are computed according to Eqs. (10), (11), (13), and (14) and by inventory analysis data. Eq. (12) provides the total carbon footprint during the life cycle of the building $CO_{2,life-cycle}$ adding all the contributions. A Monte Carlo simulation is made to account for different sources of uncertainties: fragilities curves, earthquakes occurrence, distribution of PGA and $CO_{2,K}$ (43,817 simulations for the seismically designed building and 22,789 simulations for the non-seismically designed building).

4.3 Results

The main results show that 60% of the emissions during the life cycle occur during the usage stage for the non-seismically designed and 80% for the seismically designed building, respectively. As expected, the percentage difference by about 20% is due to the higher recovery required for a non-seismically designed building. The non-seismically designed building results in a greater amount of emissions due to repair than the seismically designed building.

The comparison for the entire life-cycle between the non-seismically and seismically designed building is proposed. Figure 8 shows a cumulative plot of (a) the tCO_2e of seismically designed building, and (b) the non-seismically designed building due to repairs, considering (as an example) 30 runs of the Monte Carlo simulations. The figure also provides a cumulative plot of the yearly mean value of CO_2e over all the Monte Carlo simulations.

From the expected value of CO_2e emissions when an earthquake occurs - for each realization of the Monte Carlo simulation - we can notice that the consideration of earthquakes results in a greater amount of emissions throughout the lifetime of the system compared to the non-consideration of earthquakes. From Figure 8 one can infer that the consideration of the earthquake for the seismically designed building implies a lower increase of the emissions than the non-seismically designed building. The functional unit used is m^2year. Provided that the graphs of Figure 7 (c) and (d) are almost linear, it is possible to obtain an estimation of the results in terms of the functional unit given by constant values. The seismically designed building shows (c) 37,9 $kgCO_2e/m^2$year with an earthquake and 31,3 $kgCO_2e/m^2$year without an earthquake. The non-seismically designed building shows (d) 45,2 $kgCO_2e/m^2$year with earthquake and 33,9 $kgCO_2e/m^2$year without earthquake.

Figure 9 shows the cumulative plot of a relevant realization of the Monte Carlo simulation that represents the total GHG emissions for the seismically and non-seismically designed buildings. The results from the comparison show that a safer structure may mean a smaller environmental impact for long-term service life. This invalidates the misconception that safer usually means less environmentally friendly, largely based on the initial impact of the construction. Construction of reliable systems may incur higher environmental impact in short term, compared to the environmental impact of unsafe systems, however, as the service life of the system increases the overall environmental impact decreases. In the long run, constructing safe may also mean constructing something more environmentally friendly. For example, if we look at safer structures, it means fewer repairs over a long time for a seismic region.

5 Conclusions

This study proposed a general stochastic formulation for the life cycle assessment of the environmental impacts of engineering systems. The proposed formulation is a useful evaluation tool for making decisions on the selection of the more environmentally friendly design and construction process, to reduce greenhouse gas emissions, considering the hazard resistance of the engineering systems. Decisions made in structural design may have long term sustainability and resilience impact during the life cycle of the system. This formulation is different from the existing ones because the environmental impact is assessed as time-dependent. The proposed formulation can be used for a wide variety of typical engineering system configurations and uses.

The example shows how the formulation works, we made some simplifying assumptions based on the available information. To implement the proposed procedure, missing elements may be added. The example includes structural uncertainties. Future work can be developed in order to take into account uncertainties in calculating the embodied energy and correspondent CO_2 emissions. The results show that more than 70% of the emissions come from the usage stage of the building. Efforts are needed to increase the building's energy efficiency and reduce energy consumption during its use phase. The energy consumption and the carbon footprint due to material manufacturing account for more than 80 % of the total construction stage. Renewable energy in the usage stage, recycled materials, and innovative manufacturing technology in the recovery and construction stage could help reduce emissions.

The consideration of hazards (earthquakes in the case study) results in a greater amount of emissions throughout the lifetime of the system compared to the non-consideration of hazards. Probable hazards and consequent recoveries should thus be included in sustainability analysis. By comparing the seismically designed building with the non-seismically designed building, the results show higher emissions at the end of the service life for the non-seismically retrofitted building. The results from the comparison show that a safer structure means a smaller environmental impact considering long-term service life.

6 Data availability statement

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

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Tables

Table 1 Damage state descriptions proposed by Bai et al. (2009)

Damage state	Description
Insignificant (I)	Damage requires no more than cosmetic repair. Nonstructural repairs are necessary. For nonstructural elements, repairs could include spackling, partition cracks, picking up spilled contents, putting back fallen ceiling tiles, and righting equipment.
Moderate (M)	Repairable SD has occurred. The existing elements can be repaired essentially in place, without substantial demolition or replacement of elements. For nonstructural elements, repairs would include minor replacement of damaged partitions, ceilings, contents, and equipment or their anchorages.
Heavy (H)	While the damage is significant, the structure is still standing. SD would require major repairs, including substantial demolition or replacement of elements. For nonstructural elements, repairs would include major replacement of damaged partitions, ceilings, contents, equipment, or their anchorages.
Complete (C)	Damage is so extensive that the repair of most structural elements is not feasible. The structure is destroyed or most of the structural members have reached their ultimate capacities.

Table 2 Parameters of the fragility curves.

Seismic design level	P_{L1}		P_{L2}		P_{L3}	
	μ	σ	μ	σ	μ	σ
Seismically designed building	0.27	0.64	0.73	0.64	1.61	0.64
Non-Seismically designed building	0.13	0.64	0.26	0.64	0.43	0.64

Table 3 Parameters of the Beta distribution associated with each damage state.

Damage State (K)	**Mean value (tCO_2e)**	**Standard deviation**
Insignificant damage	16.71	3.4
Moderate damage	641.34	35.03
Heavy damage	1,407.23	78.69
Complete damage	3,853.92	217.68

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Table 1 Damage state descriptions proposed by Bai et al. (2009) [5]

Damage state	Description
Insignificant (I)	Damage requires no more than cosmetic repair. Nonstructural repairs are necessary. For nonstructural elements, repairs could include spackling, partition cracks, picking up spilled contents, putting back fallen ceiling tiles, and righting equipment.
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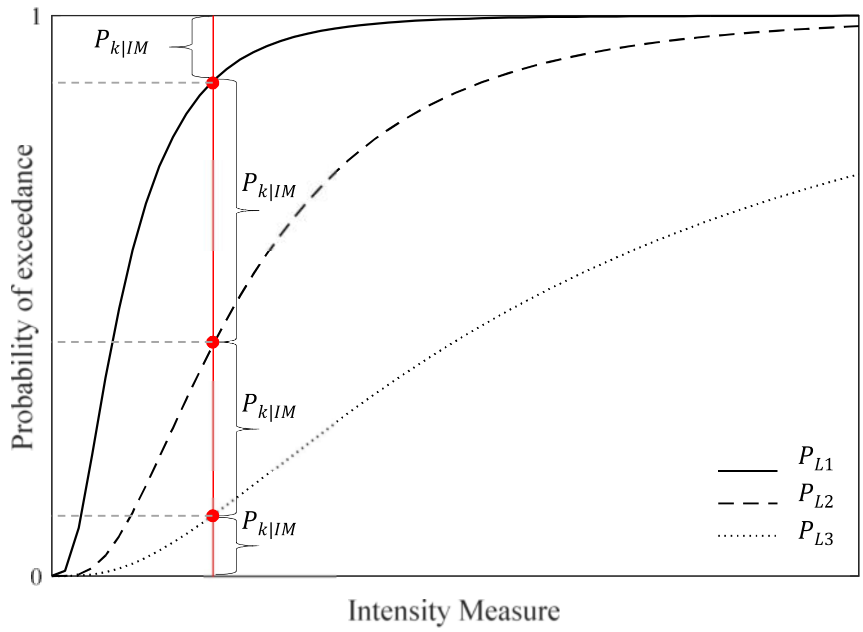
Complete damage	3,853.92	217.68

Figure 1 Illustration of the relationship between fragility curves and damage states



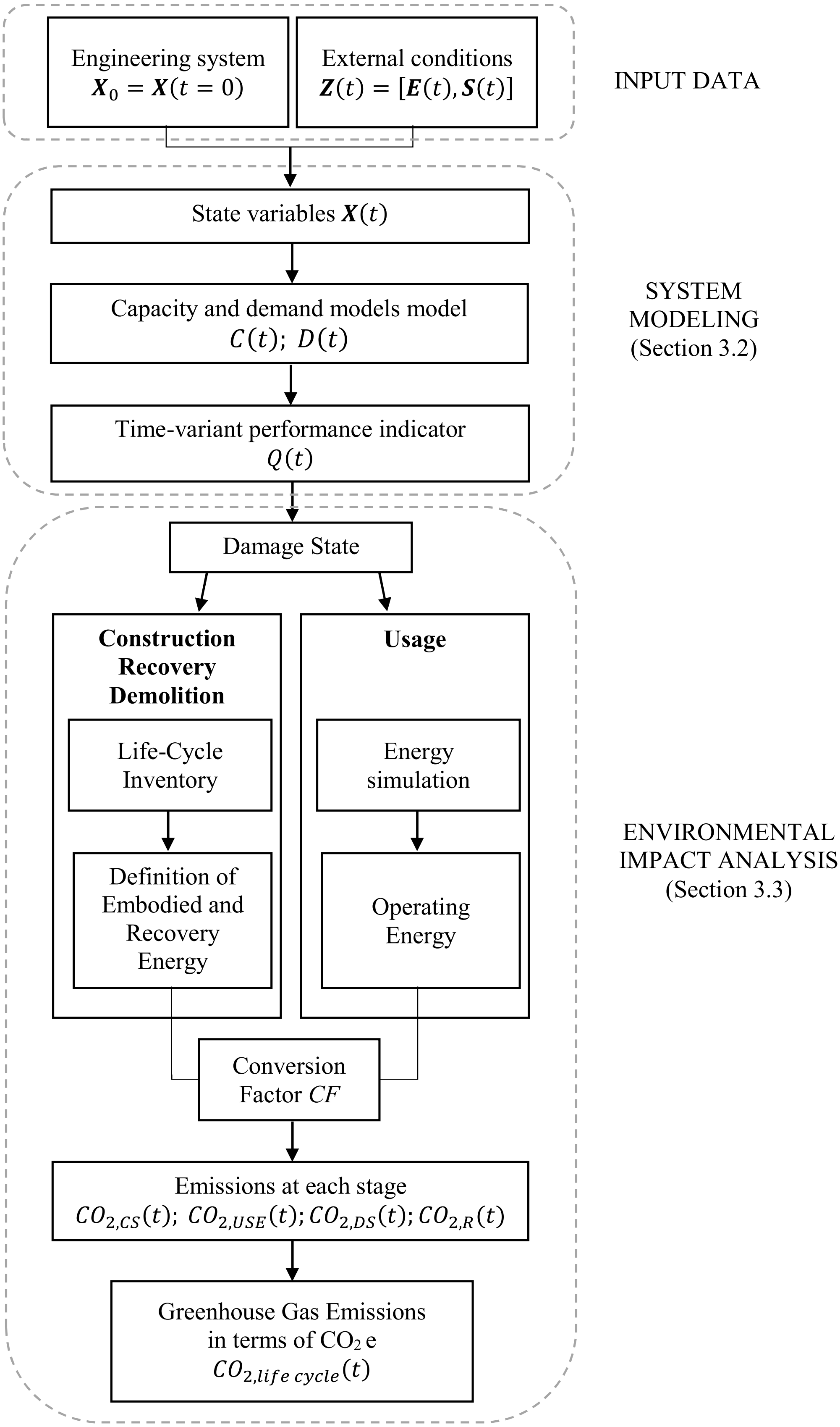


Figure 2 Flow of steps in the proposed formulation

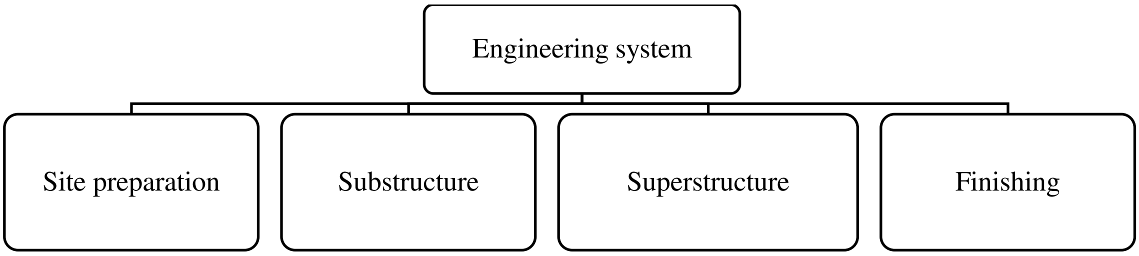


Figure 3 Illustration of a simplified WBS of a generic engineering system.

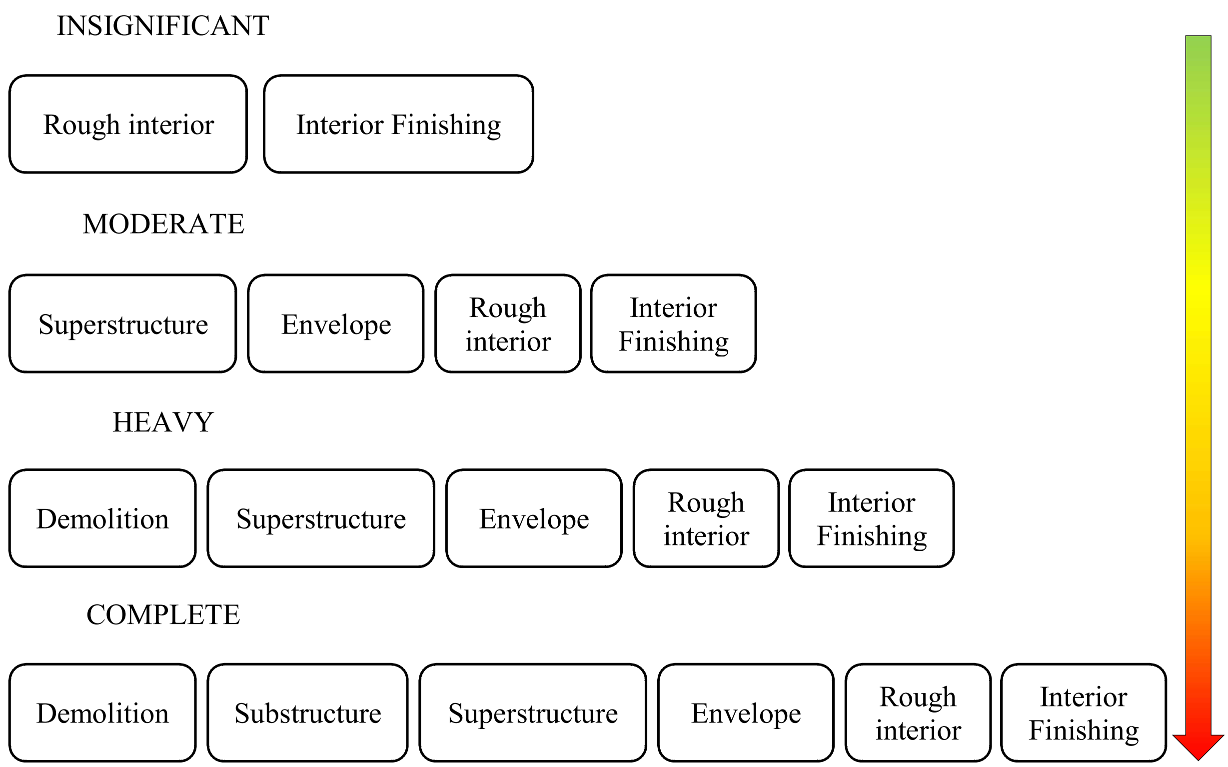


Figure 4 Schematic illustration of the Work Breakdown Structure for each damage state: insignificant, moderate, heavy, and complete.

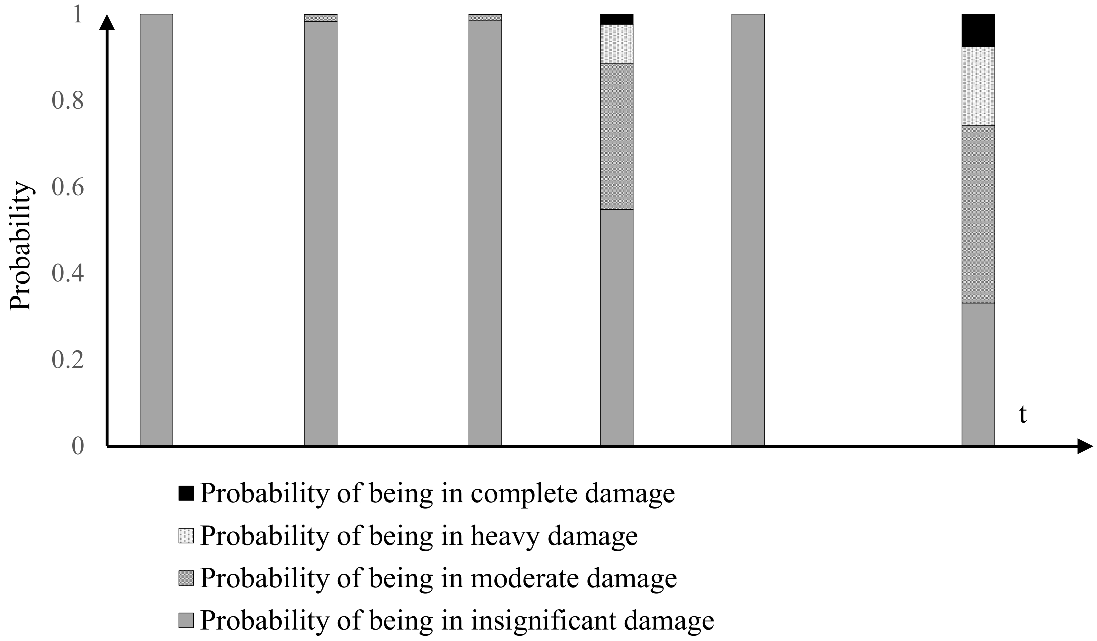
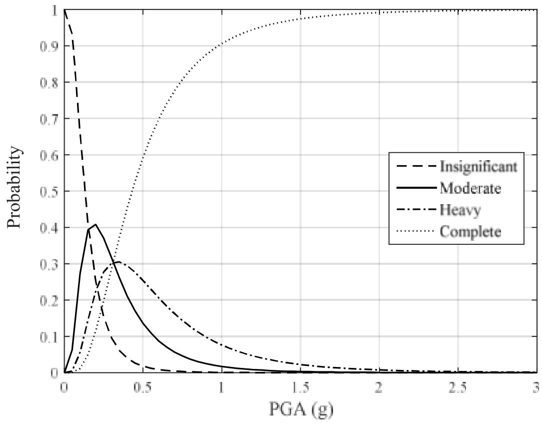
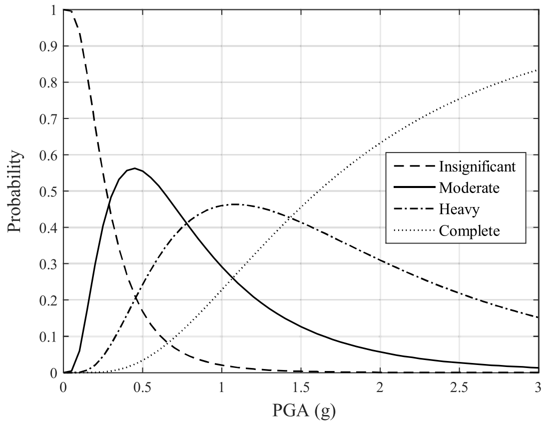


Figure 5 Probability mass function of the performance indicator $Q(t)$.



(a)



(b)

Figure 6 Probabilities of each damage state as a function of PGA for the seismically designed building (a) and the non-seismically designed building (b).

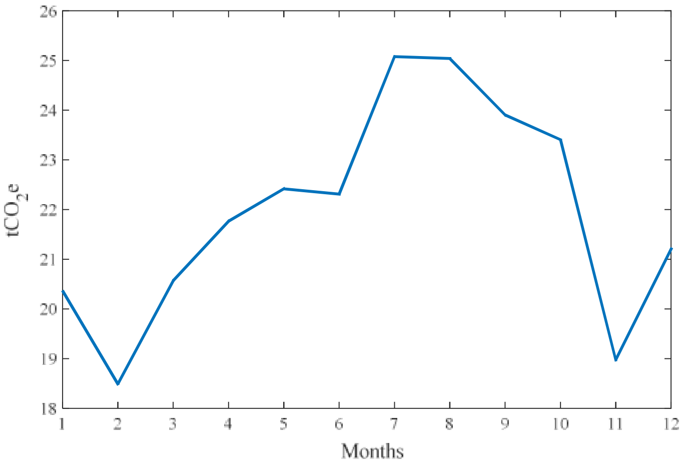


Figure 7 Annual GHG emissions in the usage stage for both seismically and non-seismically designed building.

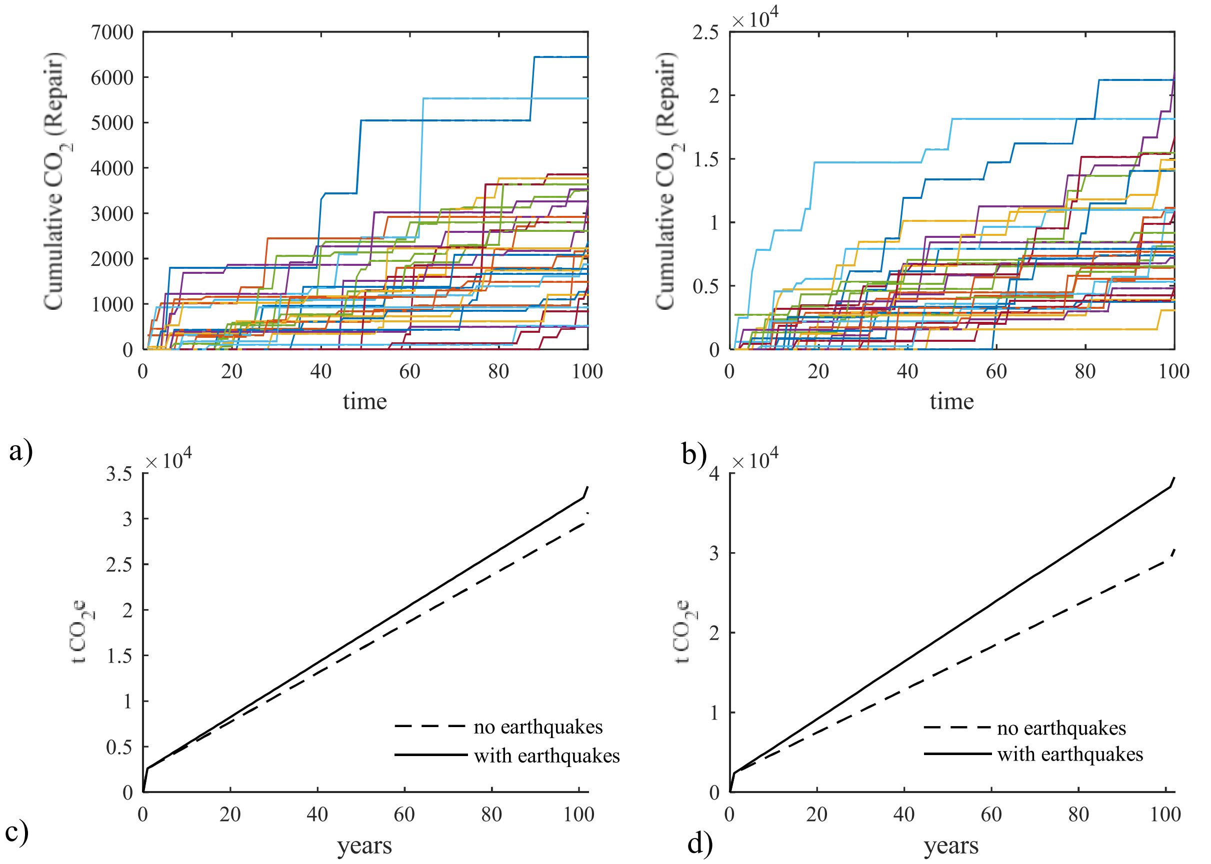


Figure 8 Sample realizations and means of the cumulative CO_{2e} emissions due to repairs for the seismically designed building (a, c) and the non-seismically designed (b, d) building.

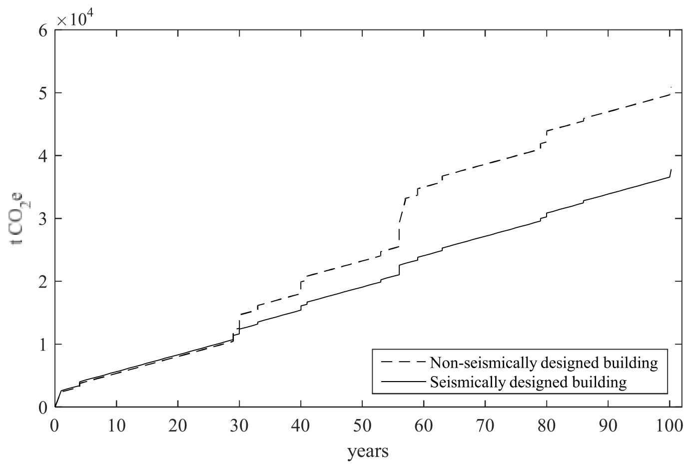


Figure 9 Total GHG emissions for non-seismically designed building and seismically design building.

Figure Caption List

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Figure 2 Flow of steps in the proposed formulation

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Figure 5 Probability mass function of the performance indicator $Q(t)$.

Figure 6 Probabilities of each damage state as a function of PGA for the seismically designed building (a) and the non-seismically designed building (b).

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