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Multicriteria lifecycle analyses for sustainable and resilient building design

UMBERTO ALIBRANDI[1] and KHALID M. MOSALAM[2]

[1]*Berkeley Education Alliance for Research in Singapore, 1 Create Way, Singapore*
E-mail: umbertoalibrandi@bears-berkeley.sg

[2]*Civil and Environmental Engineering, University of California at Berkeley,*
723 Davis Hall, Berkeley, CA 94720-1710, USA
E-mail: mosalam@berkeley.edu

In this paper, a framework of multi criteria lifecycle analyses under uncertainty for sustainable and resilient building design is presented. It adopts the Performance Based Engineering (PBE) approach for rational treatment of the uncertainties, while the Generalized Expected Utility (GEU) theory is used to address risk-informed design choices. In the literature, the design alternatives are typically ranked through the minimization of the lifecycle Expected Cost. However, research has shown that decision makers are typically risk averse toward low probability-high consequence events. In this paper, it is shown that the risk-aversion can be modeled through the GEU, while the probabilistic characterization of the seismic demand is obtained through the Kernel Density Maximum Entropy Method (KDMEM). This method provides the most honest probability distribution given the available information. Thus, the obtained fragility curves are the least biased for a chosen seismic input. The proposed framework is applied to a hypothetical office building, located in California where lifecycle economic and environmental metrics are considered. The analyses show that design by resilience means design by sustainability, since the more resilient design provides less environmental impact along the lifecycle. Interestingly, such design is also more advantageous from an economic point of view.

Keywords: Decision making under uncertainty, Information Theory, Kernel Density Maximum Entropy, Performance Based Engineering, Sustainability and Resilience.

1 Introduction

The optimal design of a construction project requires that all involved stakeholders achieve the greatest benefit. However, this is a very complicated task, since the number of stakeholders is large, the lifecycle of a building is long, and several sources of uncertainty need to be considered.

To address risk-informed decisions, several researchers propose to evaluate the expected Life Cycle Cost (LCC). However, many studies show that the preferences of the decision makers in many cases are not proportional to the expected costs. A broader framework of decision making under uncertainty is represented by the Expected Utility (EU) theory. This utility theory introduces the utility functions which describe the degree of preference of the decision maker inside the decision-making model. In this way, subjective factors of the risk evaluation, like the risk aversion, can be modeled. In the literature, it is recognized that the decision makers should be risk-neutral maximizers of the EU with a good understanding of the consequences. However, the EU theory is unable to describe the subjective evaluation in facing low-probability high-consequence events. To this aim, behavioral economists and cognitive psychologists have developed the Cumulative Prospect Theory (CPT). The CPT has been already applied for decision making under uncertainty in Civil Engineering where the main difficulty is the modeling of the risk perception. Recently, some researchers proposed to model the risk-aversion through suitable risk measures, like quantiles and superquantiles, applied directly to the performance measures of the engineering systems, e.g. cost. In this paper, the Generalized Expected Utility (GEU) theory (Mosalam et al. 2018) is adopted as a decision-making model. The GEU is a broadly general utility-based decision making theory, incorporating most decision making models as particular cases, including the minimum Expected Cost EC, the Expected Utility EU, the Cumulative Prospect Theory CPT, and the risk measures.

An important challenge of any decision support tool under uncertainty is represented by the suitable uncertainty quantification of the involved uncertainties inside the decision-making process. In this paper, the uncertainty propagation is obtained through the Performance Based Engineering (PBE) approach, which links, in a natural way, the design of the facilities to the desired performances $G_1, G_2, ..., G_n$. The final outcome of the PBE approach is a sample of data of the performances of the decision making model. In this paper, the probability distribution of the performance is determined through the Kernel Density Maximum Entropy Method (KDMEM) (Alibrandi and Mosalam 2017a), which implements the Maximum Entropy principle. KDMEM is adopted because it provides the least biased distribution given the available information. In KDMEM the adopted constraints are the fractional moments, and this also allows to predict the tails of the distribution of the performance functions from samples of small size.

The decision-making process is dynamic in the sense that the optimal decision changes when new information is available. This is obtained through Bayesian analysis (Alibrandi and Mosalam 2017b). The formulation can be used for updating the distribution of the performance measures described through not only the performance functions, but also the subjective utilities expressing the degree of preference of the decision maker and of the different stakeholders.

After describing the main features of the framework, it is applied to a hypothetical office building located in California. The numerical application shows the capabilities of the proposed approach for lifecycle integrated design under uncertainty of a building subjected to seismic hazard.

2 Lifecycle Analyses: Economic and Environmental Metrics

The main difficulty with the lifecycle analyses and the corresponding decision making is represented by the multiple sources of uncertainty. The Pacific Earthquake Engineering Research (PEER) Center developed a robust Performance-based Engineering (PBE) methodology (Cornell and Krawinkler 2000) whose focus is the explicit determination of system performance measures meaningful to various stakeholders (e.g. losses, downtime, etc.). In PBE, the following four main steps can be detected: (i) characterization and assessment of the hazard, defined through its intensity measure IM, (ii) probabilistic assessment of the demand on the structure, described through the Engineering Demand Parameter, EDP, (iii) probabilistic assessment of the resulting physical damage, described through the Damage Measure DM, and (iv) assessment of the losses modeled through chosen performance functions $G_1, G_2, \dots, G_n$. The latter step is one key feature of the PBE methodology, because it allows the explicit calculation of the performance measures, expressed in terms of the direct interest of various stakeholders. Therefore, the performance functions may include not only structural losses, but also construction and maintenance costs, CO_2 emission during the construction and operation phases, etc.

2.1 *Lifecycle cost analysis*

The Life Cycle Cost (*LCC*) represents the total cost incurred by the building during the lifecycle (Wen and Kang 1998)

$$LCC(t_n, \boldsymbol{x}) = C_0(\boldsymbol{x}) + \sum_{k=1}^{n} C_F(t_k, \boldsymbol{x}) \tag{1}$$

where $\boldsymbol{x}$ collects the design parameters, t_n is the lifespan typically measured in years, C_0 is the initial cost, while $C_F(t_k, \boldsymbol{x})$ is the lifecycle failure cost. Typically, when the design is more conservative, the initial cost $C_0(\boldsymbol{x})$ increases, while the failure cost $C_F(t_k, \boldsymbol{x})$ decreases. The initial cost $C_0(\boldsymbol{x})$ is usually assumed deterministic.

The lifecycle failure cost represents a stochastic process because of the uncertainties related to the hazard(s) demands on the building, the capacities and socio-economic changes. It is expressed as follows:

$$C_F(t_k, \boldsymbol{x}) = C_S(t_k, \boldsymbol{x}) + C_{NS}(t_k, \boldsymbol{x}) = \frac{1}{(1+\gamma_d)^{t_k}} [L_S(\boldsymbol{x}|ds) + L_{NS}(\boldsymbol{x}|ds)] \tag{2}$$

where $C_S(t_k, \boldsymbol{x})$ and $C_{NS}(t_k, \boldsymbol{x})$ are the contributions of repair costs of structural and non-structural components, respectively, $L_S(\boldsymbol{x}|ds)$ and $L_{NS}(\boldsymbol{x}|ds)$ are the corresponding annual losses under the assumption that each year the existing damages are repaired, and γ_d represents the discounting rate, which may be considered if the decision maker considers less painful future costs which are discounted to the net present value.

2.2 *Lifecycle environmental analysis*

In terms of an environmental metric, the $CO_2(t)$ emission during the lifecycle, i.e. Life Cycle Emission (*LCE*), is considered as follows,

$$LCE(t_n, \boldsymbol{x}) = CO_2(t_0, \boldsymbol{x}) + \sum_{k=1}^{n} CO_2(t_k, \boldsymbol{x}) \tag{3}$$

where $CO_2(t_0, \boldsymbol{x})$ and $CO_2(t_k, \boldsymbol{x})$ denote the CO_2 emission during the construction stage and the lifecycle, respectively.

The lifecycle CO_2 emission represents a stochastic process because of the uncertainties related to the degrading properties of material, climate change, etc. Here, it is modeled as an ergodic stationary process as follows,

$$CO_2(t_k, \boldsymbol{x}) = \sum_{i=1}^{k} CO_2(\boldsymbol{x}|ds) \tag{4}$$

where $CO_2(t_k, \boldsymbol{x})$ is the CO_2 emission because of post-hazard repairs at year $t = t_k$, while $CO_2(\boldsymbol{x}|ds)$ is the annual emission under the assumption that each year the existing damages are repaired. In a lifecycle environmental analysis, it is assumed that no discount rate is applied, because inside a sustainability framework, the future generations have the same importance of the current ones.

3 Generalized Expected Utility (GEU)

In the theory of decision under risk, the main focus of the decision maker is the choice of the optimal solution with respect to chosen performances $G_1, G_2, \ldots, G_n$ (e.g. the lifecycle cost, *LCC*, or lifecycle CO_2 emission, *LCE*) given a set of m alternatives $G_k^{(i)} = G_k\left[\boldsymbol{x}^{(i)}, \boldsymbol{v}\left(\boldsymbol{x}^{(i)}\right)\right]$,

$i = 1,2,\dots,m$. The vector $\boldsymbol{x}^{(i)} = \{x_1^{(i)} \quad x_2^{(i)} \quad \cdots \quad x_n^{(i)}\}$ collects all the *design variables* containing the control variable values representing the set of preselected alternatives. The vector $\boldsymbol{v}(\boldsymbol{x}) = \{\boldsymbol{v_B} \quad \boldsymbol{v_D}(\boldsymbol{x})\}$ collects all the uncertain parameters appearing in the decision-making problem where $\boldsymbol{v_B}$ collects the *basic random variables*, which are the parameters that cannot be controlled by the decision maker, e.g. environmental conditions or natural hazard, while $\boldsymbol{v_D}(\boldsymbol{x})$ collects the *derived parameters* that are affected by the design variables, e.g. responses of the system or damage level.

The optimal choice is determined through the definition of a functional $\mathcal{V}(\cdot)$ applied to the performance G, such that if $\mathcal{V}(G^{(1)}) \geq \mathcal{V}(G^{(2)})$, then the alternative $G^{(1)}$ is preferred over the alternative $G^{(2)}$. The Generalized Expected Utility (GEU) (Mosalam et al. 2018) is adopted and defined as follows,

$$GEU^{(i)} = \int u^{(i)}\, d\left[h\left(F_U^{(i)}\right)\right] \tag{5}$$

where $u^{(i)}$ is the utility of the i^{th} alternative, $F_U^{(i)}$ is its Cumulative Distribution Function (CDF), while $h(\cdot)$ is a suitable function describing the risk perception of the decision maker, here represented by the decision maker. The utility $u^{(i)}$ is defined through the *utility function* $u(g)$ which is a function converting the values g of the performance G into the degree of preference of the decision maker. The GEU embodies a distinction between the attitudes to the outcomes, measured by $u(g)$, and attitudes to the probabilities, distorted through $h(F_U)$. The optimal decision maximizes the GEU.

If the probabilities are not distorted by the risk perception of the decision maker, i.e. $h(F_U) \equiv F_U$, then the GEU coincides with the largely adopted Expected Utility EU (Von Neumann and Morgenstern 1944)

$$GEU^{(i)} \equiv E\left[U^{(i)}\right] = \int u^{(i)}\, dF_U^{(i)}(u) = \int u(g)\, dF_G^{(i)}(g) \equiv EU^{(i)} \tag{6}$$

where $F_G^{(i)}$ is the CDF of the performance G. In the literature, some researchers state that a rational decision maker should be risk-neutral by considering complete consequence models. Under this further assumption, then $u(g) = g$ and

$$GEU^{(i)} \equiv E\left[U^{(i)}\right] = \int g\, dF_G^{(i)}(g) = \int g f_G^{(i)}(g)\, dg \equiv E\left[G^{(i)}\right] \tag{7}$$

where $f_G^{(i)}(g)$ is the Probability Density Function (PDF) of $G^{(i)}$. The optimal alternative provides the maximum GEU, i.e.

$$\max_{G^{(i)}} GEU \equiv \max_{G^{(i)}} EU \equiv \max_{G^{(i)}} E[G] \tag{8}$$

Thus, a rational decision maker will pursue the maximum expected performance. In this paper, the considered performances are the lifecycle cost $G_1(t_n, \boldsymbol{x}) \equiv LCC(t_n, \boldsymbol{x})$ and the lifecycle CO_2 emission $G_2(t_n, \boldsymbol{x}) \equiv LCE(t_n, \boldsymbol{x})$. Thus, the maximum benefit is represented by the minimum expected value of LCC and LCE.

4 Numerical application

A hypothetical four-bay five-story Reinforced Concrete (RC) office building is considered. The floor-to-floor height is $3\ m$, the spacing of the columns is $5\ m$, the floor area is $A_f =$

$400\ m^2$, with a total area $A = 2{,}000\ m^2$. Two design alternatives are considered: (*i*) *Design* 1, where the columns are $300 \times 300\ mm$ with 8 reinforcing bars of 14 *mm* diameter, and (*ii*) *Design* 2, where the columns are $300 \times 500\ mm$ with 8 reinforcing bars of 16 *mm* diameter. In both designs, the beam sections are $300 \times 500\ mm$ with 8 reinforcing bars of 16 *mm* diameter, providing 1.07% longitudinal reinforcement.

For the two designs 1 and 2, the construction cost is $C_0^{(1)} = 2.08\ \$M$ and $C_0^{(2)} = 2.60\ \$M$, corresponding to a unit cost of $1{,}040\ \$/m^2$ and $1{,}300\ \$/m^2$, respectively. These values are quite typical of constructions in California, Berkeley area. The corresponding emission of CO_2 is $CO_2^{(1)}(t_0) = 606.4\ ton$ and $CO_2^{(2)}(t_0) = 758.0\ ton$, whose unit emission is $303.2\ kg/m^2$ and $379.0\ kg/m^2$, respectively, as derived from (Wei et al.2016).

It is assumed that the building is subjected to seismic hazard only. The building is located in Berkeley, CA whose latitude and longitude are respectively $37.877°$ and $-122.264°$. The chosen intensity measure IM is the Peak Ground Acceleration (PGA), whose hazard curve is obtained by using the hazard curve calculator application of OpenSHA. Discrete values of *PGA* between $0.05g$ and $2g$ with $0.05g$ increments are chosen, for a total of 40 IM values. A set of 81 Ground Motions (GMs) compatible with the site class and the hazard curve are selected from the PEER Next Generation Attenuation (NGA) GM database.

The structural analyses are performed using the software OpenSees. The 81 GMs are scaled for each *IM*, giving a total number of nonlinear time history analyses of $81 \times 40 = 3{,}240$. For brevity, this study considers only the Maximum peak Interstory Drift Ratio ($MIDR$) as EDP. For each value of the *IM*, the conditional annual distribution $P^{(i)}[MIDR|IM_m]$, $i = 1{,}2$ for the considered designs is determined through the Kernel Density Maximum Entropy (KDMEM), which provides the most honest and least biased distribution given the available information.

In the absence of available data to develop probabilistic capacity models, capacity values are based on HAZUS, whose suggested values are treated as median values of a lognormal distribution, while the dispersion value is assumed to be 0.3. The annual probabilities of achieving the corresponding damage states are evaluated. As expected, the first alternative requires less initial construction cost ($C_0^{(1)} < C_0^{(2)}$) and provides lower CO_2 emission during the construction stage ($CO_2^{(1)}(t_0) < C_0^{(2)}(t_0)$). However, it is more vulnerable to the seismic hazard during its lifecycle.

The loss functions and the CO_2 emission functions are derived from (Wei et al. 2016) assuming that the probability distributions follow lognormal distributions, whose dispersion is assumed to be 0.3. The evaluation of the annual losses shows that the first alternative is cheaper and moreover it requires, for each repair, minor CO_2 emission. However, damages during the lifecycle are more frequent.

The expected lifecycle cost $E[LCC(t)]$ and the expected CO_2 emissions $E[LCE(t)]$ are shown in Fig. 1, considering a lifetime of $t_n = 20$ years. It is seen that for both performance metrics, the second design option is better since it determines less lifecycle cost and less environmental impact. Since the second design alternative is less vulnerable to the hazard, it follows that: (*i*) a resilient building is sustainable, and (*ii*) a resilient building provides greater lifecycle economic benefit, although the initial cost of the construction can be greater.

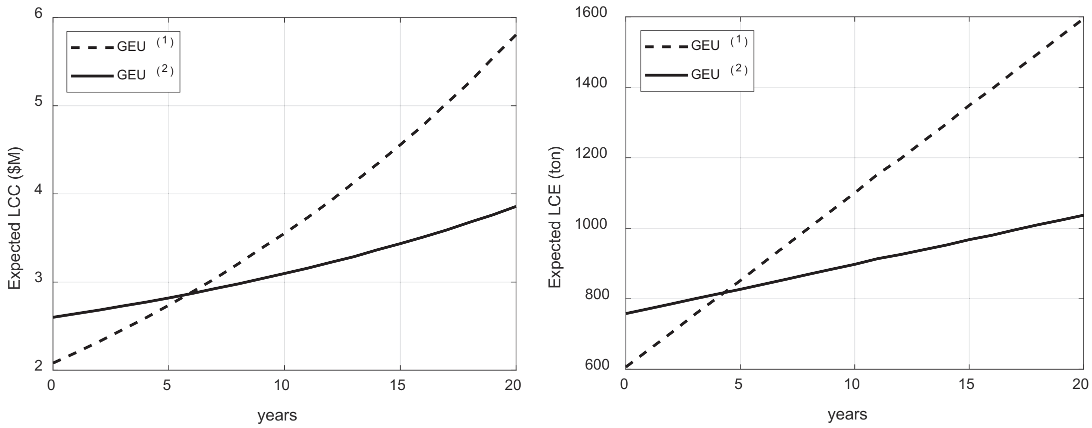

Figure 1. (left) lifecycle cost (*LCC*), (right) lifecycle emission (*LCE*)

4 Concluding Remarks

In this paper, we have developed a framework of lifecycle analyses under uncertainty for sustainable and resilient building design. A numerical example has illustrated the main features of the method. Herein, the optimal decision is determined through the Generalized Expected Utility (GEU). In the studied example, two performance measures are considered: (i) lifecycle CO_2 emission and (ii) lifecycle economic benefit. The analyses show that design by resilience means design by sustainability since it provides less environmental impact during the lifecycle. Moreover, it is more advantageous from an economic point of view.

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