A Probabilistic Decision Support System for a Performance-Based Design of Infrastructures

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ABSTRACT

Infrastructures are the most fundamental facilities and systems serving the society. Due to the existence of infrastructures in economic, social, and environmental contexts, all lifecycle phases of such fundamental facilities should maximize utility for the designers, occupants, and the society. With respect to the nature of the decision problem, two main types of uncertainties may exist: 1) the aleatory uncertainty associated with the nature of the built environment (i.e., the economic, social, and environmental impacts of infrastructures must be described as probabilistic); and 2) the epistemic uncertainty associated with the lack of knowledge of decision maker utilities. Although a number of decision analysis models exist that consider the uncertainty associated with the nature of the built environment, they do not provide a systematic framework for including aleatory and epistemic uncertainties, and decision maker utilities in the decision analysis process. In order to address the identified knowledge gap, a three-phase modular decision analysis methodology is proposed. Module one uses a formal preference assessment methodology (i.e., utility function/indifference curve) for assessing decision maker utility functions with respect to a range of alternative design configurations. Module two utilizes the First Order Reliability Method (FORM) in a systems reliability approach for assessing the reliability of alternative infrastructure design configurations with respect to the probabilistic decision criteria and decision maker defined utility functions (indifference curves), and provides a meaningful feedback loop for improving the reliability of the alternative design configurations. Module three provides a systematic framework to incorporate both aleatory and epistemic uncertainties in the decision analysis methodology (i.e., uncertain utility functions and group decision making). The multi-criteria, probabilistic decision analysis framework is tested on a nine-story office building in a seismic zone with the probabilistic decision criteria of: building damage and business interruption costs, casualty costs, and CO_2 emission costs. Twelve alternative design configurations and four decision maker utility functions under aleatory and epistemic uncertainties are utilized. The results of the decision analysis methodology revealed that the high-performing design configurations with an initial cost of up to $3.2M (in a cost range between $1.7M and $3.2M), a building damage and business interruption cost as low as $303K (in a cost range between $303K and $6.2M), a casualty cost as low as $43K (in a cost range between $43K and $1.2M), and a CO_2 emission as low as $146K (in a cost range between $133K to $150K) can be identified by having a higher probability (i.e., up to 80%) of meeting the decision makers' preferences. The modular, holistic, decision analysis framework allows decision makers to make more informed performance-based design decisions—and allows designers to better incorporate the preferences of the decision makers—during the early design process.

A Probabilistic Decision Support System for a Performance-Based Design of Infrastructures

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GENERAL AUDIENCE ABSTRACT

Infrastructures, including buildings, roads, and bridges, are the most fundamental facilities and systems serving the society. Because infrastructures exist in economic, social, and environmental contexts, the design, construction, operations, and maintenance phases of such fundamental facilities should maximize value and usability for the designers, occupants, and the society. Identifying infrastructure configurations that maximize value and usability is challenged by two sources of uncertainty: 1) the nature of the built environment is variable (i.e., whether or not a natural hazard will occur during the infrastructure lifetime, or how costs might change over time); and 2) there is lack of knowledge of decision maker preferences and values (e.g., design cost versus social impact tradeoffs). Although a number of decision analysis models exist that consider the uncertainty associated with the nature of the built environment (e.g., natural hazard events), they do not provide a systematic framework for including the uncertainties associated with the decision analysis process (e.g., lack of knowledge about decision maker preferences), and decision maker requirements in the decision analysis process. In order to address the identified knowledge gap, a three-phase modular decision analysis methodology is proposed. Module one uses a formal preference assessment methodology for assessing decision maker values with respect to a range of alternative design configurations. Module two utilizes an algorithm for assessing the reliability of alternative infrastructure design configurations with respect to the probabilistic decision criteria and decision maker requirements, and provides a meaningful feedback loop for understanding the decision analysis results (i.e., improving the value and usability of the alternative design configurations). Module three provides a systematic framework to incorporate both the random uncertainty associated with the built environment and the knowledge uncertainty associated with lack of knowledge of decision maker preferences, and tests the reliability of the decision analysis results under random and knowledge uncertainties (i.e., uncertain decision maker preferences and group decision making). The holistic decision analysis framework is tested on a nine-story office building in a seismic zone with the probabilistic decision criteria of: building damage and business interruption costs, casualty costs, and CO_2 emission costs. Twelve alternative design configurations, four decision makers, and random and knowledge sources of uncertainty are considered in the decision analysis methodology. Results indicate that the modular, holistic, decision analysis framework allows decision makers to make more informed design decisions—and allows designers to better incorporate the preferences of the decision makers—during the early design process.

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DEDICATION

To my companionate mother, Soussan;
my supportive sister, Maryam; and
my encouraging father, Shahram

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1. INTRODUCTION

Early infrastructure design decisions are highly complex due to the open-ended nature of the alternatives that complicate the assessment of economic, social, and environmental (i.e., Triple Bottom Line or TBL) tradeoffs with respect to the alternative design options. To achieve TBL-based designs, the economic, social, and environmental impacts of alternative design options should be communicated to the decision makers in the initial design phase. Furthermore, the identification of a truly optimal infrastructure design is impossible as the actual performance of the facility over its lifetime cannot be known in advance (the conditions, e.g., the occurrence of natural hazard events are unknown), and the objectives are likely to be conflicting (minimize initial cost; maximize functionality after a hazard event). If the premise of impossibility is accepted, then the only rational decision-making is to directly consider both the uncertainty and conflicting criteria by incorporating decision-maker preferences with regard to tradeoffs. However, lack of data in the initial design phase leads to considerable difficulty in implementing quantitative decision support systems. Challenges include the following:

- The broad set of alternatives available in early design and limited knowledge of the potential solution space in terms of TBL measures.
- The lack of accurate data in the initial design phase (as the design has not been performed), particularly for less common design configurations.
- The uncertainty associated with the nature of the built environment and the decision analysis methodology.
- The need for a relatively simple method for assessing preferences and finding optimal design configurations that makes tractable the complex nature of infrastructure design decisions given the limited time available time to make decisions.

A modular preference assessment methodology that can communicate the TBL impacts (tradeoffs) of a broad range of alternatives in the early design phase and assess the reliability of the alternative design configurations with respect to decision maker preferences has the potential to greatly improve the design of infrastructures.

The research gaps are categorized with respect to the challenges identified during the early design of infrastructures:

1. A broad set of alternatives: A decision support system and preference assessment methodology that is scalable and adaptable to a range of alternative design configurations, and can communicate the performance of alternative design configurations to the decision makers.
2. Multiple decision criteria: A decision frame that allows for the incorporation of multiple conflicting decision criteria, while supporting subsequent optimization and low cognitive load from the decision makers.
3. Multiple decision maker inputs (utilities): A holistic, modular decision framework that finds optimum infrastructure design configurations that maximize the decision makers' utility

function(s), while providing a feedback loop that allows the decision makers to improve the alternative design configurations with respect to their utility function.

4. Uncertainty: An optimization algorithm that allows for a full and consistent representation of all relevant uncertainties associated the nature of the built environment and the decision analysis methodology (i.e., aleatory and epistemic).

In order to address knowledge gaps one to three, the Second Chapter of the dissertation titled "*SIMPLE-Design: Sustainable Infrastructure Multi-Criteria Preference assessment of aLternatives for Early Design*", proposes a modular preference assessment framework consisting of four phases: 1) identifying the TBL-based decision criteria, 2) identifying alternative solutions of a given infrastructure (applicable subsystems and systems) that meet the requirements, 3) analyzing two or more alternative design configurations that cover the range between high- and low-performing through a detailed TBL assessment in the presence of natural hazards (and/or other risk events applicable to the built environment), 4) assessing the preference function of the decision maker(s) through a formal decision analysis methodology (i.e., utility functions/indifference curves). The resulting preference function can then be combined with multi-objective or reliability-based optimization algorithms to identify the optimal system configuration(s).

Once decision maker preferences are assessed, an optimization algorithm is required to maximize utility for the designers, occupants, and the society. However, due to the uncertainties associated with the nature of the built environment, the economic, social, and environmental impacts of infrastructure assets must be described probabilistic (knowledge gap four). For this reason, the optimization model should maximize decision maker utilities with respect to multiple and potentially conflicting probabilistic decision criteria. Although stochastic optimization and multi-objective optimization are well developed in the field of operations research, their intersection (multi-objective optimization under uncertainty) is much less developed and computationally expensive. Furthermore, due to the inherent complexity of stochastic optimization methods, integration of decision maker utilities with such complex optimization models has not been attempted. To this effect, the Third Chapter of the dissertation titled "*A Reliability-Based Decision Support System for Incorporating Decision Maker Utilities in the Design of Infrastructures*", presents a computationally efficient, adaptable decision framework for incorporating probabilistic decision criteria (uncertainty associated with the nature of the built environment) and decision maker requirements (utilities) in the design of infrastructures. The proposed model utilizes the First Order Reliability Method (FORM) for assessing the reliability of alternative infrastructure design configurations with regard to the probabilistic decision criteria and decision maker defined utilities (indifference curves) using a system reliability approach, and provides a meaningful feedback loop for understanding the decision analysis results and improving the reliability of the alternative design configurations (with respect to decision maker utilities).

Once alternative design configurations that maximize decision maker utilities have been found, the robustness of the decision analysis methodology is tested under additional sources of uncertainty. While Chapter 3 focuses on the aleatory uncertainty associated with the built environment, Chapter 4 subjects the decision analysis result to the epistemic uncertainty associated with assessing decision maker preferences.

The current state-of-the-art methods for including uncertainty in decision analysis models do not provide a systematic methodology for incorporating epistemic and aleatory uncertainty, multiple decision criteria, and alternative design configurations in the decision analysis process. In order to address the identified knowledge gap, the Fourth Chapter of the dissertation titled "*Incorporation of Multiple Decision Criteria, Decision Maker Utilities, and Uncertainty in the Design of Infrastructures*" integrates the First Order Reliability Method (FORM) along with epistemic uncertainty (from fitting curves to the decision maker defined utilities), and provides a systemic framework that allows for a full and consistent representation and quantification of all relevant uncertainties (aleatory and epistemic), decision maker utilities (both individual and group decision making), alternative design configurations, and decision criteria.

The Fifth Chapter of this dissertation presents the conclusions, contributions, limitations of research, broader impacts, and the areas of future research of the present decision support system. Appendix A presents a summary of the conducted literature review with respect to the decision support systems that support (can support) a resilient design of infrastructures.

2. SIMPLE-DESIGN: SUSTAINABLE INFRASTRUCTURE MULTI-CRITERIA PREFERENCE ASSESSMENT OF ALTERNATIVES FOR EARLY DESIGN

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1. ABSTRACT

The tradeoffs between the economic, social, and environmental aspects of infrastructures are not easily evident to decision makers and stakeholders in the initial design phase. This lack of insight, often leads to designs that compromise the social and environmental aspects of designs in order to reduce the initial construction costs of infrastructure assets. In addition to the lack of insight, currently available methods for analyzing alternative infrastructure configurations with respect to decision maker preferences: require analysis on a case-by-case (e.g., pairwise) basis; are not appropriate for the initial design phase (e.g., are time-consuming); and are not adaptable to a range of alternative design solutions (e.g., adding and removing alternatives might require a re-ranking from the decision maker). This paper presents a modular preference function development strategy that aims to address these issues, termed **S**ustainable **I**nfrastructure **M**ulti-Criteria **P**reference assessment of a**L**ternatives for **E**arly **D**esign (SIMPLE-Design). The proposed strategy develops utility functions (indifference curves) for assessing decision maker preferences with regard to various tradeoffs of alternative design options, and leverages available data to provide decision makers with a consistent frame of reference for assessing alternatives. An illustration presented for a decision support tool utilizing the Simple-Design strategy assesses decision maker preferences for commercial buildings with respect to initial construction costs, building damage and business interruption costs, casualty costs (due to the occurrence of natural hazard events), and CO_2 emission costs. The designed decision support tool provides streamlined information to support preference assessment with reasonably low cognitive load. Ten out of the twelve decision support tool users stated that allowing the decision makers to define alternatives of equal utility (value) in a systematic manner, and providing information on the various cost types (decision criteria), are the most essential elements of the assessment strategy. The presented modular preference assessment framework, as well as the tool itself, are generalizable and can be adapted to other infrastructure types. The contribution to the body of knowledge is a holistic preference assessment framework that allows decision makers to make more informed decisions—and designers to better incorporate the preferences of the decision makers—during the early design process.

Keywords

Decision Support Tool; Multi-Criteria; Design Strategies; Preference Assessment; Utility Function; Indifference Curve; Expert Elicitation; Infrastructure; Triple Bottom Line; Resilience

2. INTRODUCTION

Early infrastructure design decisions are highly complex due to the open-ended nature of the alternatives that complicate the assessment of economic, social, and environmental (i.e., Triple Bottom Line or TBL) tradeoffs of the alternative design options. To achieve TBL-based designs, the economic, social, and environmental impacts of alternative design options should be communicated to the decision makers in the initial design phase. However, lack of data in the initial design phase leads to considerable difficulty in implementing quantitative decision support systems. Challenges include: the broad set of alternatives available in early design and limited knowledge of the potential solution space in terms of TBL measures; the lack of accurate data in the initial design phase (as the design has not been performed), particularly for less common design configurations; and the need for a relatively simple method for assessing preferences that makes tractable the complex nature of infrastructure design decisions given the limited available time to make decisions. A modular preference assessment methodology that can communicate the TBL impacts (tradeoffs) of a broad range of alternatives in the early design phase has the potential to greatly improve the design of infrastructure.

An alternate framing of the problem is the effect of the cognitive limitations of the human mind on achieving holistic, sustainable infrastructure designs. One obstacle to the design of successful infrastructure solutions is the interaction of cognitive limitations and the compressed timeframe for decision-making. This phenomenon is known as bounded rationality (Simon 1982; Gigerenzer and Selten 2002). In infrastructure design, decision makers in this mindset will seek designs that are satisfactory rather than optimal. Therefore, design professionals who focus on sustainability can use life-cycle assessment and sensitivity analysis to illustrate the value of green design to owners, who may otherwise solely focus on cost-effectiveness (i.e., who will have a bounded viewpoint) (Chalifoux 2006). Additionally, the presentation of a scenario and the framing of a problem affect the decision made (i.e., decision makers are not completely rational) (Tversky and Kahneman 1985; May 2004). For example, it would be expected that providing decision makers with actual death and injury rates from earthquake events will impact the decision makers, who might otherwise favor low-cost and low-performing designs. Presenting a range of alternative designs to the decision makers in the early design phase will provide them with a holistic framing of the problem and enable them to consider a number of trade-off strategies and the consequences of various design solutions.

Elegant infrastructures are defined as solutions that break through the design complexity of infrastructures while being non-redundant and optimal (Shealy and Klotz 2016). Although there is a clear need for elegant infrastructure solutions, most decision frameworks fall short in analyzing the tradeoffs between the economic, social, and environmental impacts of alternative design solutions. Many decision frameworks analyze design and decision alternatives with regard to multiple criteria (e.g., construction time and construction cost), which target a single objective (e.g., minimize construction cost) such as efficient budget allocations (Gabriel et al. 2006) or the optimization of construction activities that aims to minimize construction time (Zhang et al. 2006). Even multi-objective approaches do not necessarily lead to elegant infrastructure outcomes due to the lack of a systematic consideration of all TBL criteria. For example, construction time-cost optimization does not consider level of service (i.e., social impacts), and water distribution network design may not consider natural hazard resilience measures (Elbeltagi et al. 2005; Ng and Zhag 2008; Xiong and Kuang 2008; Eusuff and Lansey 2010; Liao et al. 2011). Furthermore, decisions made during the planning, design, and construction of commercial buildings do not maximize utility for the designers, occupants, or the society (Klotz 2011). This lack of consideration of all stakeholders is particularly clear in the occurrence of natural hazards.

For the design of elegant infrastructure solutions, there is a need for a preference assessment methodology that 1) provides the performance of the alternative design options to the decision maker(s) at an early design stage and assesses decision maker preferences, 2) can be utilized as constraints and boundaries to find favorable building alternatives using multi-criteria and multi-objective decision analysis (optimization) models, 3) is adaptable to a range of alternative design solutions, and 4) is easily implementable. A modular preference function development strategy that covers the performance range of alternative design configurations can meet the identified needs.

This paper proposes such a modular preference assessment framework consisting of four phases: 1) identifying the TBL-based decision criteria, 2) identifying alternative solutions of a given infrastructure (applicable subsystems and systems) that meet the requirements, 3) analyzing two or more alternative design configurations that cover the range between high- and low-performing through a detailed TBL assessment in the presence of natural hazards (and/or other risk events applicable to the built environment), 4) assessesing the preference function of the decision maker(s) through a formal decision analysis methodology. The resulting preference function can then be combined with multi-objective optimization algorithms to identify the optimal system configuration(s). Through careful selection of approaches in each step, a modular decision support system can be developed that is both generally applicable and consistent with the needs of early design.

The following section of this paper reviews the role of TBL objectives in the design phase, as well as the current state of the art, with an emphasis on building infrastructure. Section 4 describes the proposed SIMPLE-Design framework, which is used in a pilot implementation for a nine-story office building described in Section 5. Finally, the implementation tool's success is evaluated and suggestions are made for future work.

3. BACKGROUND

3.1. Understanding the Role of Triple Bottom Line Objectives in the Design Phase

A sustainable design is one that positively impacts the economy, environment, and society (Brundtlad Commission 1987). Applied to buildings and other infrastructure, sustainable designs have the ability to systematically address TBL objectives. Considering buildings, specifically, a number of sustainable design models exist for defining performance criteria, objectives, and attributes. Sustainable building design models started with frameworks that mainly focused on resource use and energy consumptions, and are shifting towards frameworks that integrate natural resources and economic, societal and environment goals (ARUP 2012; Cole 2012; Cole et al. 2012; Plaut et al. 2012; Svec et al. 2012; Gou and Xie 2017). Green buildings and sustainable designs aim to minimize the negative economic (e.g., natural hazard losses), environmental (e.g., CO_2 emission), and social (e.g., death and injuries) impacts of designs and serve the intended purpose of buildings. Furthermore, decisions made in the early design phase are more impactful (Basbagil et al. 2013) and address sustainability in a more effective way, making early design a prime target for the implementation of design analysis tools.

3.2 Current State of Building Design Models under Triple Bottom Line Objectives

The current state of building design models with respect to TBL objectives can be categorized as models that 1) measure TBL impacts, 2) rate building performance, 3) assess decision maker values, and/or 4) find the optimum design option(s), as arrayed in Figure 1. The following sections review the literature based on the primary focus of each approach (noting that some approaches span multiple categories).

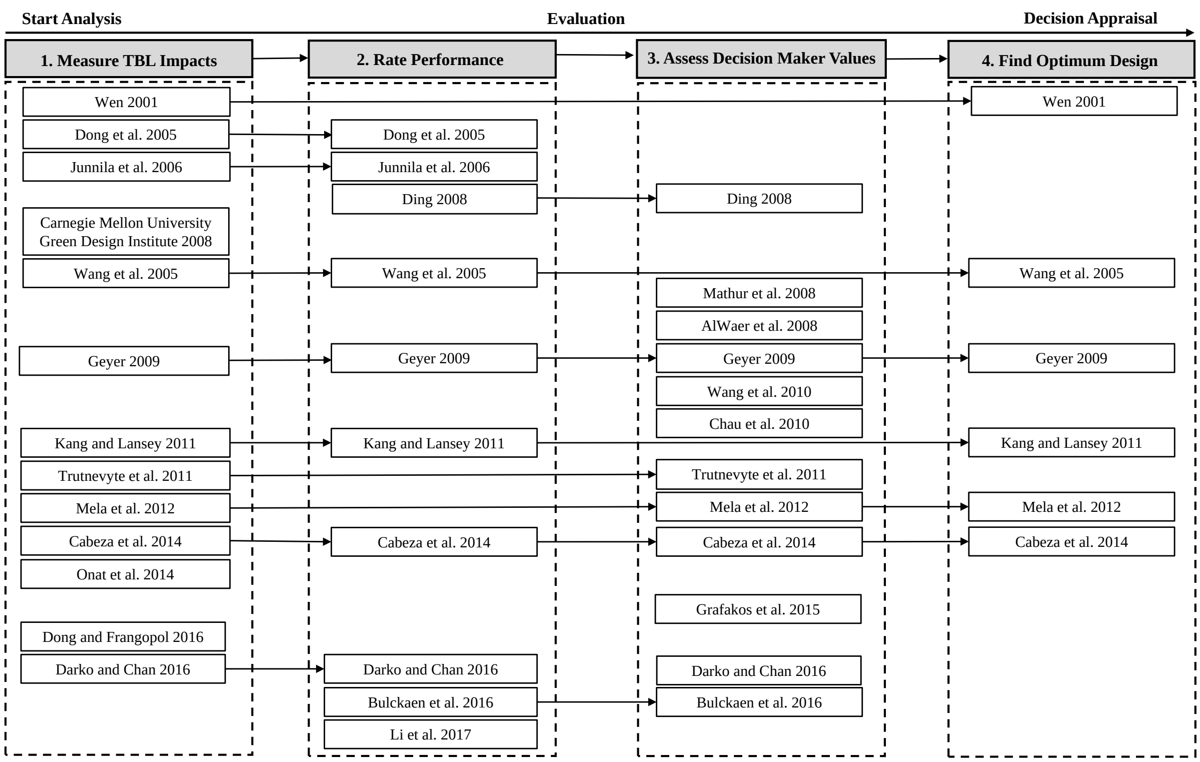

Figure 1: Building Design Models under Triple Bottom Line Objectives

3.2.1 Measure Triple Bottom Line Impacts

Input-output models, life cycle cost analysis methods, and performance-based assessment techniques (performance-based seismic design and assessment approaches) are the primary types of TBL impact analysis methods. Such models solely measure the economic, social and environmental aspects of building design options (Dong et al. 2005; Junnila et al. 2006; Carnegie Mellon University Green Design Institute 2008; Cabeza et al. 2014; Onat et al. 2014; Dong and Frangopol 2016). Although TBL impact analysis models are informative, the results of the impact analysis require multi-objective/multi-criteria optimization, and/or a preference assessment framework to analyze multiple alternatives and identify high-performing building configurations.

3.2.2 Rate Performance

Environmental assessment tools are the most common method for sustainability assessments of buildings, construction sites, and other aspects of built infrastructure (Ding 2008; Darko and Chan 2016; Li et al. 2017). Among the green building environmental assessment tools, LEED (US Green Building Council 1998), BREEAM (Prior 1993), and CASBEE (The Institute for Building Environment and Energy Conservation 2004), are the most-studied worldwide. Each uses a credit-weighting scale to assess buildings, with primary focus on environmental rather than economic or social aspects of designs (Cole 1998; Crawley and Aho 1999; Larsson 1999; Cole 2005; Seo et al. 2006; Yau et al. 2006; Li et al. 2017). The revised Green Building Challenge (GBC) model includes economic issues in the assessment framework (Larsson 1999), and the adoption economic and social measures would significantly benefit other building performance assessment methods (such as LEED) from a TBL perspective.

3.2.3 Assess Decision Maker Values

The current state-of-the-art methods that assess decision maker values with respect to TBL measures are multi-criteria decision making methods, discrete choice experiment methods, utility functions, methods that facilitate stakeholder dialogues, and further stakeholder perception assessment techniques. A number of multi-criteria decision making methods exist for: comparing sustainability measures to stakeholder preferences in urban and regional mobility measures; incorporating economic and political concerns in the life-cycle assessment of commercial buildings; and incorporating stakeholder preferences in the sustainability evaluation (Wang et al. 2010; Grafakos et al. 2015; Bulckaen et al. 2016). Additional studies have been conducted to analyze the perceptions of sustainability in commercial buildings, conceptualize stakeholder engagement in the context of sustainability, and assess the willingness of stakeholders to pay for green building features (AlWaer et al. 2008; Mathur et al. 2008; Chau et al. 2010). Sustainable disaster recovery planning has also been achieved by integrating economic vulnerability into the objective functions of stakeholders using an agent-based approach, objective functions, and utility functions (Eid and El-adaway 2016). However, most of the available methods do not provide a modular preference assessment methodology that can be adapted to various infrastructures and optimization frameworks.

While TBL guidelines are commonly used in the design of infrastructure assets, and utility functions are even more commonly used in the field of decision analysis, their intersection is much less developed. i.e., decision maker preferences (utilities) are not formally assessed in the initial design process with regard to TBL measures. Value and risk tradeoff models can assess decision maker values for a range of alternative solutions and can be developed using stochastic dominance (Hadar and Russell 1969; Whitmore 1970), multi-attribute utility theory (von Neumann 1953), and expected/non-expected utility (Edgeworth 1881; Raiffa 1968; Hadar and Russell 1969). Utility functions have the ability to develop a preference function that can be adapted to a range of alternative design solutions, which meets the modularity requirement of the preference assessment methodology. Indifference curves are a category of utility functions that have the ability to capture the utility of an individual with regard to multiple and potentially conflicting decision criteria (e.g., the tradeoffs between higher initial costs, lower environmental impact, and higher level of service) and range of decision alternatives and are particularly promising for developing generalizable preference functions that can be adapted to a range of alternative design solutions.

3.2.4 Find Optimum Design

An optimal design configuration is one that best meets the defined constraints, requirements, and preferences. Since the nature of an infrastructure design problem under TBL objectives includes multiple and potentially conflicting decision objectives, multi-objective optimization (e.g., metaheuristic algorithms, exact methods, and reliability based approaches) and multi-criteria optimization (e.g., weighted sum method, and PROMETHEE) are used to find the optimal design solution. Decision problems such as green building design, structural component-oriented multidisciplinary design optimization in building design, and water distribution network design problems under TBL objectives (Wang et al. 2005; Geyer 2009; Kang and Lansey 2011) are solved using multi-objective genetic algorithms (a metaheuristic optimization algorithm inspired by the process of natural selection). Other building design problems use multi-criteria optimization techniques for analyzing the life-cycle cost and environmental impact trade-offs of building design options and building materials at a building and component level (Mela et al. 2012; Maskell et al. 2017). Such optimization frameworks, if integrated with decision maker utilities, can find optimal design configurations that best meet the design requirements.

3.2.5 Research Gap

Although the building design methods under TBL objectives are well developed, a systematic integration of all four design methods shown in Figure 1 will better support elegant design outcomes. The current building performance rating methods (e.g., LEED) (Step 2 in Figure 1) are designed to rate the TBL impacts of buildings (Step 1 in Figure 1). Similarly, decision maker preferences can be assessed with regard to both the TBL impact assessment results and the TBL performance ratings (Step 1 and 2 in Figure 1). In order to complete the decision appraisal process, the preference assessment methods require integration with optimization techniques. However, few methods exist that analyze decision maker's utilities (preferences or requirements) with respect to TBL tradeoffs that are adaptable to a range of alternative design solutions. Furthermore, the current state-of-the-art models for preference assessment are not modular and require analysis on a case-by-case basis for various alternative solutions, nor are they adaptable to the current multi-objective optimization methods (Step 4 in Figure 1). For these reasons, there is a need for a holistic preference assessment framework that is adaptable to a variety of alternative design options (versus a fixed number of alternative design solutions), that can assess multiple and potentially conflicting decision criteria, and that is compatible (combinable) with the state-of-the-art multi-objective optimization tools.

4. PROPOSED METHODOLOGY

The TBL building design models presented in Section 3 are typically applied in isolation, but, if integrated, have high potential to identify elegant infrastructure designs. The SIMPLE-Design framework is a modular preference function development strategy for bridging the gap between the frameworks that assess decision maker values and the models that find the optimal design configuration.

The proposed methodology can be divided into four steps associated with a limited number of methods that support the low cognitive load:

1. Select TBL criteria: quantitative criteria are compatible with optimization.
2. Identify alternative systems: the alternatives selected should be plausible and should involve TBL tradeoffs.
3. Estimate performance range: a frame of reference is needed for the complex multi-criteria decision problem.
4. Assess decision maker preferences: indifference curves are adaptable, can be applied to a range of alternative design configurations, and can act as constraints for finding the optimal infrastructure configuration that meets the decision maker's needs.

Due to the modular nature of the overall framework, a selected number of different methods could be used in each step. Within each method, there generally exist multiple options, which may be combined, as detailed in Figure 2. In order to meet its goals of: (a) ease of use in early design; (b) use of quantitative TBL measures; and (c) development of constraints applicable to a broad set of alternative designs, the SIMPLE-Design approach is most compatible with the use of (1) midpoint indicators as decision criteria; (2) a combination of literature review and structured expert elicitation to identify alternative systems; (3) estimates of performance measures for initial costs, hazards costs, and CO_2 emissions derived from multiple case studies and supplemented by life-cycle analysis; and (4) use of perfect indifference curves to represent decision maker preferences.

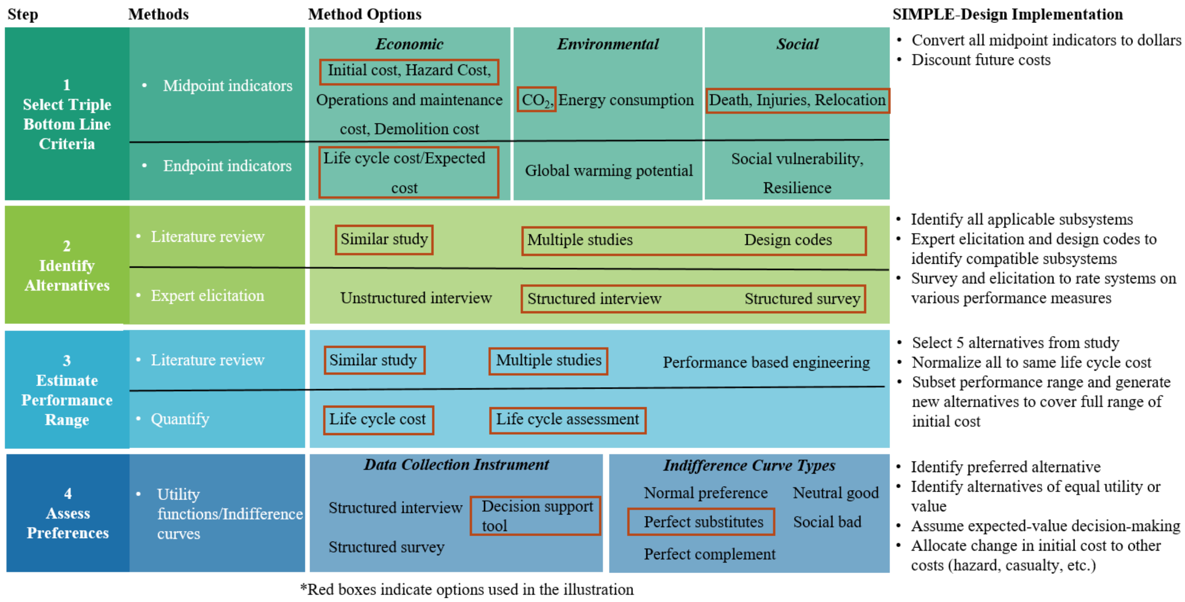

Figure 2: Organization of SIMPLE-Design Framework, Possible Methods, and Description of Implementation for Buildings in Illustrative Example

While the SIMPLE-Design framework (and suggested methods) aims to be applicable to a broad range of infrastructure and site conditions, further detailing of the procedure would likely be incomprehensible if the descriptions remain at a generic level. Therefore, office buildings exposed to seismic and hurricane hazards were selected for the development of the framework. Office buildings are designed by integrated design teams and are centers for economic and governmental functions. Figure 3 depicts the modular preference assessment framework for the design of hazard resilient and sustainable office buildings comprised as criteria of Soil-Foundation-Structure-Envelope (SFSE) subsystems.

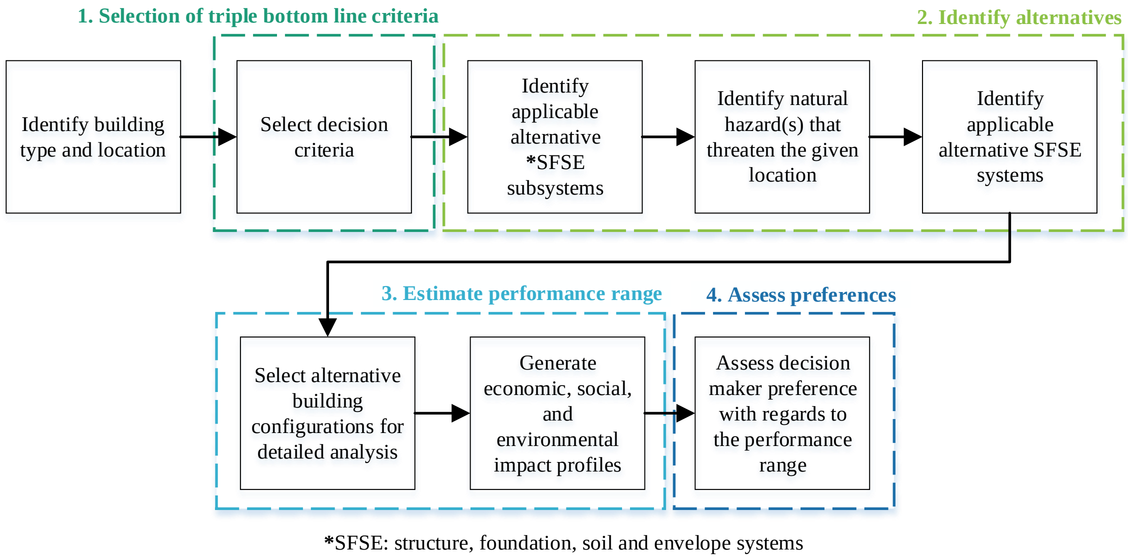

Figure 3: SIMPLE-Design Framework for the design of Hazard Resilient and Sustainable Buildings

4.1 Selection of Triple Bottom Line Decision Criteria

In order to develop a decision analysis framework for the design of elegant infrastructure solutions, the three main criteria of life-cycle cost, environmental impact, and social impacts must be considered with regard to the TBL. Due to the exponential growth in disaster losses (National Research Council (NRC) 2009), natural hazard losses (e.g., repairs costs, casualties) are selected as the third pillar of a TBL-based design, social impact. The midpoint indicators in this case can be chosen as the initial cost, hazard-related costs, CO_2 emission, and death and injury rate due occurrence of natural hazard events. To simplify the preference assessment methodology, all mid-point indicators can be converted to expected dollar values. For this reason, the decision criteria of initial cost, building damage and business interruption cost, casualty cost, and CO_2 emission cost have been chosen as criteria for the decision framework development. It should be noted that even if all decision criteria are translated into economic criteria, it is recommended to also provide the decision maker with a tangible measure for each decision criteria, e.g., number of death and injuries, lb. of CO_2 emissions, and number of downtime days of the building.

4.2 Identification of Alternatives

Once the decision criteria are defined, all alternative infrastructure subsystems need to be identified to understand the TBL tradeoffs of various alternative design configurations. The described subsystems will vary with respect to the building type. The identification of subsystems can be made through similar studies, and/or expert elicitation (i.e., surveys and interviews). Once the subsystem categories are identified, all alternative subsystems that meet the minimum code requirements, or all other applicable requirements with regard to the site location, will be determined. Considering the office building example, the alternative structural subsystems could consist of cold formed steel shear walls, steel eccentrically braced frames, steel buckling restrained braced frames, steel plate shear walls, and steel moment frames. If all of the described structural subsystems meet the minimum code requirements of the given site location, they can be considered as alternative office building structural subsystems. The same methodology can then be followed for all other subsystems.

For example, Tahir (2016) provides a list of alternative SFSE subsystems for midrise office buildings. Moving from individual subsystems to SFSE systems is a combinatoric problem, yielding 4,224 possible sets. Using expert elicitation methodology, the compatible subsystems can be identified. For example, shear wall systems are incompatible with single footings and therefore all combinations pairing shear walls with single footings are not plausible and can be excluded from further consideration. Similarly, it is unlikely to both improve the soil and use deep foundations. After this procedure of winnowing down to plausible systems, a set of SFSE alternatives will be available. One example of the 2,566 identified was unimproved soil, mat foundation, steel buckling-restrained braced frame, and curtain walls .

If the number of plausible systems is too high, another round of expert elicitation through survey and/or interview may be warranted to categorize the performance of the subsystems with regard to performance measures of interest (e.g., cost, durability, repairability). In order to ease the identification of alternative design configurations, a pre-assessment can be conducted on the individual soil, structure, foundation, and envelope subsystems. Use of a pre-assessment may be particularly advantageous when no decision-maker has expertise over all subsystems of interest (i.e., when the assessment should include geotechnical, structural, and architectural engineers).

Charleston, South Carolina, where hurricanes and earthquakes are the prominent natural hazards of the region and soil is poor (Type D), can be taken as an example. Table 1 and Table 2 provide examples of initial performance surveys for infill walls and steel structure subsystems. A set of criteria should be selected as befits the problem of interest, and might include initial cost, repairability, durability, energy performance, constructability, weight, likelihood of damage, ductility, peak drift, and other performance measures. The individual survey results can then be integrated using a formal multi-expert interview to obtain a limited set of promising systems for use in Steps 2 and 3 of the SIMPLE-Design methodology.

Table 1: Infill Wall Subsystem Initial Performance Assessment

	Initial Cost	Repair-ability	Dur-ability	Energy Performance	Construct-ability	Weight
Infill Wall Systems	L	L	H	M	L	H
• Anchored infill	L	M	H	L	L	H
○ Masonry veneer + Concrete Masonry Unit backup	L	M	H	L	L	H
○ Masonry veneer + Steel stud backup	M	M	M	M	M	M
• Adhered infill	M	L	M	M	M	M
○ Stucco	L	H	L	L	L	L
○ Exterior Insulation Finishing System	M	L	M	M	L	L

L: Low M: Medium H: High

Table 2: Steel Structure Subsystem Initial Performance Assessment

	Initial Cost	Likelihood of Damage	Repar-ability	Duc-tility	Peak Drift	Construct-ability	Weight
Cold Formed Steel Shear Walls	L-M	M-H	L-M	M	M	H	L
Steel Eccentrically Braced Frame	H	L	L-M	H	L-M	L	L-M
Steel Concentrically Braced Frame	L-M	H	L	L	L	H	L-M
Steel Buckling Restrained Braced Frames	M-H	L	H	M-H	L-M	L-M	L-M
Steel Plate Shear Walls	H	L-M	L	H	L-M	L	L-M
Steel Moment Frames	H	L-M	L	H	H	H	L-M

4.3 Estimation of Performance Range

Once all alternative infrastructure systems are identified, a number of candidate system configurations are selected to obtain an estimate of the range of TBL performance across alternatives. The range will frame the complex multi-criteria decision problem for use in early design, while still meeting the adaptability requirement of the SIMPLE-Design framework. The number of the selected configurations will depend on the complexity of the decision problem, and the computational expense. Candidate infrastructure configurations should include varying economic, social, and environmental tradeoffs, as their primary purpose is to provide a reasonable estimate of the full performance range of all the alternative design configurations. This selection of candidates can be based on expert elicitation, historical data, and/or simulations of the performance of alternative infrastructure configurations under natural hazards. Ideally, a high-performing design option is one with a low loss of functionality after a natural hazard event. The high-performing option may also have a relatively lower life-cycle cost and environmental impact compared to the other alternative infrastructure configurations. A low-performing design may trade low initial cost for high life-cycle cost.

Again considering office buildings and hurricane hazard in Charleston, SC, use of a point-loaded glazing system will likely result in significant debris impact damage and could be considered as a low performing design option. For the same location and structure, a curtain wall system might be considered as high performing design option. If both envelope systems are assessed and approved as reasonable proxies for the true best- and worst-performing envelope systems, they can undergo detailed performance assessment and serve as candidate subsystems in the alternative system configurations. In order to meet the goal of cognitive ease and early design compatibility of the SIMPLE-Design framework, two or more alternative building system configurations are recommended for estimation of the performance range (i.e., detailed performance analysis) and the preference function development strategy. For the detailed performance assessment, the decision criteria can be presented to the decision maker in their original units (e.g., number of injuries, lb. of CO_2 emissions) or as transformed expected costs.

If all the decision criteria are translated into economic criteria, an expected value decision maker is likely to add all the various cost types together and select the lowest cost alternative. However, the small set of alternatives is not a true representation of all the available design alternatives, and rather are estimates of the performance range. Furthermore, the goal of the SIMPLE-Design framework is to assess and understand the preference of the decision maker with respect to the TBL criteria and not to find the alternative with the lowest cost from a small set of alternatives. Normalizing all alternatives to the same life-cycle cost allows the decision maker to look beyond total cost, and ensures that the resulting utility function can be applied to a range of alternative design configurations. It should be noted that the biasing resulting from the normalization will not impact the slope of the indifference curve.

4.4 Assessment of Preferences

At this step, a detailed performance assessment is conducted using the candidates to develop utility functions applicable to a range of alternative design configurations. The detailed performance assessment is conducted with respect to the decision criteria (identified in Step 3.1) and the life cycle of the asset, e.g., 50 years. Indifference curves (a category of utility functions) are recommended for assessing decision maker preferences in order to meet the goal of adaptability to a range of alternative design solution, noting that most other methods are ranking-based and therefore not generalizable.

Indifference curves represent the quantities of two different goods (decision criterion) to which the decision maker is indifferent. In theory, multiple paired curves could be developed in the case of three or more criteria, but for the purposes of early design it is appropriate to select one criteria as the consistent independent variable. The first step in developing an indifference curve is to select one of the candidate configurations as the starting point or base case. This configuration is then used to generate a set of equal-utility configuration that cover the range of the independent variable. While several strategies could be used to cover the range, an approach appropriate for early design is to decrement and/or increment the independent variable, forcing the decision maker to allocate the change in cost to the dependent variables. Finally, a regression is performed between the independent and each dependent variable to obtain a set of generalized indifference curve from the identified indifferent configurations.

As shown in Figure 4, a number of curves exist (Edgeworth 1881; Pareto 1971). Convex shaped indifference curves or normal preferences (Figure 4.a) represent one decision criterion that can be substituted by another decision criterion (e.g., substitute a higher initial cost for a lower repair costs). Perfect substitutes (Figure 4.b) represent decision makers that value both decision criteria and the relative importance of the decision criteria with respect to each other (e.g., initial costs is twice as important as repair cost). Perfect complements (Figure 4.c) are the minimum of two decision criteria (e.g., the minimum of both initial cost and repair cost). When the decision-maker values one decision criterion but does not have an opinion regarding the other decision criterion, it is a neutral good (Figure 4.d) (e.g., only initial cost is valued). When the decision-maker does not value one decision criterion, it is a social bad (Figure 4.e). In this case, if the decision maker is forced to improve the unfavorable decision criterion, they will require an improvement in the other decision criterion to compensate for it (e.g., a decision-maker who does not value environmental impact will demand a lower initial cost if forced to improve the environmental impact).

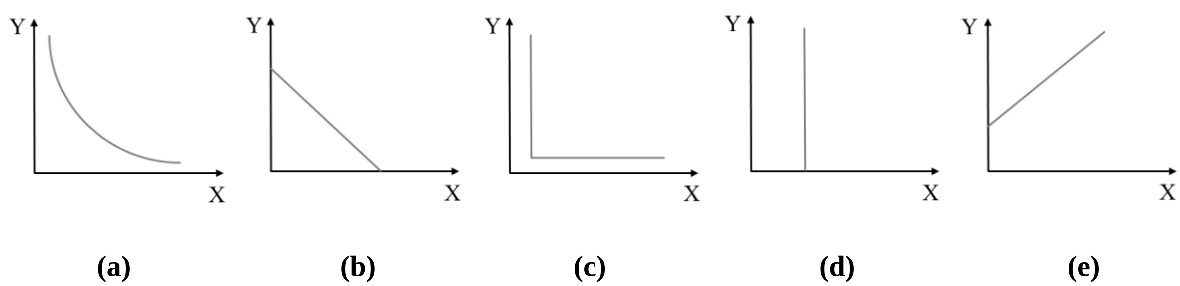

Figure 4: Different Types of Indifference Curves: (a) Normal Preferences, (b) Perfect Substitutes, (c) Perfect Complements, (d) Neutral Goods, and (e) Social Bads

More concretely, for the design scenario described, the decision criteria of initial costs, building damage and business interruption costs, casualty costs and CO_2 emission costs of the limited set of candidate configurations would be presented to the decision maker, who would select their preferred alternative. An example of such as set is provide in Table 3. Given this initially preferred alternative (e.g., alternative 3), the decision maker answers a (limited) series of questions of the form, "if you are forced to increase the initial cost to [$2.5M], for this new design configuration, how much building damage and business interruption cost, casualty cost, and CO_2 emission cost would make you equally as satisfied as with your initial selection?” A rational decision maker would require a lower damage and business interruption cost, casualty cost, and/or CO_2 emission cost to be equally satisfied, but decision makers would be expected to vary in how they allocate across the criteria (e.g., in their values).

A number of important assumptions are made in this approach to the indifference curve development and the SIMPLE-Design framework. Considering first the decision criteria themselves, costs related to natural hazards (building damage and business interruption and casualty) are expected costs over the distribution of possible hazard events over the building’s lifetime. Even given a hazard event of a certain intensity, the building may be in one of several damage states, with variable effects on casualty considering variability in building occupancy. As hazard events and impacts occur at an unknowable future point in the time, their costs are also a function of the time value of money and may be associated with a discount rate. This complex, probabilistic description of hazard-related costs differs from the initial cost and CO_2 emission cost, which are considered to be fixed expenses (with some degree of error and contingency) that the stakeholder is responsible for regardless of the occurrence of any natural hazard events. For this reason, the changes that the decision maker makes to the cost values of their initial selection to generate configurations of equal utility maintains the expected value.

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A second assumption relates to the selection of a category of indifference curves. Given that each of the decision criteria are expected to be of value and that the preference of the decision maker will remain constant in the performance range, the perfect substitute (Figure 4.b) is the only compatible indifference curve. A major advantage of the linear indifference curve is that it supports the goal of developing constraints applicable to a broad of decision alternatives, as the slope of the indifference curves (m) can be used to understand the preference of the decision maker with respect to the two decision criteria regardless of the value of the independent variable. Furthermore, in the case where further alternatives are identified that might be out of the range of the original alternative design configurations, indifference curves can be shifted in parallel to the original indifference curve (towards the satisfactory alternatives; e.g., lower initial cost, lower damage cost, lower casualty cost, and lower CO_2 emission cost solution space). It is also noted that the perfect substitute indifference curve is a first-degree polynomial, theoretically requiring only two points to be described. However, since the decision makers might require a few trials to reveal their true preferences, 3 or 4 points (depending on the initial selection of the decision maker and the performance range) of equal utility are assessed.

A simple or orthogonal regression can be used for fitting a line to the points of equal utility. In simple regression, one of the variables of the indifference curve is the independent variable and the dependent variable is predicted as a function of the independent variable (i.e., one of the two decision criterion is important). In the orthogonal regression, the sum of squared perpendicular distances is minimized from the data points to the regression line (i.e., both decision criteria are important).

5. PILOT IMPLEMENTATION: OFFICE BUILDING IN LOS ANGELES, CA

A pilot implementation was undertaken to demonstrate the SIMPLE-Design framework for the design of hazard resilient and sustainable office buildings. The purpose of the pilot implementation is twofold: (1) to demonstrate the application of the SIMPLE-Design framework using a specific illustration, and (2) to assess the type of information that is helpful for experts acting as hypothetical decision-makers. An earthquake-exposed nine-story, 75×180 ft^2 steel office building in Los Angeles, California previously assessed by Kang and Wen (2001) is chosen for the pilot implementation.

5.1 Implementation of SIMPLE-Design Methodology

5.1.1 Selection of Triple Bottom Line Criteria

The decision criteria of life-cycle cost (including building damage and business interruption from earthquakes), CO_2 emissions, and human casualties were selected as the TBL criteria. It was further determined that all criteria would be translated into discounted costs. The initial cost is the construction cost for building the facility. The building damage and business interruption costs, and the casualty costs from the earthquake hazard are respectively the expected failure cost, and the expected death and injury rate in the 50-year lifetime of the building considering a 5% discount rate (Kang and Wen 2001; Wen and Kang 2001). The CO_2 emission decision criteria considers: the total weight of structural steel and the associated emissions of $0.517\,\frac{\text{lb. CO}_2}{\text{lb. Steel}}$ (González and Navarro 2006); operational emissions, including electrical service, heating service, and maintenance; and demolition emissions per unit area of $567\,\frac{\text{lb. CO}_2}{\text{ft}^2}$ (Junnila and Horvath 2003). Costs are obtained assuming every 100 lbs. of CO_2 emissions is associated with \$1.68 of 2016 USD (Environmental Protection Agency 2016).

5.1.2 Identification of Alternatives

The SFSE subsystems have been described in Section 4.2. For illustration purposes and simplifying the performance assessment process, alternative structural subsystem configurations of a steel moment frame building have been selected, and it is assumed that the soil, foundation, and envelope systems have been pre-selected and are consistent across the configurations.

5.1.3 Estimation of Performance Range

For the estimation of the performance range, it was determined that alternative structural subsystem configurations obtained from a single study can provide a sufficiently broad performance range for the preference assessment methodology. Kang and Wen (2001) analyze twelve alternative configurations of the selected steel office building. The alternative building configurations have the same plan and elevation, and meet the National Earthquake Hazards Reduction Program and Load and Resistance Factor Design requirements for width-thickness ratio, beam-column moment ratio, panel zone shear strength, and panel zone thickness. The alternative building configuration vary in the intensity of the design basis earthquake, and therefore have different member sizes (Kang and Wen 2001; Wen and Kang 2001). To lower the cognitive burden and the survey time, five of the twelve alternative building configurations have been chosen as the candidate configurations (Table 3). The selected configurations represent the low and high initial cost configurations and three mid-range alternatives. The performance criteria values of initial costs, business damage and business interruption costs, and casualty costs for the alternative building configurations was retrieved from Wen and Kang (2001); i.e., alternative design configuration 1 to 5 (in Table 3) respectively represent alternative structure 1, 4, 7, 10, and 12 analyzed by Wen and Kang (2001). The CO_2 emission costs were estimated for each alternative building configuration using available data on CO_2 emissions per every lb. of structural steel; and the electrical service, heating service, maintenance, and demolition emissions (OM&D) per unit area (Junnila and Horvath 2003; González and Navarro 2006; Environmental Protection Agency 2016). An example of the CO_2 emission cost calculations for alternative design configuration 1 (in Table 3) is presented is Equation 1 and 2:

$$\text{Structure: } 414{,}000 \text{ lb. steel} \times 0.517 \frac{\text{lb. CO}_2}{\text{lb. Steel}} \times 1.68 \frac{\$\text{USD}}{100 \text{ lb. CO}_2} \cong \$4{,}000\text{USD} \quad (1)$$

$$\text{OM\&D: } 13{,}500 \text{ ft}^2 \times 567 \frac{\text{lb. CO}_2}{\text{ft}^2} \times 1.68 \frac{\$\text{USD}}{100 \text{ lb. CO}_2} \cong \$129{,}000\text{USD} \quad (2)$$

Table 3: Cost Breakdowns for the Alternative Design Configurations (Unnormalized)

Design Alternative	*Initial Cost	*Building Damage and business Interruption Cost ($)	*Casualty Cost	Structural Weight (lb.)	Structural CO_2 Emission (lb.)	Structural CO_2 Emission ($)	[Δ]Total CO_2 Emission ($)	Sum of All Costs
1	1,694,000	6,244,000	1,233,000	413,999	214,038	3,592	132,233	9,303,233
2	1,990,000	1,489,000	237,000	879,748	454,830	7,633	136,274	3,852,274
3	2,267,000	755,000	113,000	1,228,498	635,133	10,659	139,300	3,274,300
4	2,577,000	534,000	83,000	1,462,497	756,111	12,690	141,330	3,335,330
5	3,234,000	303,000	43,000	2,346,745	1,213,267	20,362	149,003	3,729,003

*Retrieved from Wen and Kang (2001)

[Δ] Structural, electrical service, heating service, maintenance, and demolition emissions

All decision criteria are discounted and translated to dollar values as explained in Section 5.1.1. The summation of all costs is normalized to $4M, in order to allow the decision maker to fully focus on the allocation of the costs and how much they value each decision criterion. Table 4 represents the normalized costs.

Table 4: Alternative Design Configurations of a nine-story Office Building (Normalized)

Design Alt-ernative	*Initial Cost ($)	*Building Damage and Business Interruption Cost ($)	*Casualty Cost ($)	$^{\Delta}CO_2$ Emission Cost ($)	Sum of all Costs ($)	Death and Injury Rate (#People)
1	728,000$^{(-)}$	2,684,000$^{(+)}$	530,000$^{(+)}$	57,000$^{(-)}$	4,000,000	[7-8]
2	2,066,000	1,546,000	246,000	142,000	4,000,000	[1-2]
3	2,769,000	922,000	138,000	171,000$^{(+)}$	4,000,000	[0-1]
4	3,090,000	640,000	100,000	170,000	4,000,000	[0-1]
5	3,468,000$^{(+)}$	325,000$^{(-)}$	46,000$^{(-)}$	161,000	4,000,000	[0-1]

*Retrieved from Wen and Kang (2001) and normalized to a total cost value of $4M

$^{\Delta}$Calculated using Equation 1+2, and normalized to a total cost value of $4M

(+)Upper limit of allowable performance range

(-)Lower limit of allowable performance range

Once the decision maker has initially selected one of the five alternative building configurations from Table 4, the next step is to generate additional points within the performance range (as defined in Table 4) that are of equal utility or value. A set of increments and/or decrements (depending on the decision maker's initial selection) in the initial cost are provided and the decision maker is required to offset those values by changing earthquake-related costs and CO_2 emissions cost. The decision maker will create two or three new alternatives based on the in(de)crements, noting that the number of points was selected to balance the number of tradeoff questions with coverage of the full performance range.

5.1.4 Assessment of Preferences

A decision support tool was developed using Microsoft Excel for finding the utility function of the decision maker with respect to the alternative design configurations in Table 4. An example of the tradeoff questions and the tool setup for a decision maker that has selected alternative design configuration 1 is shown in Figure 5. In the initial step, the decision maker is required to select one of the five building design configurations (presented in Table 4) to construct in Los Angeles. Based on the decision maker's initial selection, tradeoff questions are pre-populated to cover the performance range.

The first step of the tool provides information on the utility assessment instrument itself and the building specifications (Section A in Figure 5). The entry table (Section B in Figure 5) allows the decision maker to create three new alternatives based on the provided initial cost increments. The summation table (Section C in Figure 5) and column chart (Section D in Figure 5) show the final values (considering the inputs/changes in the entry table) of each cost for the new alternatives and the original alternatives with highest (alternative 5) or lowest (alternative 1) initial costs. The summation table also provides a percentage of change of the newly developed alternatives with respect to the decision maker's initial selection.

Next, the decision maker will allocate the increases in the initial cost to decrease building damage and business interruption cost and casualty cost, and increase CO_2 emission costs (based on the calculations a higher initial cost corresponds to a heavily reinforced structure and higher CO_2 emissions). Upon completion of the decision support tool, all the costs are allocated, and the new alternatives are within the performance range, the final preference/utility functions of the decision maker are plotted and presented as the final indifference curve (Section E in Figure 5). A line is fitted through the points of equal utility, representing the perfect substitute indifference curve.

Several decisions were made in the development of the decision support tool to lower cognitive burdens. The decision-maker must enter at most 9 values, and several visual cues provide immediate feedback on the acceptability of the entered values. One cue is the cell shading and colormap (Section C in Figure 5) that provides feedback on whether the criteria is in or outside the initial performance range. Dark purple represents the limits of the cost range (alternative 1 and 5), and light blue represents mid-range cost values (e.g., alternatives 2 and 3). The yet to allocate column in the entry table (Section C in Figure 5) is also associated with a colormap. The yet to allocate value starts with the change/increase in the initial cost value, which is shown in lime (lighter shade) and changes to green (darker shade) when the allocation process is complete and $0 is left to allocate. The bar chart (Section D of Figure 5) also updates and guides are provided to highlight any discrepancies from the expected total cost of $4M. The relative value of these cues was assessed in a post-survey instrument where they were ranked.

Figure 5: Decision Support Tool in Microsoft Excel (Shahtaheri et al. 2018)

5.2 Pilot Implementation Results

Twelve industry experts with the point of view of stakeholders, construction managers, engineers, office users, general contractors, and the ASCE's code of ethics and policies used the decision support tool. All decision maker completed the survey in less than 30 minutes. Indifference curves for four of the twelve survey respondents are presented in Figure 6. Decision makers A, B, C, and D each have at least 10 years of experience in: decision analysis for natural hazards, Structural Engineering, and Construction Engineering and Management. The four decision support tool users (decision maker A, B, C, and D, respectively) utilized the tool as an engineer, office user, engineer and construction manager, and selected alternatives 5, 4, 1, and 4 as their initial selection.

Using simple regression, the indifference curves are fitted to the alternatives of equal utility assessed from the decision makers, and are plotted for the independent variable of initial cost for each of the dependent variables. In addition to the indifference curves, the solution space direction (the preferred decision/design alternatives) is indicated with an arrow for each decision maker. Since each decision maker will prefer the alternative with the lower costs in each category, and indifference curves can be shifted, the solution space consists of the alternative design configurations that are either on the indifference curve or are closer to the origin. In the case of the initial cost versus CO_2 emission cost indifference curve, the goals are conflicting, with the solution space can containing high initial-low CO_2 emission cost solutions or low initial-high CO_2 emission cost solutions. The reason for this conflict is the assumption that the CO_2 emissions increased with initial cost (i.e., more steel was used), whereas the hazard-related costs decreased with the initial cost increase (i.e., more steel increases resilience). However, the decision makers had the incentive to lower the CO_2 emissions in their new alternatives, and higher initial cost, lower CO_2 emission options are considered for the solution space. Furthermore, each of the decision makers had a near- zero slope (between -0.02 to 0.04) for the casualty cost, and/or CO_2 emission cost indifference curves (Table 5). This implies that the decision makers are willing to pay any initial cost in order to reduce CO_2 emissions and casualties, and are therefore neutral to initial cost (have a neutral goods indifference curve). This neutrality suggests that using initial cost as the base may not capture all decision maker preference for the casualty cost and CO_2 emission cost indifference curves.

The slope of the indifference curves can be used to understand the preferences of the decision makers and the design alternatives that meets the decision maker's preferences. The slope of the indifference curve represents the change in the two decision criteria with respect to each other that would make the decision maker equally as satisfied. As mentioned earlier, indifference curves can be shifted (in parallel to the original curve). For example, for decision maker A, the slope of the initial cost versus building damage and business interruption cost indifference curve (Figure 6.a) is -1.04. This implies that decision maker A is willing to accept a \$1M or \$$C_i$ M increase in the initial cost for a \$1.04M or \$$C_{D,A}$ M decrease in the building damage and business interruption cost and vice versa (will demand a \$1M decrease in the initial cost for a \$1.04M increase in the building damage and business interruption cost). Considering the initial cost versus casualty cost indifferent curve (Figure 6.b), decision maker A will only accept casualty cost values that are smaller than or equal to the minimum value of \$46,000, or, in other words, will accept any initial cost value as long as the casualty cost ($C_{c,A}$) is less than or equal to \$46,000. Considering the initial cost versus CO_2

emission cost indifference curve (Figure 6.c), decision maker A again has lower concern for initial costs, and will accept a \$0.04M or \$$C_{e,A}$ M increase in CO_2 emission cost for a \$1M or \$$C_i$ M increase in initial cost.

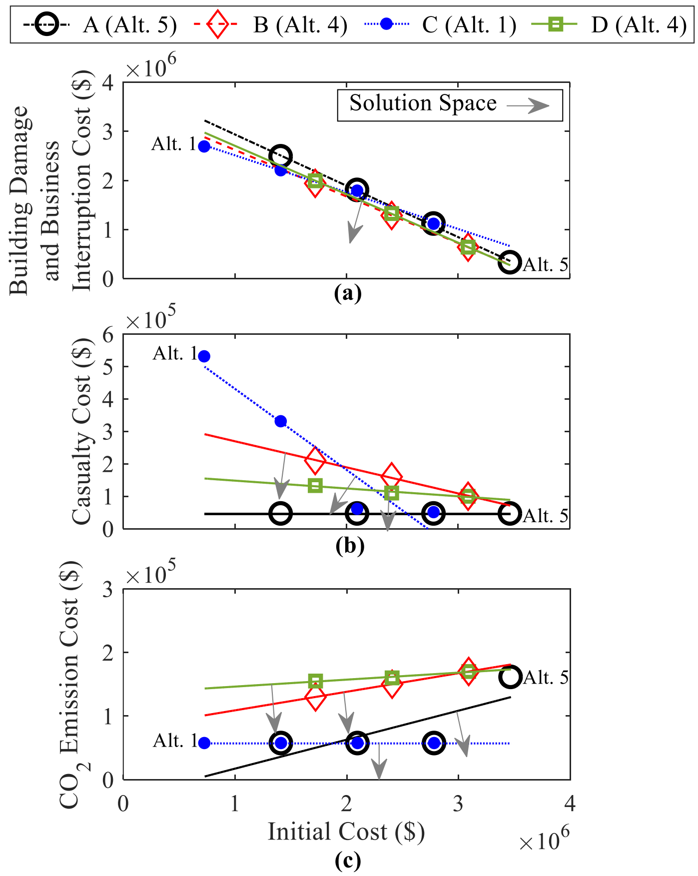

Figure 6: Indifference Curves for Initial Cost vs. (a) Building Damage and business Interruption Cost, (b) Casualty Cost, and (c) CO_2 Emission Cost (Decision Makers A-D)

The goodness of fit (R^2) values are over 91% for all indifference curves, with the exception of the initial cost versus CO_2 emission cost indifference curve for decision maker A. This close fit indicates that a linear function sufficiently represents the relationship between the points of equal utility. The residual values for all the fitted curves are less than 2% of the total costs (of \$4M), and for this reason the fitted curves shown in Table 5 are deemed an acceptable representation of the decision maker's utility function. Each Equation takes the form shown in Equation 3:

$$m_{C_x} C_i + b_{C_x} - C_x \geq 0 \tag{3}$$

Where C_i is the initial cost, and C_x stands for one of C_d, the building damage and business interruption cost, C_c, the casualty cost, or C_e, the CO_2 emission cost.

Table 5: Indifference Curve Equations with Respect to Initial Cost (Ci), Building Damage and Business Interruption Cost (Cd), Casualty Cost (Cc), and CO_2 Emission Cost (Ce)

Decision Maker	Slope (m)			Intercept (b)			Goodness of fit (R)		
	m_{C_d}	m_{C_c}	m_{C_e}	b_{C_d}	b_{C_c}	b_{C_e}	R_{C_d}	R_{C_c}	R_{C_e}
A	-1.04	0	0.04	3,982,000	46,000	-28,000	0.99	1.00	0.60
B	-0.95	-0.08	0.03	3,570,000	350,000	80,000	0.99	0.99	1.00
C	-0.75	-0.25	0	3,261,000	681,000	57,000	0.99	0.91	1.00
D	-0.99	-0.02	0.01	3,692,000	172,000	135,000	0.99	0.95	0.96

5.3 Assessment of Pilot Implementation

The post-survey instrument was used to assess the success of the pilot implementation in framing the problem and reducing the cognitive load. There was a general consensus (<30% coefficient of variation on numerical rankings) on the high usefulness of: allowing the decision makers to define alternatives of equal utility; and providing information on various cost categories (decision criteria). Conversely, providing extra information on the decision criteria calculations, as well as a detailed description on the design of the alternative configurations (e.g., variation in the intensity of the design basis earthquake and member sizes) received polarized ratings from the decision makers (with up to a 70% coefficient of variation). However, as no aspect of the SIMPLE-Design decision support tool was universally disliked (and each was rated useful by a majority of respondents), it was determined that no element should be removed. It is also noted that some decision makers asked for additional information, including more details on the breakdowns of the various cost types, the contract type for constructing the project (e.g., design-bid-build versus design-build), and a table that shows the newly developed alternatives with respect to the original alternative design configurations.

6. CONCLUSIONS AND FUTURE RESEARCH

Current practices and state-of-the-art methods of infrastructure design frequently focus on finding solutions that optimize the cost—and sometimes time—of the construction process. Alternatively, existing holistic decision analysis frameworks that consider triple bottom line metrics (i.e. economic, social, and environmental impacts) fail to capture decision maker utilities during early design or are not easily implementable during early design. Decision makers who are not aware of hazard-resilient designs, and environmental impact and design cost tradeoffs are less likely to make informed decisions at an early design stage. The presented four-module SIMPLE-Design decision framework and decision support tool provide an avenue for communicating the performance of alternative infrastructure configurations to the decision makers and assessing their preferences at an early design phase. Key aspects of each module of the SIMPLE-Design framework include:

1. Supporting subsequent optimization by using quantitative criteria to describe the triple bottom lines.

2. Lowering cognitive burden and avoiding bounded rationality by pre-selecting a limited set of alternatives that describe the possible tradeoffs between decision criteria and the performance range.
3. Ensuring that the preferences obtained are applicable to the full solution space through use of indifference curves.

Several choices intended to reduce cognitive load and to provide an appropriate frame of reference were made in developing the pilot implementation decision support tool, and were generally identified as being useful by the twelve survey respondents. While the implementation focused on office buildings exposed to earthquake hazard, the tool could be modified to reflect a different design scenario (e.g., different types of infrastructure), decision criteria (e.g., separate damage and business interruption costs), or number of candidate alternatives and size of the performance range. The framework and decision support tool's modularity also supports the substitution of different approaches, e.g., a different type of utility function.

While the framework and decision support tool are generalizable and flexible, the pilot implementation required several significant assumptions that could potentially bias the results and should be fully explored in future work. These include:

- All decision criteria are transformed to a dollar value and this transformation is not customized to the decision-maker, and therefore may not adequately reflect the value of global warming potential or human casualties.
- The candidate alternatives are normalized to the same total life-cycle cost, implicitly assuming an expected-value decision maker. This normalization may penalize high-performing design options.
- The initial cost is used as a basis for developing new alternatives, and while this basis is in line with the current state of practice, it may not best promote elegant design solutions.
- The perfect substitutes (linear) indifference curves is assumed, and may not accurately reflect the true form of a decision maker's utility function. This was found to be the case for one survey respondent, who was neutral to initial costs when considering human casualties and environmental impact.

Further improvements and extensions of this research might include the combination of indifference curves to combine different decision maker preferences in group decision making problem, defining archetype indifference curves by assessing the preferences of a larger number of decision makers in each category of stakeholder (e.g., owner, engineer), and the comparison of simple regression and orthogonal regression for fitting indifference curves to the alternatives of equal utility.

The SIMPLE-Design framework bridges the gap between frameworks that assess decision maker values (utilities or preferences) regarding triple bottom line measures and models that find the optimal design configuration(s). The proposed framework frames a complex multi-criteria decision problem with conflicting decision objectives by offering two main contributions: 1) a modular preference function development strategy that is adaptable to a range of alterative design solutions and optimization algorithms, and does not require analysis on a case-by-case basis; 2) a decision framework with a low cognitive load, low effort, and high impact that is compatible with the early design phase and can be completed in less than

30 minutes. The developed indifference curves can be used as constraints in multi-objective decision making or reliability-based decision analysis frameworks. Due to the modular nature of the preference assessment methodology, it is also adaptable to any number of decision criteria and infrastructure types and is anticipated to be useful for the design of elegant infrastructure solutions.

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3. A RELIABILITY-BASED DECISION SUPPORT SYSTEM FOR INCORPORATING DECISION MAKER UTILITIES IN THE DESIGN OF INFRASTRUCTURES

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1. ABSTRACT

Infrastructures are the most fundamental facilities and systems serving society. Due to the existence of infrastructures in economic, social, and environmental contexts, all lifecycle phases of such fundamental facilities should maximize utility for the designers, occupants, and society. However, due to uncertainties associated with the nature of the built environment, the economic, social, and environmental (i.e., triple bottom line) impacts of infrastructure assets must be described as probabilistic. For this reason, optimization models should aim to maximize decision maker utilities with respect to multiple and potentially conflicting probabilistic decision criteria. Although stochastic optimization and multi-objective optimization are well developed in the field of operations research, their intersection (multi-objective optimization under uncertainty) is much less developed and computationally expensive. This article presents a computationally efficient, adaptable decision framework for incorporating probabilistic decision criteria and decision maker requirements (utilities) in the design of infrastructures. The proposed model utilizes the First Order Reliability Method (FORM) in a system reliability approach for assessing the reliability of alternative infrastructure design configurations with regard to the probabilistic decision criteria and decision maker defined utilities (indifference curves), and provides a meaningful feedback loop for understanding the decision analysis results. A pilot implementation is undertaken on a nine-story office building in Los Angeles, CA for illustrating the capabilities of the reliability-based decision analysis framework. Through the hypothetical pilot implementation, the presented decision framework is shown to have the ability to: 1) find the optimal probability of success for alternative design configurations in terms of meeting the decision maker defined multi-criteria constraints (utilities), 2) measure the effect of all decision criteria associated with the alternative design configurations on the probability of meeting the decision maker defined preferences (utilities), 3) include the correlation between the decision criteria in the reliability analysis, 4) find the correlation between multiple utility functions and solution spaces, and 5) adapt to various types of probability distributions and allow full and consistent representation of all relevant uncertainties. The results of the pilot implementation revealed that high-performing design configurations (with higher initial costs and lower failure costs) had a higher probability of meeting the decision maker's preferences. This result implies that combining decision maker utilities with multiple design options and probabilistic decision criteria can lead to identifying high-performing infrastructure design configurations that also

maximize decision maker utilities. This novel utilization of the systems First Order Reliability Method provides a computationally efficient and adaptable multi-criteria probabilistic decision support system for finding optimal infrastructure configurations with respect to multiple probabilistic decision criteria (e.g., life-cycle cost and level of service) and decision maker utilities, while prioritizing the important performance criteria that require improvement.

Keywords

Decision Analysis, Multi-Criteria, Multi-Objective, Optimization, Probabilistic, Reliability Analysis, Sensitivity Assessment, Design Strategies, Performance-Based, First Order Reliability Method, System Reliability, Utility Function, Indifference Curve

2. INTRODUCTION

Infrastructures design decisions are complex due to the number of conflicting objectives that can significantly impact the design of such fundamental facilities and the uncertainty associated with the nature of the built environment (e.g., natural disasters and environmental stressors). The identification of a truly optimal infrastructure design is impossible as the actual performance of the facility over its lifetime cannot be known in advance—the conditions, e.g., the occurrence of natural hazard events are unknown—and the objectives are likely to be conflicting—minimize initial cost and maximize functionality after a hazard event. If the premise of impossibility is accepted, then the only rational decision is to directly consider both the uncertainty and conflicting criteria by incorporating decision-maker preferences with regard to tradeoffs.

When decisions are made in the context of early design, they must also: consider a broad range of alternatives and multiple attributes, be relatively easy to implement, and provide practical design guidance. The identification of a decision-making method itself becomes highly constrained, as almost all multi-criteria and multi-objective decision making methods fail one or more of the early design decision framework requirements.

For example, the multi-objective decision making methods do not provide a meaningful feedback loop for allowing the decision maker to the understand the decision analysis results (and improve the performance of the alternative designs). Such optimization algorithms mainly focus on finding an optimal alternative design solution with respect to the defined constraints. The multi-criteria decision making methods do not provide an adaptable, easy to implement preference assessment framework that aligns with the complex nature of early design decisions, the available time to make decisions, and the dynamic nature of the decision space (e.g., new alternative design configurations might be added to the solution space and decision maker utilities should be adaptable).

In order to meet the specific requirements described of: incorporation of uncertainty, generality to a range of alterative designs, multiple decision criteria, decision maker utilities, alternative design configurations, and a meaningful feedback loop, this paper proposes a holistic, modular, multi-criteria decision support system that combines and builds upon two widely-accepted methods to create a probabilistic decision support system. Multiple utility functions in the form of indifference curves are used to capture decision maker utilities with respect to the decision criteria, while lifetime performance of the design alternatives are characterized using probabilistic distributions such that the problem collapses to a simple optimization: find the alternative that has the highest probability of meeting the decision maker's preferences. A systems formulation of the First Order Reliability Method (FORM) is utilized for incorporating multiple decision maker utilities in the decision analysis framework.

The integration of utility functions and FORM in a system reliability approach with multiple decision criteria offers a significant advancement over related work. Two of the most closely related research are presented by Bisadi and Padgett (2015), and Wei at el. (2016). Bisadi and Padgett (2015) conduct time-dependent multi-hazard reliability analysis on deteriorating structures to optimize the design of structures. This framework utilizes the unified reliability method, in order to solve a single criterion decision problem in the form of a constraint and not a limit state function (i.e., find design parameters based on the probability of exceeding a defined level of loss). Wei et al. (2016) utilize FORM with multiple decision criteria for comparative life-cycle assessments (comparing two insulation systems) to find the alternative with the smallest environmental impact. However, the presented method for assessing decision confidence probability does not integrate decision maker utilities with the decision criteria. Therefore, to the authors' knowledge the proposed approach represents a novel application of FORM in integration with decision maker utilities.

In addition to the complexity of infrastructure design decisions, a number of decision biases exist that hinder the decision analysis process in uncertain environments. Among many others, the availability bias, representation bias, and overconfidence bias are three types of biases that directly apply to the design of infrastructures. The availability bias occurs when individuals assess the frequency of an event with the occurrences that they can recall (Tversky and Kahneman 1974). The representativeness bias is when individuals attribute characteristics of a process to the events that they generate (Tversky and Kahneman 1974; Tversky and Kahneman 1981). Overconfidence bias is when the individual's subjective confidence is greater than the objective accuracy of the judgments (Kahneman et al. 1982; Pallier et al. 2002). All the mentioned biases can lead to poor infrastructure design decisions that do not consider the uncertainty associated with the nature of the built environment and infrastructure design decisions. This requires a risk and reliability-based decision analysis framework that finds the reliability of various infrastructure design alternatives with respect to unforeseen risk measures, decision maker preferences, and probabilistic decision criteria.

Lifetime optimization methodologies have provided optimal design and repair strategies for structures by estimating cost of failures, and social and environmental impacts at a single infrastructure and community level (Stewart 2001; Wen and Kang 2001; Frangopol et al. 2004; Liu and Frangopol 2005; Geyer 2009; Kang and Lansey 2011; Mela et al. 2012; Bonstrom and Corotis 2014; Bisadi and Padgett 2015; Burton et al. 2015; Chandrasekaran and Banerjee 2015; Mackie et al. 2015; Wei et al. 2015; Bocchini et al. 2016; Daneshkhah et al. 2017). Similarly, Performance-Based Earthquake Engineering Research assesses probabilistic seismic performance of individual buildings and facilities (Cornell and Krawinkler 2000; FEMA 2012).

Considerable effort has been made in changing deterministic performance measures to probabilistic assessments that consider multiple hazards during the infrastructure lifetime. However, the available multi-criteria and multi-objective decision making models under uncertainty do not provide a computationally efficient and adaptable decision analysis framework for analyzing such holistic probabilistic decision criteria while providing meaningful feedback loops for interpreting the decision analysis results during the early design phase (where decisions are more impactful).

In order to maximize utility for designers, occupants, and the society, a two-step decision analysis model is required for assessing decision maker utilities and finding the best design alternative that maximizes decision maker utilities with respect to probabilistic decision criteria. In step one, for assessing decision making utilities, the proposed decision analysis model uses a modular preference assessment framework, **S**ustainable **I**nfrastructure **M**ulti-Criteria **P**reference assessment of a**L**ternatives for **E**arly **D**esign or SIMPLE-Design proposed by Shahtaheri et al. (2018). In step two, a novel utilization of the First Order Reliability Method (FORM) is proposed by the aim of incorporating decision maker utilities and multi-criteria probabilistic decision criteria in the design of infrastructures and maximizing decision maker utilities.

The proposed probabilistic multi-criteria decision analysis framework is demonstrated using a nine-story office building with three conflicting decision criteria (decision objectives) of building damage and business interruption costs, casualty costs, and CO_2 emission costs; twelve alternative design configurations; and decision maker defined indifference curves (utility functions). The reliability of each building design alternative and further decision appraisal measures are found with respect to the decision maker utilities.

3. BACKGROUND

3.1 Uncertainty in Decision Analysis Models

Uncertainty in decision problems can be categorized as aleatory or external uncertainty, related to the nature of the environment, and epistemic or internal uncertainty, related to the structure and analysis of the problem (French 1995; Friend et al. 2010). For example, uncertainty in design of resilient infrastructures can manifest itself in the natural variability of natural hazards (aleatory uncertainty), the uncertainty associated with lack of knowledge regarding individual hazard probabilities (epistemic uncertainty), and the response of the infrastructure to the natural hazard event (epistemic uncertainty). It should be noted that aleatoric and epistemic uncertainties are not mutually exclusive, however as epistemic uncertainty can be reduced by searching for patterns or casualties, aleatory uncertainty cannot be reduced and can be managed using relative propensities (Brun et al. 2011). Table 1 represents the distinguishing features of aleatory and epistemic uncertainty:

Table 1: Distinguishing Features of Aleatory and Epistemic Uncertainty (Retrieved from Brun et al., 2011)

	Aleatory (External)	**Epistemic (Internal)**
Representation	Class of possible outcome	Single case
Focus of Prediction	Event propensity	Binary truth value
Probability Interpretation	Relative frequency	Confidence
Attribution of Uncertainty	Stochastic behavior	Inadequate knowledge
Information Search	Relative frequencies	Patterns, causes, facts
Linguistic Marker	"Chance", "Probability"	"Sure", "Confident"

Advancements in decision analysis under uncertainty and probabilistic assessment techniques have been an active area of research since the 1990s, and were identified as an important decision analysis methodology from 1990 to 2001 (Keefer et al. 2004). As this area of research has been evolving, the recent state-of-the-art techniques in Multi-Criteria Decision Making (MCDM) under uncertainty are mainly focused on unpredictable events (e.g. lotteries and uncertain tradeoffs) (Pratt et al. 1964; Massala and Tsetlin 2015), uncertainty in value of judgment and decision weights (Levary and Wan 1999; Hyde et al. 2005; Banuelas and Antony 2007; El Hanandeh and El-Zein 2010; Fan et al. 2010; Durbach and Stewart 2012; Wang et al. 2013), and fuzzy decisions (Cetin et al. 2002; Wang et al. 2008; Zarghami et al. 2008; Dalalah et al. 2011; Liao et al. 2014).

Figure 1 illustrates the state of the art decision making methods under uncertainty with respect to aleatory and epistemic uncertainties, and the capabilities of the decision analysis models.

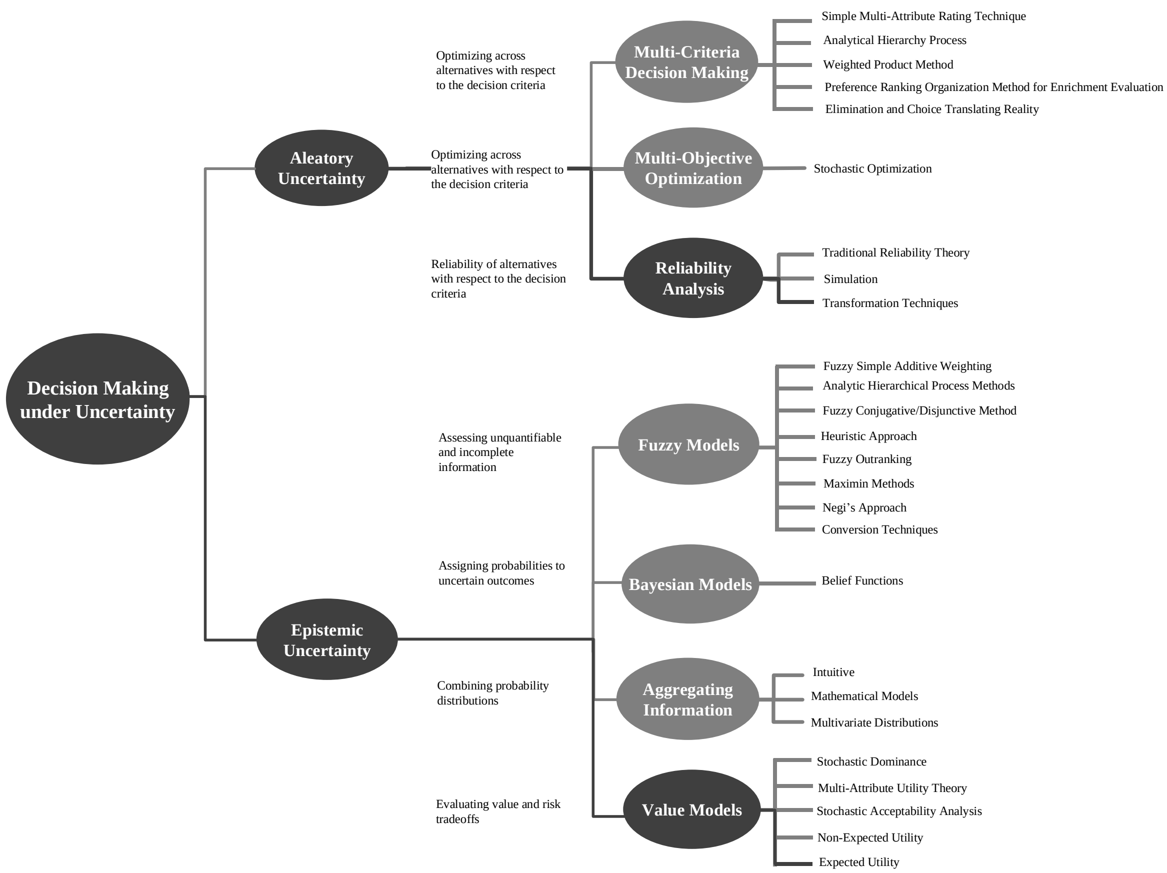


Figure 1: Decision Making Methods under Uncertainty and the Proposed Approach for the Decision Problem

The uncertainty associated with the decision criteria as probabilistic performance measures is mainly associated with the natural variability of the built environment, i.e., aleatory uncertainty. Multi-objective optimization and reliability-based decision analysis models have the ability to analyze decision maker requirements, and the aleatory uncertainty associated with the probabilistic decision criteria. Multi-objective decision making (MODM) models have the ability to incorporate uncertainty in the decision objectives, which is known as stochastic MODM. Although stochastic optimization and multi-objective optimization are well developed in the field of operations research, their intersection (multi-objective optimization under uncertainty) is much less developed (Gutjahr and Pichler 2016) and computationally demanding. Moreover, as decision analysis frameworks are moving towards methodologies that allow for elaborations, sensitivity analysis, assessments of preferences, and trade-off strategies (Edwards et al. 2007; Howard and Abbas 2016; Wei et al. 2016), fewer decision models are analyzed using MODM techniques. For this reason, risk and reliability-based decision analysis frameworks are explored as an option for solving MCDM problems under aleatory uncertainty.

3.2 Risk and Reliability Measures

If the decision criteria and the stochastic behavior of the alternatives (with respect to the decision criteria) can be found, and the goal is to find optimal design configurations that meet the decision maker defined constraints (utilities), the probability of failure (p_f) can be defined as shown in Equation 1:

$$p_f = p\,(g(\boldsymbol{X}=\boldsymbol{x}) \leq 0) \quad (1)$$

In Equation 1, p_f is the probability of failing to meet the decision maker defined performance constraints (limit state function or utility function), and $g(\boldsymbol{X})$ is a limit state function based on a vector of decision criteria values $\boldsymbol{X}$, which takes on values $\boldsymbol{x}$. In this case, each alternative design configuration will have a probability distribution associated with each decision criterion. The optimal design configuration that best meets the decision maker's requirements, is the one with the highest probability of achieving the required performance criteria, decision maker defined constraints, utilities, and preferences.

p_f can be found using traditional reliability theory (estimating the volume of the solution space, First Order Second Moment Method, and Monte Carlo Simulation), simulation techniques (reducing the order of integration), and transformation techniques (transforming the variables to standard normal variables) (Shinozuka 1983; Ang and Tang 1984; Bjerager 1988; Bucher 1988; Bjerager 1990; Ditlevsen and Madsen 1996). However, the main factor that separates the transformation techniques from other methods (i.e., traditional reliability methods and simulation techniques) is its ability to provide a number of different measures for conducting sensitivity assessments on the decision criteria, utility function uncertainty, and decision confidence probability (Cetin et al. 2002; Wei et al. 2016). The transformation methods include the First Order Second Moment (FOSM) method, First Order Reliability Method (FORM), and Second Order Reliability Method (SORM). The transformation methods are presented with respect to the complexity of each method (less complexity and more approximation to more complexity and less approximation).

If the stochastic behavior of alternative infrastructure configurations can be found with respect to the decision criteria, it is best to incorporate the full probability distribution of the alternative design options in the reliability analysis. In this case, the traditional FORM can be used. It should be noted that FORM linearizes the limit state function in the transformation process and might lead to grossly inaccurate results in extreme situations. SORM uses a second order polynomial in the transformation process. However, this method is inherently more complex and might require numerical methods for solution (Melchers 1999). FORM has the capability to systematically combine the individual capabilities of different decision analysis tools (i.e., multi-criteria/multi-objective decision analysis under uncertainty and decision maker utilities), provide a meaningful feedback loop for the decision maker (by prioritizing the important decision criteria), and obtain stochastic results with low computational expense compared to stochastic optimization methods (Skaggs and Barry 1996) and other reliability-based approaches. Infrastructure design decisions include multiple decision criteria, multiple design alternatives, uncertainty, and might require sensitivity assessments on the performance criteria and the decision analysis results. For this reason, FORM can be utilized for finding the reliability of alternative design configurations with respect to decision make utilities.

3.3 Knowledge Gap and Contribution

Figure 2 represents the effectiveness of available methods for solving multi-criteria decision problems under uncertainty. MCDM models under uncertainty can significantly benefit from a holistic, computationally efficient, adaptive reliability-based approach that also provides measures for conducting sensitivity assessments on the decision analysis results. A novel utilization of FORM is proposed for integrating the individual capabilities of multi-criteria decision analysis models under uncertainty. FORM has the ability to 1) measure the effect of each performance criterion or decision criterion (e.g., life-cycle cost) on the reliability of alternative infrastructure configurations with regard to the decision maker defined utilities (preferences, requirements, and constraints), 2) include the correlation between the probabilistic decision criteria in the reliability analysis, 3) measure the correlation between the decision maker defined utility functions and solution spaces, and 4) include the full probability distribution of multi-criteria performance measures of infrastructure design configurations in the decision making process. The proposed probabilistic multi-criteria decision analysis model has the ability to analyze multiple and potentially conflicting probabilistic decision criteria for a number of decision alternatives with respect to a system of decision maker defined utilities, constrains, limits, and requirements.

	Avenues for Solving Probabilistic Multi-Criteria Decision Problems			
Decision Analysis Model Requirements	Stochastic Optimization	Traditional Reliability Methods	First Order Reliability Method	Second Order Reliability Method
Multi-Criteria	●	●	●	●
Probabilistic	●	●	●	●
Sensitivity measures	○	○	●	●
Computationally efficient	◒	○	◒	○
Adaptive to various types of probability distributions	◒	◒	●	●

Effectiveness: low-○, medium-◒, high-● Proposed Method: ▢

Traditional Reliability Methods: estimating the volume under the acceptable surface, First Order Second Moment Method, and Monte Carlo Simulation

Figure 2: Effectiveness of Available Methods for Solving Multi-Criteria Decision Making Problems under Uncertainty as Based on the Literature Review

3.4 Integration of FORM and the SIMPLE-Design Framework

In order to implement FORM, decision maker defined utility functions (limits, constraints, or requirements) are required for finding the reliability of each alternative infrastructure configuration (decision alternative) with respect to the defined decision criteria (i.e., maximizing decision maker utilities). Shahtaheri et al. (2018) have developed a modular preference assessment methodology (i.e., SIMPLE-Design) for creating decision maker defined indifference curves (utility functions or preference functions) that can be used as limit state functions in FORM. This framework is superior to other preference assessment methodologies due its ability to systematically addresses the cognitive limitations of the decision makers, and adapt to a range of alternative design configurations and optimization algorithms, while framing a complex multi-objective decision problem.

4. METHODOLOGY

Figure 3 depicts the probabilistic multi-criteria, decision analysis using FORM. This framework consists of three main steps: 1) generation of decision criteria, 2) assessment of preferences, and 3) decision appraisal. The presented decision analysis methodology starts with the identification of the probabilistic decision criteria that are relevant to the decision problem. Once the decision criteria are identified, alternative infrastructure configurations are identified for detailed analysis; i.e., measuring the probabilistic performance of the alternative infrastructure configurations; and estimating the first, second, and mixed moments of the decision criteria probability distributions for each alternative design configuration. The alternative design configurations will also feed into the SIMPLE-Design framework (Shahtaheri et al. 2018)for assessing decision maker preferences and developing decision maker defined utility functions. Utilizing FORM, the reliability of alternative building systems can be found with respect to each alternative design configuration (decision alternative) and the decision criteria. FORM also provides means for conducting sensitivity assessments and finding the impact of the decision criteria on the reliability of alternative infrastructure configurations. The decision appraisal is based on the probability of meeting the multi-objective decision maker defined preferences (p_f in Equation 1), and the sensitivity assessment measures. The proposed methodology is shown in Figure 3.

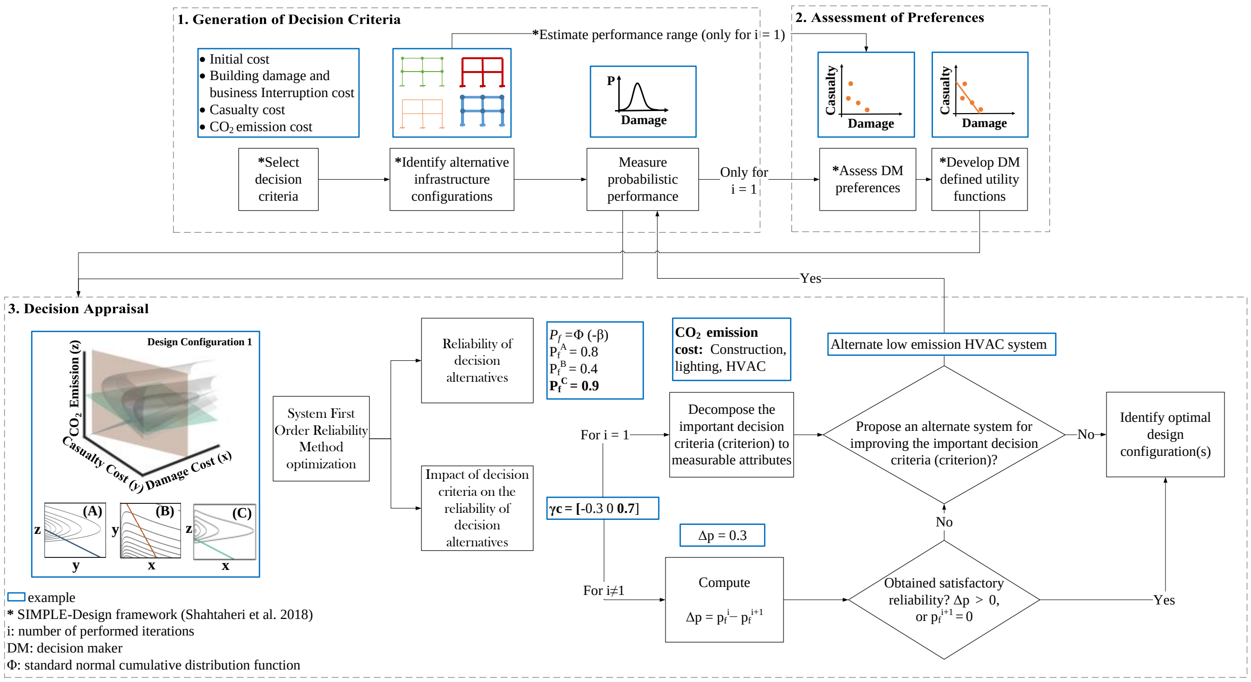


Figure 3: Probabilistic, Multi-Criteria, Decision Analysis using the First Oder Reliability Method

While the presented decision analysis framework using FORM is applicable to a broad range of infrastructure and site conditions, further detailing of the procedure would be incomprehensible if the descriptions remain at a generic level. For this reason, midrise office buildings subjected to the earthquake hazard are selected for illustrating the decision analysis framework.

4.1 Generation of Decision Criteria

4.1.1 Select Decision Criteria

The selection of the decision criteria depends on the infrastructure type, infrastructure location, unforeseen risk measures, and the computational expense associated with analyzing the alternative infrastructure configurations against the defined decision criteria. An example of set of triple-bottom-line-based (i.e., economy, environment, and society) decision criteria for the design of hazard resilient and sustainable office buildings is initial design costs, building damage and business interruption costs due to natural hazard events, casualty costs due to natural hazard events, and CO_2 emission costs (Shahtaheri et al. 2018; Kang and Wen 2001; Wen and Kang 2001).

4.1.2 Identify Alternative Infrastructure Configurations

Once the decision criteria are identified, alternative infrastructure configurations need to be defined for detailed analysis. In order to address the cognitive limitations of the decision makers, the alternative infrastructure configurations used for detailed analysis should include varying economic, social, and environmental impact tradeoffs (e.g., high initial cost, low environmental impact versus low initial cost, high environmental impact options). With regard to the computational expense associated with the design and analysis of each alternative design configuration, and the available time to make decision during the early design phase, four or five alternative infrastructure configurations are recommended for the preference assessment methodology (Shahtaheri et al. 2018). However, once the decision maker defined utility functions are developed, using the SIMPLE-Design framework, the utility functions can be adapted to a range of alternative design configurations. For this reason, if the performance range of the alternative design configurations is identified correctly, further alternative infrastructure configurations (e.g., more than five) can be selected for detailed analysis and implementation in FORM.

4.1.3 Measure Probabilistic Performance

Considering the decision criteria of initial cost, building damage and business interruption costs and casualty costs due to natural hazard events, and CO_2 emission costs, due the aleatory uncertainty associated with natural hazard events, the decision criteria associated with the alternative infrastructure configurations will be in the form of a probability density function. These probability distributions will represent the likelihood of a specific office building configuration (or infrastructure configuration) having various building damage and business interruption cost, casualty cost, and CO_2 cost values during its lifetime (e.g., 50 years). An example of a systematic framework for estimating the life-cycle environmental performance of buildings due seismic events has been presented by Chhabra et al. (2018) .This framework simulates a random earthquake scenario (by performing Monte Carlo simulations with 10^5 scenario realizations), finds the corresponding repairs (if any damages occurs), estimates the environmental impacts associated with the repairs for each realization, and fits a probability distribution to all the realizations. A similar methodology can be followed for estimating the probability density function associated with each decision criterion.

4.2 Assessment of Preferences

4.2.1 Assess Decision Maker Preferences

Once the decision criteria are defined and the alternative design configurations are assessed with respect to the decision criteria, decision maker utilities can be found (with respect to the performance range). In the SIMPLE-Design framework (Shahtaheri et al. 2018), a modular preference function development strategy is proposed for finding decision maker defined utility functions for a triple-bottom-line-based design of infrastructures. This study considers the decision criteria of initial cost, building damage and business interruption cost due the occurrence of the earthquake hazard, casualty cost due to the occurrence of the earthquake hazard, and CO_2 emission cost (Shahtaheri et al. 2018; Kang and Wen 2001; Wen and Kang 2001). In SIMPLE-Design framework, utility functions are presented with respect to two decision criteria, representing the indifference curve of the decision maker. The preference assessment methodology consists of four main steps: 1) selection of triple bottom line criteria, 2) identification of alternatives, 3) estimation of performance range, and 4) assessment of preferences. Decision maker preferences are assessed using five alternative design configuration of a midrise office building by allowing the decision maker to initially select one of the five alternative office building configurations. Changes are then applied to the decision maker's initial selection (e.g., changing the initial cost of decision maker's original selection), by the aim of finding further design configurations that are of equal value or utility to the decision maker, and estimating the indifference curves of the decision maker (Shahtaheri et al. 2018).

4.2.2 Develop Decision Maker Defined Utility Functions

The developed indifference curves for the decision criteria represent the utility of the decision maker with respect to a performance range of alternative design configurations and are presented with respect to two costs (e.g., initial cost and building damage and business interruption cost). An example of a building damage and business interruption cost (D), casualty cost (C) indifference curve for the midrise office building is shown in Equation 2 (Shahtaheri et al. 2018):

$$C = 0.02D + 82{,}000 \tag{2}$$

Equation 2 be reformulated as a reliability problem, where building damage and business interruption cost, and casualty cost are in the form of a probability density function. Probability of failure, p_f, or the probability of failing to meet the decision maker's preferences, can be defined as shown in Equation 3:

$$p_f = p\,(0.02D + 82{,}000 - C) \leq 0 \tag{3}$$

FORM, can be utilized for solving this reliability problem and finding the reliability of alternative infrastructure configurations with respect to the indifferent curves (limit state functions).

4.3. Decision Appraisal

4.3.1 First Order Reliability Method (FORM)

In order to utilize FORM, the distributions of all basic random variables (i.e., decision criteria) needs to be identified. The decision criteria probability distributions can be in the form of a marginal probability density function (PDF), cumulative density function (CDF), or joint distribution. Once the probability distributions are identified, in order to find the exact p_f (failing to meet the decision maker defined performance requirements), the variables are transformed into equivalent standard normal variables (Hasofer and Lind 1974; Rackwitz 1976). With regard to the nature of the decision variables, four different types of transformations exist for jointly normal random variables, independent non-normal variables, and correlated non-normal variables (Nataf 1962; Liu and Der Kiureghian 1986; Melchers 1999).

The correlated non-normal random variable transformations are reviewed herein (Nataf 1962; Liu and Der Kiureghian 1986) since they can be used for all types of distributions with any degree of correlation. Considering n random variables X_i, the marginal CDFs ($F_{(X_i)}$), and correlation matrix $\boldsymbol{R}$ (for variables i and j) can be defined as shown in Equation 4 and 5:

$$F_{(x_i)},\ i = 1, 2, \ldots, n \tag{4}$$

$$\boldsymbol{R_{ij}} = \rho_{x_i x_j} \text{ (and equals 1 for } i=j) \tag{5}$$

The random variables ($F_{(X_i)}$) have a Nataf distribution when the marginally transformed variables defined in Equation 6 are multivariate normal (Liu and Der Kiureghian 1986):

$$\boldsymbol{Z} = [Z_1, Z_2, \dots, Z_n]^T, \text{ where } Z_i = \Phi^{-1}[F_{(X_i)}(x_i)],\ i = 1,2,\ \dots,\ n \tag{6}$$

In Equation 6, $\boldsymbol{Z}$ represents the marginally transformed variables, and $\Phi^{-1}[F_{(X_i)}(x_i)]$ is the transformation of the marginal CDF to correlated standard normal variables, $\boldsymbol{Z}$. In this case, the components of $\boldsymbol{Z}$ might be correlated due to the dependence between the basic variables, $\boldsymbol{X}$. In practice this relationship is often taken as $\rho_{Z_i,Z_j} = \rho_{X_i,X_j}$. The correlated normal variables, **Z**, are transformed into uncorrelated standard normal variables, $\boldsymbol{U}$, using the Cholesky decomposition (lower triangular matrix, $\boldsymbol{L}$) of correlation matrix $\boldsymbol{R}$, as shown in Equation 7:

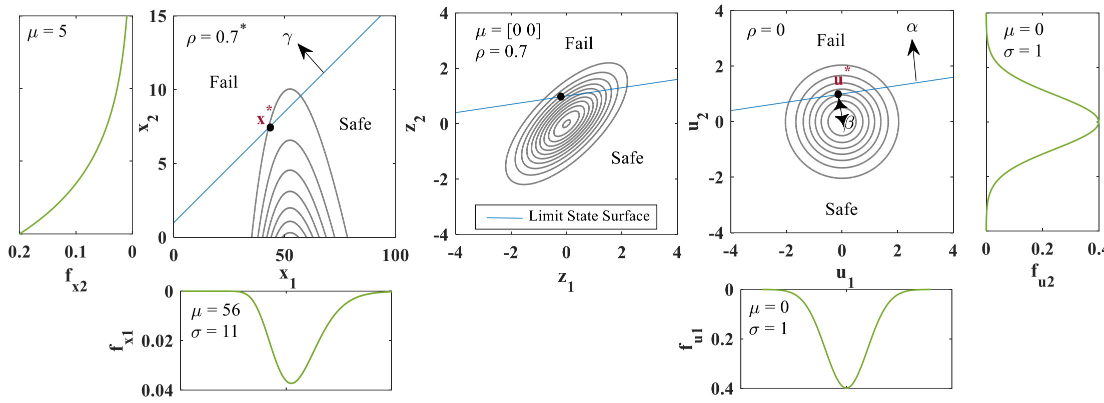
$$\boldsymbol{U} = \boldsymbol{L}^{-1}\boldsymbol{Z} \tag{7}$$

Figure 4 depicts the transformation of variables X_1 with a lognormal distribution and X_2 with an exponential distribution to the correlated normal space, *Z*, and uncorrelated standard normal space, *U*. Once the variables are transformed into the standard normal space (Figure 4), the Reliability Index β (Cornell 1969) and p_f can be computed from the standard normal space with respect to the decision maker defined limit state function (indifference curve; e.g., Equation 3) as shown in Figure 4.

The point with the highest probability of failure, $\boldsymbol{u}^*$, or the design point, is a point on the limit state surface with the smallest distance from the transformed distribution mean. An optimization algorithm is required to find the point with the highest probability of failure, the reliability index, and the probability of meeting the decision maker's preferences. This constrained optimization problem can be formulated as shown in Equation 8:

$$\boldsymbol{u}^* = Min\ \{||\boldsymbol{u}||\ |\ h(\boldsymbol{u}) = 0\} \tag{8}$$

In Equation 8, $h(\boldsymbol{u})$ is equivalent to $g(\boldsymbol{x})$, in the basic variable space, $\boldsymbol{X}$.



(a) (b) (c)

Figure 4: (a) Probability Density function of X_1 and X_2 in Real Variable Space, Design Point x^*, and Direction Vector, γ; (b) Correlated Multivariate Contours of Z_1 and Z_2 in Standard Normal Space; and (c) Uncorrelated Multivariate Contours of U_1 and U_2 in Standard Normal Space, Reliability Index β, Design Point u^*, and Direction Vector α

4.3.2 Reliability of Decision Alternatives

A gradient based algorithm, the improved Hasofer-Lind Rackwitz-Feissler (HL-RF) algorithm is utilized for solving the optimization problem (Zhang and Der Kiureghian 1995; Melchers 1999). Once the basic variables, $\boldsymbol{X}$ are transformed to standard normal variables, $\boldsymbol{U}$, using the HL-RF algorithm, an initial guess for $\boldsymbol{x}$ is chosen (typically chosen as the mean of the distributions) and the direction vector $\boldsymbol{\alpha_k}$ (perpendicular to the limit state surface and pointing the failure region)**,** is computed at the current value of $\boldsymbol{u}$, $\boldsymbol{u_k}$**.** The reliability index, β_k, can be computed using using Equation 9:

$$\beta_k = \boldsymbol{\alpha_k^T u_k} \tag{9}$$

The new estimate of the design point $\boldsymbol{u}^*$, $\boldsymbol{u_{k+1}}$, can be estimated using the gradient of the limit state surface in the standard normal space $\boldsymbol{U}$, $\nabla h(\boldsymbol{u_k})$:

$$\boldsymbol{u_{k+1}} = \boldsymbol{\alpha_k} \left[\beta_k + \nabla h(\boldsymbol{u_k}) \middle/ ||\nabla h(\boldsymbol{u_k})||\right] \tag{10}$$

The next estimate of $\boldsymbol{x}^*$ associated with the new $\boldsymbol{u}^*$ is estimated based on the inverse transformation used in Section 4.3.1 (the correlated non-normal random variable transformations).

The algorithm is repeated until the convergence goal, defined in Equation 11 has been achieved:

$$|\beta_k - \beta_{k-1}| < \varepsilon_1,\ |h(\boldsymbol{u_k})| < \varepsilon_2, \text{ where } \varepsilon_1 \text{ and } \varepsilon_2 \text{ is typically taken as } 10^{-3} \tag{11}$$

The final estimate of β is the FORM reliability index, β_{FORM}, and probability of failure, p_f, can be computed using Equation 12:

p_f = Φ(-β) (12)

In Equation 12, Φ is the standard normal cumulative distribution function.

4.3.3 System Reliability

In the case of having more than one limit state function, FORM can be expanded to a system reliability problem. The system reliability problem can be solved using a series or parallel formulation. In a series system, it is assumed that all the limit state functions are equally important and that the reliability of the decision alternatives should be assessed with regard to all the limit state functions. In this case using De Morgan's law, P_f can be estimated as follows:

$$P_f = P(\bigcup_{i=1}^{n}\{g(\boldsymbol{x})_i \leq 0\}) \cong 1 - P\left(\bigcup_{i=1}^{n}\left\{\boldsymbol{\alpha_i^T U} \leq \beta_i\right\}\right) = 1\text{-}\Phi(\beta,\boldsymbol{R_{zz}}) \quad (13)$$

In Equation 13, β is the reliability index for each limit state function and $\boldsymbol{R_{zz}}$ is the correlation between the solutions spaces of the limit state functions and is shown in Equation 14:

$$\boldsymbol{R_{zz}} = \begin{bmatrix} 1 & \alpha_1^T\alpha_2 & \dots & \alpha_1^T\alpha_n \\ \alpha_2^T\alpha_1 & 1 & \dots & \alpha_2^T\alpha_n \\ \vdots & \vdots & 1 & \vdots \\ \alpha_n^T\alpha_1 & \alpha_n^T\alpha_2 & \dots & 1 \end{bmatrix} \quad (14)$$

In Equation 14, n represents the number of decision variables and the correlation between the solution spaces of limit state functions i and j can be described as $\sigma_{Z_iZ_j} = \alpha_i^T\alpha_j$. The correlations between the solution spaces of the limit state function can be utilized to understand the interactions of the limit state functions with the decision criteria variables. i.e., a correlation of 0 between the limit state functions means that the indifference curves are perpendicular to each other, whereas a correlation of 1 and -1 between the limit sate functions means that the indifference curves are parallel and respectively one of the limit state function solution spaces is contained within the other (in this case one of the limit sate functions is redundant), or the limit state functions have opposite solutions spaces.

For a parallel system, where the reliability of the alternative design configurations depends on the probability of meeting or failing to meet all the decision makers defined preferences, P_f can be defined as follows:

$$P_f = P(\bigcap_{i=1}^{n}\{g(\boldsymbol{x})_i \leq 0\}) \cong P\left(\bigcap_{i=1}^{n}\left\{-\boldsymbol{\alpha}_i^T\boldsymbol{U} \leq -\beta_i\right\}\right) = \Phi(-\beta,\boldsymbol{R_{zz}}) \quad (15)$$

4.3.4 Impact of Decision Criteria on the Reliability of Decision Alternatives

In order to evaluate the effect of the decision criteria on the alternative infrastructure configurations, the importance measure, $\boldsymbol{\gamma}$, needs to be calculated. The $\boldsymbol{\gamma}$ vector is equivalent to the $\boldsymbol{\alpha}$ vector in the basic variable space, $\boldsymbol{X}$ and is defined as shown in Equation 16:

$$\boldsymbol{\gamma} = \frac{\boldsymbol{\tilde{D}J_{u^*x^*}^T\alpha}}{||\boldsymbol{\tilde{D}J_{u^*x^*}^T\alpha}||}\text{, where } \boldsymbol{\tilde{D}} = diag(\sqrt{diag(\tilde{\Sigma})}\text{, and } \tilde{\Sigma} = \boldsymbol{J_{x^*u^*}J_{x^*u^*}^T} \quad (16)$$

It should be noted that the number of elements in the importance vector $\boldsymbol{\gamma}$ depend on the number of the decision criteria. A large absolute value of the elements of $\boldsymbol{\gamma}$, $|\gamma_i|$, represents an important random variable that has a high impact on the reliability of the decision alternative. A positive γ_i represents a random variable that affects (increases) P_f or failing to meet the decision maker's preferences. A negative γ_i represents a decision variable that decreases P_f.

A pilot implementation is undertaken to further illustrate the capabilities of the proposed decision analysis framework. The pilot implementation utilizes the SIMPLE-Design framework for assessing decision maker utilities, and applies the decision maker utilities to alternative infrastructure design configurations with probabilistic performance.

5. APPLICATION TO THE OPTIMUM DESIGN OF OFFICE BUILDINGS

The design of hazard resilient and sustainable office buildings is chosen for the illustration of the proposed probabilistic multi-criteria decision analysis framework using FORM. A nine-story, 75×180 ft^2 steel moment frame office building (Kang and Wen 2001; Wen and Kang 2001) in Los Angeles, CA, with earthquake as the dominant natural hazard is considered for illustrating the decision analysis methodology.

5.1 Generation of Decision Criteria

5.1.1 Select Decision Criteria

The decision criteria initial cost, building damage and building interruption costs, casualty costs, and CO_2 emission costs are chosen with regard to the triple bottom line, the building location, and the earthquake hazard. Furthermore, for simplifying the preference assessment methodology and implementation in FORM, all decision criteria are translated to a cost value. The initial cost is the construction cost of building the facility. The building damage and business interruption cost, and casualty cost are respectively the expected failure cost and expected death and injury rate during the 50-year lifetime of the building considering a 5% discount rate (Kang and Wen 2001; Wen and Kang 2001). The CO_2 emission cost decision criteria considers the emission per weight of structural steel; and the electrical service, heating service, maintenance, and demolition emissions per unit area (Junnila and Horvath 2003; González and Navarro 2006; Environmental Protection Agency 2016).

5.1.2 Identify Alternative Infrastructure Configurations

It was determined that alternative design configurations from a single case study provide a sufficient representation of the tradeoffs between the decision criteria, and a broad performance range for the performance assessment methodology and implementation in FORM. For this reason, alternative office building configurations of the same plan and elevation were retrieved from Kang and Wen (2001). This study analyzes twelve alternative structural design configurations of the nine-story, 75×180 ft^2 steel office building. The alternative design configurations meet the National Earthquake Hazards Reduction Program; and Load and Resistance Factor Design requirements for width-thickness ratio, beam-column ratio panel zone shear strength, and panel thickness. The alternative design configurations vary in the intensity of the design basis earthquake, therefore have different member sizes (Kang and Wen 2001; Wen and Kang 2001).

Five of the twelve alternative design configuration are selected for the implementation of the SIMPLE-Design preference assessment methodology, and all twelve alternative design configurations are selected for detailed analysis and implementation in FORM. Table 2 represents all alternative design configurations, the six design configurations chosen for illustration purposes, and the five alternatives used for implementation of the SIMPLE-Design framework (Shahtaheri et al. 2018).

Table 2: Alternative Design Configurations of a Nine-Story Office Building (Adapted from Wen and Kang 2001)

Design Alternative	Initial Cost ($)	Building Damage and Business Interruption Cost ($)	Casualty Cost ($)	CO_2 Emission Cost ($)	Sum of all Costs ($)	Death and Injury Rate (#People)
$1^{*\Delta}$	1,694,000	6,244,000	1,233,000	133,000	9,304,000	[7-8]
2	1,787,000	3,611,000	504,000	134,000	6,036,000	[3-4]
3^{Δ}	1,893,000	2,045,000	266,000	136,000	4,340,000	[1-2]
4^{*}	1,990,000	1,489,000	237,000	137,000	3,853,000	[1-2]
5	2,079,000	1,138,000	171,000	138,000	3,526,000	[1-2]
6^{Δ}	2,172,000	863,000	130,000	139,000	3,304,000	[0-1]
7^{*}	2,267,000	755,000	113,000	140,000	3,275,000	[0-1]
8	2,360,000	641,000	105,000	141,000	3,247,000	[0-1]
9^{Δ}	2,470,000	589,000	97,000	141,000	3,297,000	[0-1]
10^{*}	2,577,000	534,000	83,000	142,000	3,336,000	[0-1]
11^{Δ}	2,880,000	379,000	52,000	146,000	3,457,000	[0-1]
$12^{*\Delta}$	3,234,000	303,000	43,000	150,000	3,730,000	[0-1]

*used in the SIMPLE-Design preference assessment framework (Shahtaheri et al. 2018)

$^{\Delta}$used in the illustrations (Figure 5, Table 3, and Table 4)

5.1.3 Measure Probabilistic Performance

The decision criteria of building damage and business interruption cost, casualty cost, and CO_2 emission cost are the three decision criteria that can be impacted by the natural variability of natural hazard events. In the case study analyzed by Wen and Kang (2001), the building damage and business interruption cost, and casualty cost from the earthquake hazard is respectively the expected cost (including the time value of money and discount rate) of failures and the expected death and injury cost. The CO_2 emission cost also considers the heating, service, and demolition emissions. Although these estimations involve probabilistic and expected value analysis, as shown in Table 2, the final result of the calculations is a deterministic number.

Furthermore, although building and infrastructure performance assessment methodologies are moving toward stochastic analysis and the consideration of the aleatoric behavior of the built environment (e.g., natural variability of natural hazard events) in the performance assessment frameworks, the inventory of such rigorous performance assessment measures is still in the development phase. Due to this lack of data, for illustrating the decision analysis methodology using FORM, the data for the twelve office building configurations has been used as the probability distribution means (μ) of a lognormal distribution (as recommended by Weidema 2013 and implemented by Chhabra et al., 2018). The variance and correlation between the decision criteria will also be hypothetical, covering a wide variety of hypothetical scenarios. For computing the standard deviation (σ) of the hypothetical distributions, a coefficient of variation $(\frac{\sigma}{\mu})$ of 20% and 80% has been considered for all decision criteria, analyzing low-dispersion and high-dispersion cases. The correlation coefficient (ρ) between the decision criteria for both the high-dispersion and low-dispersion cases has been taken as both 0 and 1 for all decision criteria (both in the correlated normal space, $\boldsymbol{Z}$ and in the basic variable space, $\mathbf{X}$; assuming Nataf distribution) to consider a wide variety of correlation, and dispersion cases.

5.2 Assessment of Preferences

5.2.1 Assess Decision Maker Preferences

Decision maker preferences are assessed with respect to the five alternative building configurations shown in Table 2 and the performance range (provided by the highest initial cost and lowest initial cost alternative design configuration) as presented in the SIMPLE-Design framework (Shahtaheri et al. 2018).

5.2.2 Develop Decision Maker Defined Utility Functions

Using the modular preference function development strategy (proposed in the SIMPLE-Design framework) in Microsoft Excel, decision maker utility functions (indifference curves) can be found. One of the decision maker defined utility functions presented by Shahtaheri et al. (2018) has been chosen for illustrating the decision analysis methodology using FORM. Decision maker D, a construction manager with 30 years of experience that selected alternative design configuration 10 as their initial selection has been chosen for the decision analysis methodology. The alternatives of equal equality assessed from the decision maker using the SIMPLE-Design framework are presented in Table 3 with respect to the decision criteria.

Table 3: Alternatives of Equal Utility Assessed from the Decision Maker using the SIMPLE-Design Framework

Alternatives of Equal Utility	Initial Cost ($)	Building Damage and Business Interruption Cost ($)	Casualty Cost ($)	CO_2 Emission Cost ($)
Original Selection (Alt. 10)	3,090,000	640,000	100,000	170,000
New Alt. 10.1	2,405,000	1,325,000	110,000	160,000
New Alt. 10.2	1,720,000	1,992,000	133,000	155,000

It should be noted that the indifference curves developed by Shahtaheri et al. (2018) are normalized to a total cost value of $4M similar to Table 3). However, the alternative design configurations presented in

Table 2 and the indifference curves presented in figure 5 are de-normalized in order to show the individual values of all costs. Shahtaheri et al. (2018) provide an example of the CO_2 emission cost calculations before and after the normalization process. Equation 17 to 19 represent the building damage and business interruption cost (x_1) versus casualty cost (y_1) indifference curve, building damage and business interruption cost (x_2) versus CO_2 emission cost (y_2) indifference curve, and the CO_2 emission cost (x_3) versus casualty cost (y_3) indifference curve.

$$y_1 = 0.02x_1 + 82{,}000 \tag{17}$$

$$y_2 = -0.01x_2 + 176{,}000 \tag{18}$$

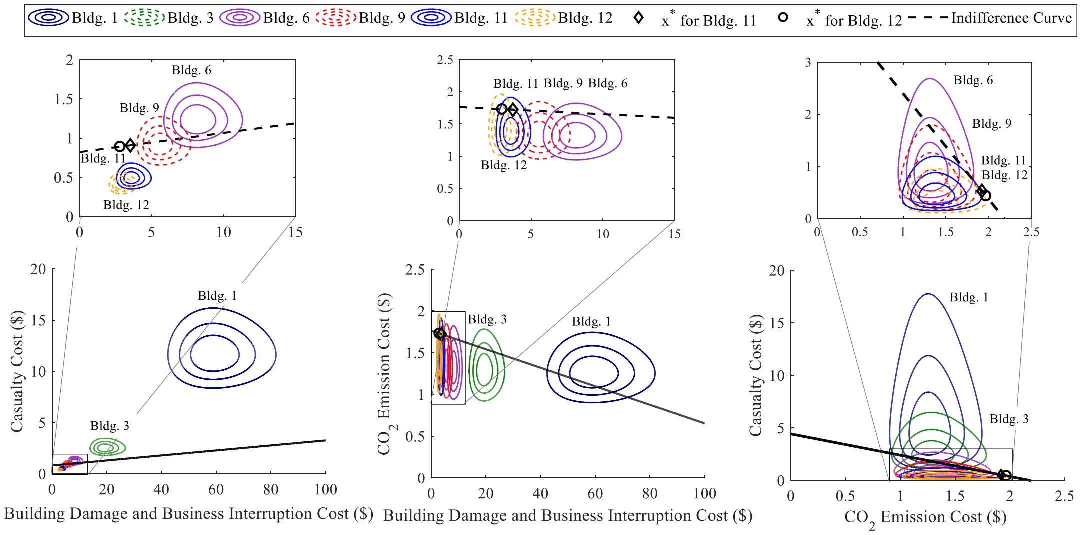
$$y_3 = -2.03x_3 + 442{,}000 \tag{19}$$

It should be mentioned that, if required, the indifference curves can be shifted (by changing its intercept) to cover the performance range of the alternative design configurations. However, in the case of the pilot implementation, the alternatives are obtained from a single case study on a nine-story office building, and therefore fall within the same performance range as the alternatives used in the preference assessment methodology.

5.3 Decision Appraisal and Pilot Implementation Results

5.3.1 First Order Reliability Method (FORM)

Figure 5 illustrates the indifference curves of decision maker and the uncorrelated joint probability density functions (with a 20% coefficient of variation) for building damage and business interruption cost versus CO_2 emission cost, building damage and business interruption cost versus casualty cost, and CO_2 emission cost versus casualty cost, in addition to the design point (x^*) with the highest probability of failure for the optimal design configurations.



(a) **(b)** **(c)**

Figure 5: (a) Building Damage and Business Interruption Cost vs. Casualty Cost, (b) Building Damage and Business Interruption Cost vs. CO_2 Emission Cost, (c) CO_2 Emission Cost vs. Casualty Cost Uncorrelated Probability Density Function Contours with a Coefficient of Variation of 20% for Six Building Configurations with Respect to the Decision Maker Defined Indifference Curves (all costs are presented in $100,000 USD)

The correlated non-normal random variable transformations will be used for transforming the decision criteria (with lognormal distributions) into the standard normal decision criteria (variables).

5.3.2 Reliability of Decision Alternatives

The reliability of the alternative design configurations with respect to the three decision maker defined indifference curves can be found using a systems reliability approach. All three bi-criteria indifference curves represent the preference of the decision maker. For this reason, a series system formulation is used for finding the reliability of the alternative design configurations with respect to the indifference curves (limit state functions) shown in Equation 20 to 23:

$$p_{f,A} = 0.024x_1 + 82000 - y_1 \le 0 \tag{20}$$

$$p_{f,B} = -0.01x_2 + 176000 - y2 \le 0 \tag{21}$$

$$p_{f,C} = -2.03x_3 + 442000 - y3 \le 0 \tag{22}$$

$$P_{f,System} = p_{f,A} \cup p_{f,B} \cup p_{f,C} \tag{23}$$

Utilizing FORM, with respect to the three indifference curves, the reliability of each building configurations can be identified. p_f for each of the individual indifference curves (Equation 20 to 22), and $P_{f,System}$ for a series system of all limit state functions (Equation 23) is shown in Table 4 and Table 5 for a coefficient of variation (CV) of 20% and 80%, and a correlation coefficient (ρ) of 0 and 1 for all the decision variables. In addition to the mentioned parameters, the correlation between the solution spaces of the indifference curves (limit state functions), R_{ZZ} is also computed for each building configuration. Table 6 represents the ranked alternative design configurations with respect to the probability of meeting the decision maker's preferences for a coefficient of variation (CV) of 20% and 80%, and a correlation coefficient (ρ) of 0 and 1 for all decision variables.

Table 4: Reliability of Alternative Building Configurations for Coefficient of Variation (CV) = 20% and Correlation Coefficient (ρ) = 0, 1

Bldg.	CV = 20%, ρ = 0 (for all variables)						CV = 20%, ρ = 1 (for all variables)					
1	$P_{f,system}$	1.00	$p_{f,A}$	1.00	$R_{A,B}$	-0.30	$P_{f,system}$	1.00	$p_{f,A}$	1.00	$R_{A,B}$	0.99
			$p_{f,B}$	0.79	$R_{A,C}$	0.71			$p_{f,B}$	0.72	$R_{A,C}$	1.00
			$p_{f,C}$	1.00	$R_{B,C}$	0.37			$p_{f,C}$	1.00	$R_{B,C}$	0.99
3	$P_{f,system}$	1.00	$p_{f,A}$	1.00	$R_{A,B}$	-0.06	$P_{f,system}$	1.00	$p_{f,A}$	1.00	$R_{A,B}$	0.99
			$p_{f,B}$	0.23	$R_{A,C}$	0.64			$p_{f,B}$	0.26	$R_{A,C}$	1.00
			$p_{f,C}$	0.90	$R_{B,C}$	0.71			$p_{f,C}$	0.82	$R_{B,C}$	1.00
6	$P_{f,system}$	0.88	$p_{f,A}$	0.85	$R_{A,B}$	-0.01	$P_{f,system}$	1.00	$p_{f,A}$	0.90	$R_{A,B}$	0.99
			$p_{f,B}$	0.15	$R_{A,C}$	0.39			$p_{f,B}$	0.17	$R_{A,C}$	0.99
			$p_{f,C}$	0.27	$R_{B,C}$	0.92			$p_{f,C}$	0.32	$R_{B,C}$	1.00
9	$P_{f,system}$	0.55	$p_{f,A}$	0.47	$R_{A,B}$	-5×10^{-3}	$P_{f,system}$	0.47	$p_{f,A}$	0.47	$R_{A,B}$	0.99
			$p_{f,B}$	0.15	$R_{A,C}$	0.28			$p_{f,B}$	0.16	$R_{A,C}$	0.99
			$p_{f,C}$	0.15	$R_{B,C}$	0.96			$p_{f,C}$	0.20	$R_{B,C}$	1.00
***11**	$P_{f,system}$	0.18	$p_{f,A}$	1.7×10^{-3}	$R_{A,B}$	-2×10^{-3}	$P_{f,system}$	0.18	$p_{f,A}$	3.4×10^{-4}	$R_{A,B}$	0.99
			$p_{f,B}$	0.17	$R_{A,C}$	0.13			$p_{f,B}$	0.18	$R_{A,C}$	0.99
			$p_{f,C}$	0.07	$R_{B,C}$	1.00			$p_{f,C}$	0.09	$R_{B,C}$	1.00
12	$P_{f,system}$	0.21	$p_{f,A}$	7.6×10^{-5}	$R_{A,B}$	-1×10^{-3}	$P_{f,system}$	0.21	$p_{f,A}$	8×10^{-6}	$R_{A,B}$	0.99
			$p_{f,B}$	0.20	$R_{A,C}$	0.11			$p_{f,B}$	0.21	$R_{A,C}$	0.99
			$p_{f,C}$	0.07	$R_{B,C}$	1.00			$p_{f,C}$	0.09	$R_{B,C}$	1.00

$P_{f,system}$: series system probability of failure; limit state A, $p_{f,A}$: damage cost vs. casualty cost probability of failure; limit state B, $p_{f,B}$: damage cost vs. CO_2 emission cost probability of failure; limit state C, $P_{f,C}$: CO_2 emission cost vs. casualty cost probability of failure; R: correlation between the limit state functions (indifference curves); *optimal design configuration

Table 5: Reliability of Alternative Building Configurations for Coefficient of Variation (CV) = 80% and Correlation Coefficient (ρ) = 0, 1

Bldg.	CV = 80%, ρ = 0 (for all variables)						CV = 80%, ρ = 1 (for all variables)					
1	$P_{f,system}$	0.99	$p_{f,A}$	0.98	$R_{A,B}$	-0.03	$P_{f,system}$	1.00	$p_{f,A}$	0.99	$R_{A,B}$	-0.09
			$p_{f,B}$	0.48	$R_{A,C}$	1.00			$p_{f,B}$	0.48	$R_{A,C}$	-0.02
			$p_{f,C}$	0.96	$R_{B,C}$	-0.03			$p_{f,C}$	0.92	$R_{B,C}$	0.99
3	$P_{f,system}$	0.82	$p_{f,A}$	0.74	$R_{A,B}$	-4×10^{-3}	$P_{f,system}$	0.88	$p_{f,A}$	0.77	$R_{A,B}$	-0.03
			$p_{f,B}$	0.30	$R_{A,C}$	1.00			$p_{f,B}$	0.31	$R_{A,C}$	0.01
			$p_{f,C}$	0.46	$R_{B,C}$	-4×10^{-3}			$p_{f,C}$	0.47	$R_{B,C}$	1.00
6	$P_{f,system}$	0.63	$p_{f,A}$	0.49	$R_{A,B}$	-9×10^{-4}	$P_{f,system}$	0.65	$p_{f,A}$	0.49	$R_{A,B}$	0.01
			$p_{f,B}$	0.27	$R_{A,C}$	1.00			$p_{f,B}$	0.27	$R_{A,C}$	0.04
			$p_{f,C}$	0.28	$R_{B,C}$	-9×10^{-4}			$p_{f,C}$	0.33	$R_{B,C}$	1.00
9	$P_{f,system}$	0.54	$p_{f,A}$	0.37	$R_{A,B}$	-4×10^{-4}	$P_{f,system}$	0.54	$p_{f,A}$	0.36	$R_{A,B}$	0.03
			$p_{f,B}$	0.27	$R_{A,C}$	1.00			$p_{f,B}$	0.27	$R_{A,C}$	0.05
			$p_{f,C}$	0.25	$R_{B,C}$	-4×10^{-4}			$p_{f,C}$	0.29	$R_{B,C}$	1.00
***11**	$P_{f,system}$	0.44	$p_{f,A}$	0.12	$R_{A,B}$	-2×10^{-4}	$P_{f,system}$	0.36	$p_{f,A}$	0.12	$R_{A,B}$	0.04
			$p_{f,B}$	0.28	$R_{A,C}$	1.00			$p_{f,B}$	0.28	$R_{A,C}$	0.05
			$p_{f,C}$	0.22	$R_{B,C}$	-2×10^{-4}			$p_{f,C}$	0.24	$R_{B,C}$	1.00
***12**	$P_{f,system}$	0.45	$p_{f,A}$	0.08	$R_{A,B}$	-1×10^{-4}	$P_{f,system}$	0.34	$p_{f,A}$	0.08	$R_{A,B}$	0.04
			$p_{f,B}$	0.29	$R_{A,C}$	1.00			$p_{f,B}$	0.29	$R_{A,C}$	0.05
			$p_{f,C}$	0.22	$R_{B,C}$	-1×10^{-4}			$p_{f,C}$	0.24	$R_{B,C}$	1.00

$P_{f,system}$: series system probability of failure; limit state A, $p_{f,A}$: damage cost vs. casualty cost probability of failure; limit state B, $p_{f,B}$: damage vs. CO_2 emission cost probability of failure; limit state C, $p_{f,C}$: CO_2 emission cost vs. casualty cost probability of failure; R: correlation between the limit state functions (indifference curves); *optimal design configuration

Table 6: Alternative Design Configurations Ranked in the Order of Preference (Best to Worst)

	CV = 20%		CV = 80%	
	$\rho = 0$	$\rho = 1$	$\rho = 0$	$\rho = 1$
Ranked Alternatives	11	11	11	12
	12	10	12	11
	10	12	10	10
	9	9	9	9
	8	8	8	8
	7	7	7	7
	6	6	6	6
	5	5	5	5
	4	4	4	4
	3	3	3	3
	2	2	2	2
	1	1	1	1

Variations in the correlation between the decision criteria and the coefficient of variation (by changing the standard deviation of the variables), has been considered in order to analyze the sensitivity of the decision analysis results to the decision model inputs. In the case of the pilot implementation, changes in the correlation coefficient does not have a significant impact on the reliability of the alternative design configurations (leads to less than a 15% variation in the reliability of the alternative design configurations). However, the correlation between the indifference curve solution spaces is highly impacted by the changes in the correlation between the decision criteria (leading to up to a 99% variation in the correlation between the limit state functions). Similarly, changes in the standard deviation of the data can lead to up to a 99% variation in the correlation between the limit state function solution spaces. This variation also impacts the reliability of the alternative design configurations. Although the design configurations that maximize the decision maker's utilities remain constant with the changes in coefficient of variation, the reliability of the optimal design configurations can reduce by 25%, which is significant.

This implies that, the correlation between the decision criteria can be neglected in the decision analysis process, as is does not have significant impact on the decision analysis results. However, the variation between the decision criteria variables impacts the reliability of the decision analysis results and should be identified accurately (assuming the decision criteria means have been estimated correctly). It should be noted that the alternative design configurations (i.e., alternative 11 and 12), that maximize the decision maker's utilities remain constant with the changes in the decision model inputs (i.e., changing the standard deviation and correlation coefficient).

It should also be noted that the decision maker selected alternative design configuration 10, with an initial cost of $2,577,000 as their initial selection. However, the optimal design configurations that maximize the decision maker's utilities are alternative 11 and 12, which have a higher initial cost that the decision maker's original selection. This implies that the decision maker's utilities (e.g., low damage, casualty, and CO_2

emissions) can be achieved with a higher initial cost. The decision maker can choose to select the high-performing design configurations (i.e., alternative 11 and 12) with a higher initial cost than their initial selection or the initial alternative design configuration (with a lower initial design cost and higher damage, casualty, and CO_2 emissions, i.e., alternative 10).

5.3.3 Impact of Decision Criteria on the Reliability of Decision Alternatives

The importance vector, $\boldsymbol{\gamma}$, for alternative design configuration 11 and 12 has been computed for coefficient of variation of 20% and 80%, and correlation coefficient of 0 and 1 as shown in Table 7. The order of the random variables is respectively taken as building damage and business interruption cost, casualty cost, and CO_2 emission cost. For this reason, for indifference curve A (building damage and business interruption cost vs. casualty cost), for example, the importance vector $\boldsymbol{\gamma}$ shows an importance value of 0 for the CO_2 emission cost decision criteria (variable).

Table 7: Importance Vectors for the Optimal Design Configurations

Bldg.	Importance Vector	CV = 20% (for all variables)		CV = 80% (for all variables)	
		ρ = 0	ρ = 1	ρ = 0	ρ = 1
11	γ_A	$\begin{bmatrix}-0.09\\0.99\\0.00\end{bmatrix}$	$\begin{bmatrix}-0.17\\0.98\\0.00\end{bmatrix}$	$\begin{bmatrix}-0.03\\1.00\\0.00\end{bmatrix}$	$\begin{bmatrix}-0.03\\1.00\\0.00\end{bmatrix}$
	*****γ_B	$\begin{bmatrix}0.02\\0.00\\1.00\end{bmatrix}$	$\begin{bmatrix}0.03\\0.00\\1.00\end{bmatrix}$	$\begin{bmatrix}7\times10^{-3}\\0.00\\1.00\end{bmatrix}$	$\begin{bmatrix}8\times10^{-3}\\0.00\\1.00\end{bmatrix}$
	γ_C	$\begin{bmatrix}0.00\\0.13\\1.00\end{bmatrix}$	$\begin{bmatrix}0.00\\0.17\\0.98\end{bmatrix}$	$\begin{bmatrix}0.00\\0.11\\1.00\end{bmatrix}$	$\begin{bmatrix}0.00\\0.17\\0.98\end{bmatrix}$
12	γ_A	$\begin{bmatrix}-0.08\\1.00\\0.00\end{bmatrix}$	$\begin{bmatrix}-0.17\\0.98\\0.00\end{bmatrix}$	$\begin{bmatrix}-0.02\\1.00\\0.00\end{bmatrix}$	$\begin{bmatrix}-0.03\\1.00\\0.00\end{bmatrix}$
	*****γ_B	$\begin{bmatrix}0.02\\0.00\\1.00\end{bmatrix}$	$\begin{bmatrix}0.02\\0.00\\1.00\end{bmatrix}$	$\begin{bmatrix}5\times10^{-3}\\0.00\\1.00\end{bmatrix}$	$\begin{bmatrix}6\times10^{-3}\\0.00\\1.00\end{bmatrix}$
	γ_C	$\begin{bmatrix}0.00\\0.11\\1.00\end{bmatrix}$	$\begin{bmatrix}0.00\\0.14\\0.99\end{bmatrix}$	$\begin{bmatrix}0.00\\0.09\\1.00\end{bmatrix}$	$\begin{bmatrix}0.00\\0.14\\1.00\end{bmatrix}$

γ_A: damage cost vs. casualty cost importance vector, γ_B: damage cost vs. CO_2 emission cost importance vector, γ_C: CO_2 emission cost vs. casualty cost importance vector, *****limit state function with the highest probability of failure

The important decision criteria (random variables) can be identified using the importance vector, $\boldsymbol{\gamma}$, by identifying the decision criteria with a corresponding large absolute value in the $\boldsymbol{\gamma}$ vector. These decision criteria have the highest impact on the reliability of the building configurations. For this reason, the importance vector provides the decision maker with means of improving the reliability of alternative building configurations.

For instance, for the building configurations with the lowest $P_{f,system}$ (i.e., alternative 11 and 12), indifference curve B (i.e., building damage and business interruption cost versus CO_2 emission cost) has the highest probability of failure ($p_{f,B}$). For this reason, the importance vector of indifference curve B is further investigated for finding means of reducing probability of failure for indifference curve B and improving the performance of the alternative design configurations. For a coefficient of variation of 20% and 80% and a correlation coefficient of 0 and 1, the CO_2 emission decision criterion has the highest impact on the reliability of the alternative design configuration 11 and 12. For this reason, for improving the reliability of alternative design configuration 11 and 12, the CO_2 emission needs to be reduced. In other words, the high CO_2 emission cost is the main reason that alternative design configurations 11 and 12 respectively have an 18% (for a 20% coefficient of variation) and 34% (for an 80% coefficient of variation and a correlation coefficient of 1) probability of not meeting the decision maker defined preferences (indifference curves). The CO_2 emission cost probability distribution for the alternative design configurations can be improved by exploring alternative building systems and building materials using the Leadership in Energy and Environmental Design certification guidelines and other green building rating systems. For instance, using non-ducted, natural ventilation cooling can significantly reduce the CO_2 emission cost of the structural system. This can be proposed as an alternative ventilation system. Once the new system is confirmed with the decision maker, the relevant probability distributions should be computed for the proposed ventilation system. Implementation of FORM is required for confirming if the non-ducted, natural ventilation and cooling system has higher probability of meeting the decision maker defined preferences (indifference curves). This feedback loop provides the decision maker with means of improving the alternative building configurations, and understanding the performance of the alternative design configurations with respect to the defined indifference curves (decision maker preferences).

6. CONCLUSIONS AND FURTHER RESEARCH

Infrastructure design decisions are moving toward the consideration of multiple and conflicting decision criteria that consider the uncertainties associated with the nature of the built environment. Such holistic probabilistic performance assessment frameworks, require the involvement of decision makers in order find optimal infrastructure design configurations that meet the decision maker's needs (maximize decision maker utilities). However stochastic optimization methods are computationally expensive and do not provide means for conducting sensitivity assessment on the decision analysis results. Furthermore, due to the inherent complexity of stochastic optimization methods, integration of decision maker utilities with such complex optimization models has not been attempted. For addressing the identified knowledge gap, this research proposes as a key contribution to the body of knowledge, a probabilistic multi-criteria decision analysis model that provides sensitivity assessment measures for developing a meaningful feedback loop for decision makers. The decision analysis model uses the First Order Reliability Method (FORM) for incorporating multiple probabilistic decision criteria and decision maker utilities in the design of infrastructures.

Key aspects of the probabilistic multi-criteria decision making decision making model, integrating FORM and utility functions include:

1. Allowing full and consistent representation of all relevant uncertainties associated with the decision criteria variables.
2. Incorporating decision maker utilities, alternative design configurations, and multiple probabilistic decision criteria in the decision analysis process.
3. Adapting to various types of probability density functions, decision variable correlations, and first and second order estimate measures.
4. Providing a meaningful feedback loop for understanding the decision analysis results and improving the performance of the alternative design configurations with respect to decision maker utilities.
5. Obtaining stochastic results with low computational expense.

A pilot implementation is undertaken on an office building in Los Angeles, CA with 3 conflicting and probabilistic decision criteria (objectives) of building damage and business interruption cost, casualty cost, and CO_2 emission cost, and twelve alternative office building configurations. The results of the pilot implementation revealed that optimal design configurations can be found using a systems reliability approach (with multiple indifference curves or preference functions) with respect to multiple conflicting decision objectives, alternative design configurations, and probabilistic decision criteria. It was also found that changes in the correlation between the decision criteria leads to a minor variation in the reliability of the alternative design configurations, which is negligible. However, changes in the standard deviation of the decision criteria, can lead to up to a 25% variation in the probability of meeting the decision make's preferences. In the case where such discrepancies exist, further data collection is required for improving the coefficient of variation (or standard deviation) estimates. However, since the main objective of the pilot implementation is the illustration of the decision analysis methodology using the FORM, further data collection has not been attempted.

In the pilot implementation the decision maker defined limit functions are assumed to have a series reliability formulation. This means that all limit state functions are equally important and violating one limit state function will impact the reliability of the alternative design options. In cases where the union of the limit state functions only affects the reliability of alternative design options, a parallel systems formulation can be used. Furthermore, in the case where a large number of decision criteria exist (e.g., more than 3), a nested reliability approach can be implemented. Where, the probability of meeting the decision maker's requirements with respect to the important decision criteria (such as building damage cost and casualty cost) can be analyzed first for all the alternative design configurations and the decision maker defined indifference curves. Then, if further analysis is required, the reliability of the alternative design configurations can be assessed with respect to the remaining decision criteria (e.g., CO_2 emission cost and level of service) for a detailed performance assessment.

The presented decision analysis framework can be also extended to further infrastructure design decisions that involve multiple probabilistic criteria and decision maker requirements. The scope of future research can involve a group decision making problem, where various decision maker defined limit state functions (indifference curves) can be simultaneously analyzed using a series or parallel reliability formulation. Exploring further sources of uncertainty such as the epistemic uncertainty associated with the decision analysis process, i.e., uncertainty in the limit state functions, can also be explored for studying the sensitivity of the decision analysis results.

This novel utilization of the First Order Reliability Method, in addition to its integration with utility functions (indifference curves), presents a new decision analysis model for analyzing the probabilistic performance of alternative infrastructure design configurations with regard to decision maker performance requirements (utilities). The presented framework has the ability to find an optimal probability of meeting the decision maker defined requirements and maximize decision maker utilities, while including the correlation between the decision criteria and the stochastic behavior of the decision alternatives in the reliability analysis, and providing a meaningful feedback loop for the decision maker. The integration of uncertainty, multiple decision criteria (objectives), and decision maker utilities in a systematic manner, introduces a new generation of decision analysis models, which can be used in the early design phase of infrastructure assets. Allowing design engineers and risk analysists to analyze multiple alternative design options with respect to the designated probabilistic decision criteria and decision maker requirements in order to maximize decision maker utilities in the early design phase.

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4. INCORPORATION OF MULTIPLE DECISION CRITERIA, DECISION MAKER UTILITIES, AND UNCERTAINTY IN THE DESIGN OF INFRASTRUCTURES

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1. ABSTRACT

Infrastructure design decisions can significantly benefit from a holistic decision analysis framework that considers the performance of the alternative design configurations with respect to the designated decision criteria and decision maker utilities. Although a number of models exist that consider the uncertainty associated with the nature of the built environment (aleatory uncertainty from a random process), they do not provide a systematic framework for including both epistemic uncertainties (due to lack of knowledge) associated with the decision analysis process (e.g., decision maker utility assessment process) and aleatory uncertainties in the decision framework. To this effect, this article presents the First Order Reliability Method (FORM) as an efficient optimization algorithm for finding the probability of various alternative infrastructure design configurations meeting the decision maker's preferences. The decision maker defined utility functions are subjected to epistemic uncertainty, in order to assess the sensitivity of the decision analysis methodology to various sources of certainty. The proposed stochastic decision analysis model allows full and consistent representation of all relevant uncertainties (aleatory and epistemic), decision maker utilities, alternative design configurations, and decision criteria. The multi-criteria and multi-objective probabilistic decision analysis framework is tested on a nine-story office building with the probabilistic decision criteria (subjected to aleatory or external uncertainty) of building damage and business interruption cost, casualty cost, and CO_2 emission cost; twelve alternative design configurations; decision maker utility functions; and the epistemic uncertainty associated with assessing decision maker utilities and combining a number of decision maker defined utility functions (e.g., group decision making). The results of the pilot implementation reveal that the errors associated with assessing decision maker utilities (i.e., fitting a curve to the alternatives of equal utility or regression error), does not change the reliability of the alternative design configurations in the case where the regression error is less than 2.5% of the total summation of all costs. Furthermore, combining decision maker utilities does not lead to a consensus on the optimal design configuration that meets the decision makers' needs (the decision makers have heterogeneous utilities). Which implies that the alternative design configurations need to be tailored with respect to decision maker utilities.

Keywords

Decision Analysis, Optimization, Probabilistic, Stochastic, Multi-Criteria, Multi-Objective, Aleatory Uncertainty, Epistemic Uncertainty, Reliability Analysis, System Reliability, Sensitivity Assessment, Design Strategies, Performance-Based, Utility Function, First Order Reliability Method, Group Decision Making

2. INTRODUCTION

Infrastructure design and retrofit decisions include a number of conflicting decision criteria (objectives), multiple decision makers, and various sources of uncertainty. Such complex decision problems require a formal decision analysis methodology, which finds optimal design configurations that maximize decision maker utilities with respect to multiple probabilistic decision criteria (decision variables). Two types of uncertainties can be associated with infrastructure design decisions: 1) aleatory uncertainty, external uncertainty, or statistical uncertainty associated with the nature of the built environment such as the natural variability of natural hazard events; and 2) epistemic uncertainty or internal uncertainty associated with the decision analysis process such as the assessment of decision maker utilities (French 1995).

Risk informed decision models, fuzzy logic models, and Bayesian models are three types of decision analysis models that are frequently used for solving complex decision problems in uncertain environments. Risk assessment frameworks mainly model the aleatory uncertainties associated with the built environment, whereas fuzzy models and Bayesian models provide a consistent framework for incorporating the epistemic uncertainties associated with the decision analysis process in the decision framework. Risk assessment models have been used for assessing stakeholder related risks (e.g., conflicts and claims) in construction project, life-cycle performance assessment in uncertain environments, and integrated with expert opinion for developing probabilistic economic loss functions (including building and population loss) under different hazard scenarios (Biondini and Frangopol 2016; Chen et al. 2016; Xia et al. 2017). Fuzzy models have addressed similar problems such as the identification of risk interactions in construction projects, which analyzes the unavailability of funds and change of scope (Tavakolan and Etemadinia 2017). A risk-based seismic resiliency evaluation of reinforced concrete buildings has also been achieved using fuzzy rule based modelling, which develops risk index contours and ranks alternative retrofit options with respect to building damage and building importance indices, multiple decision makers, and fuzzy utility (payoff) values (Tesfamariam and Saatcioglu 2008; Tesfamariam et al. 2010). Bayesian models have also provided valuable information on natural hazard probabilities and risk estimation. Boulanger and Idriss (2015) have developed Bayesian limit-state models for seismic soil liquefaction initiation. Such frameworks can aid infrastructure retrofit decisions for post-earthquake decisions. However, in order to satisfy multiple decision makers' needs and incorporate various types of uncertainty in the decision analysis methodology, there is a need for a systematic decision analysis framework that also minimizes the cognitive load on the decision maker.

To this effect, Chapters 2 and 3 propose a modular preference assessment framework (SIMPLE-Design by Shahtaheri et al. 2018), and a reliability-based decision support system for developing decision maker defined utility functions, and finding optimal infrastructure design configurations with respect to multiple probabilistic decision criteria. However, although the integration of the SIMPLE-Design framework and the First Order Reliability Method (FORM) provides a computationally efficient, stochastic decision framework for analyzing alternative design configurations with respect to a number of probabilistic decision criteria and decision maker utilities, the model only incorporates aleatory uncertainty. As mentioned by Loucks and Van Beek (2017), the usefulness of any model is dependent on the reliability of its output data. For this reason, the sensitivity of the computationally efficient, multi-criteria decision making framework under aleatory uncertainty using FORM (Chapter 3), is tested under epistemic uncertainty. The epistemic uncertainty associated with fitting utility functions to the alternatives of equal utility assessed from the decision maker, and integration of various decision maker utilities in a group decision making problem are analyzed for understanding the sensitivity of the output results (optimal design configurations) to epistemic uncertainty.

3. BACKGROUND

The literature is reviewed with regard to the three categories of decision analysis models of risk informed models, fuzzy logic models, and Bayesian models that can model uncertainty and multiple decision criteria. Then, the First Order Reliability Method (FORM) is proposed as an efficient algorithm for solving multi-criteria decision making problems under both aleatory and epistemic uncertainty.

3.1 Risk Informed Models

One of the major sources of uncertainty associated with the built environment is natural disasters, for this reason the reviewed risk-informed decision frameworks aim to evaluate, communicate and reduce the risks and negative consequences of natural hazard events. Risk informed decision models have aided the initial design of structures by identifying the vulnerability of buildings to natural hazard events and estimating the probability of failure of structural components (Ellingwood 2005; Li and Ellingwood 2006; Zhu and Frangopol 2016; Gardoni 2017). Similar frameworks exist for finding the annual probability of exceeding certain pre-defined performance levels or damage states for structures for a risk-informed evaluation of civil infrastructure with respect to natural hazard events (Ellingwood and Kinali 2009; Fukutani et al. 2018; Sousa et al. 2018). However, as mentioned in a review on risk assessment for Civil Engineering facilities by Faber and Steward (2003), there is a need for the adoption of standardized risk analysis techniques that can incorporate judgmental and frequentistic information. To this effect, Dolšek (2012) presents a sampling-based approach coupled with non-linear static analysis for finding an annual frequency of exceeding a limit state function for seismic risk, incorporating both aleatory (incorporating the random nature of the ground motion) and epistemic (using a set of structural models) uncertainty. The current state of the art Civil Engineering risk informed decision analysis frameworks under uncertainty do not: 1) provide a meaningful feedback loop for the decision maker to understand the impact of the decision criteria (such as damage cost) on the reliability of the structural systems, 2) provide a systematic framework for analyzing multiple alternative design configurations, and 3) integrate the decision criteria and the probabilistic performance of the design configurations with decision maker requirements.

3.2. Fuzzy Logic Models

Fuzzy logic provides a systematic tool for dealing with qualitative data, quantitative data, and group decision making problems. Fuzzy logic models in Civil Engineering have mainly focused on the quantification of construction project risks. Such frameworks use a risk assessment methodology with fuzzy reasoning for assessing construction project risks such as natural hazards, site constraints, and communication issues (Zeng et al. 2007; Kuo and Lu 2013; Salah and Moselhi 2016). Selection of planning and design alternatives for public building construction, development of customer quality functions that incorporate customer requirements in the design and the construction process, subcontractor evaluation assessing factors like safety and level of coordination in a group decision model, and group decision making (Yang et al. 2003; Hsieh et al. 2004; Lin et al. 2008; Zavadskas et al. 2008) has also been achieved using fuzzy models. Although fuzzy logic provides a systematic method for addressing the epistemic uncertainty associated the construction process, it ranks the alternative strategies based on qualitative expert input. If the performance of the alternative design or project delivery strategies are quantifiable, is it best to assess decision maker preferences with respect to the quantitative decision criteria, and integrate decision maker values with the performance of the alternative strategies. This will lead to finding optimal design or project delivery strategies that incorporate decision maker values with respect to the uncertain environment and the performance of the alternatives.

3.3. Bayesian Models

Bayesian models are mainly used for understanding and incorporating conditional uncertainty in decision analysis models. Bayesian probabilistic approach has aided the selection of structural response models, prediction of structural performance, quantification of model uncertainty for improving the reliability of model predictions, the optimization of infrastructure decisions, and the analysis of uncertainty in building design evaluations (De Wit and Augenbroe 2002; Beck and Yuen 2004; Park et al. 2010; Haukaas and Gardoni 2011; Sierra et al. 2018). As Bayesian models mainly allow for the incorporation of various sources of uncertainty in decision analysis process, they require integration with an optimization algorithm, in order to find optimum design configurations that meet the defined constraints.

3.4. Identified Knowledge Gap

The current state-of-the-art methods for including uncertainty in decision analysis models, do not provide a systematic methodology for incorporating epistemic and aleatory uncertainty, multiple decision criteria, and alternative design configurations in the decision analysis process. In order to address the identified knowledge gap, a holistic decision framework is required that allows for modeling both aleatory and epistemic uncertainty in a systematic manner, while providing a meaningful feedback loop for the decision maker, and including multiple decision criteria, and decision maker requirements in the decision analysis process.

3.5 Proposed Approach: First Order Reliability Method (FORM)

Chapter 2 and 3 utilize the First Order Reliability Method (FORM), integrated with utility functions by the aim of finding optimal infrastructure design configurations that maximize decision maker utilities. The superiority of FORM to stochastic optimization and other reliability-based algorithms is its computational efficiency and its ability to provide a number of difference measures for conducting sensitivity assessments on the decision analysis results. FORM transforms the basic random variables, $\boldsymbol{X}$, to standard uncorrelated random variables, $\boldsymbol{U}$, in order to estimate the point with the highest probability of failure on the joint probability density function of the variables with respect to the defined limit state function, *g(x)* (Melchers 1999). This requires an optimization algorithm, which minimizes the distance from the distribution mean in the uncorrelated standard normal space from the limit state surface in order to find the shortest distance from the distribution mean to the limit state surface, β. Equation 1 shows the optimization goal for finding β:

$$\boldsymbol{u}^* = Min\ \{||\boldsymbol{u}||\ |\ h(\boldsymbol{u}) = 0\} \tag{1}$$

In Equation 1, $\boldsymbol{u}^*$ and $h(\boldsymbol{u})$ are respectively the design point with the highest probability of failure and the limit state surface in the uncorrelated standard normal space.

The shortest distance, β, can be estimated using a gradient based algorithm, the improved Hasofer-Lind Rackwitz-Feissler (HL-RF) algorithm (Zhang and Der Kiureghian 1995; Melchers 1999). Once β is estimated, the probability of not meeting the defined constraints, p_f, can be estimated using β using:

$$p_f = \Phi(-\beta) \tag{2}$$

In Equation 2, Φ is the standard normal cumulative distribution function. In the case where multiple limit state function exists, a system reliability approach can be implemented. For a system reliability calculation, the direction vector, $\boldsymbol{\alpha}$ (perpendicular to the limit state surface, in the direction of the solution space), needs to be identified for each limit state function. The correlation between the limit state function solution spaces, $\boldsymbol{R_{zz}}$ can be calculated as:

$$\boldsymbol{R_{zz}} = \begin{bmatrix} 1 & \alpha_1^T\alpha_2 & \dots & \alpha_1^T\alpha_n \\ \alpha_2^T\alpha_1 & 1 & \dots & \alpha_2^T\alpha_n \\ \vdots & \vdots & 1 & \vdots \\ \alpha_n^T\alpha_1 & \alpha_n^T\alpha_2 & \dots & 1 \end{bmatrix} \tag{3}$$

In Equation 3, *n* represents the number of decision variables and the correlation between the solution spaces of limit state functions *i* and *j* can be described as $\sigma_{Z_iZ_j} = \alpha_i^T\alpha_j$. The formulation for a series and parallel system of limit state functions (*i*) are respectively shown in Equation 4 and 5.

$$P_f = P(\cup_{i=1}^{n}\{g(\boldsymbol{x})_i \leq 0\}) \cong 1 - P\left(\cup_{i=1}^{n}\left\{\boldsymbol{\alpha_i^T U} \leq \beta_i\right\}\right) = 1\text{-}\Phi(\beta,\boldsymbol{R_{zz}}) \tag{4}$$

$$P_f = P(\cap_{i=1}^{n}\{g(\boldsymbol{x})_i \leq 0\}) \cong P\left(\cap_{i=1}^{n}\left\{-\boldsymbol{\alpha}_i^T\boldsymbol{U} \leq -\beta_i\right\}\right) = \Phi(-\beta,\boldsymbol{R_{zz}}) \tag{5}$$

In order to provide means for conducting sensitivity assessments on the decision analysis results, the importance vector, $\boldsymbol{\gamma}$, also needs to be computed in the basic variable space, $\boldsymbol{X}$. $\boldsymbol{\gamma}$ is equivalent to $\boldsymbol{\alpha}$ in the basic variable space.

$$\boldsymbol{\gamma} = \frac{\widetilde{\boldsymbol{D}}\boldsymbol{J}^{\boldsymbol{T}}_{\boldsymbol{u}^*\boldsymbol{x}^*}\boldsymbol{\alpha}}{||\widetilde{\boldsymbol{D}}\boldsymbol{J}^{\boldsymbol{T}}_{\boldsymbol{u}^*\boldsymbol{x}^*}\boldsymbol{\alpha}||} \text{, where } \widetilde{\boldsymbol{D}} = diag(\sqrt{diag(\tilde{\Sigma})}, and\ \tilde{\Sigma} = \boldsymbol{J}_{\boldsymbol{x}^*\boldsymbol{u}^*}\boldsymbol{J}^{\boldsymbol{T}}_{\boldsymbol{x}^*\boldsymbol{u}^*} \quad (6)$$

In Equation 6, $\boldsymbol{J}$ is the Jacobian matrix at the design point $\boldsymbol{x}^*$ and $\boldsymbol{J}_{\boldsymbol{x}^*\boldsymbol{u}^*} = \boldsymbol{J}^{-1}_{\boldsymbol{u}^*\boldsymbol{x}^*}$.

The elements of the $\boldsymbol{\gamma}$ vector, γ_i, have a value between -1 and 1. A positive and negative γ_i correspondingly represent a decision variable that increases and decreases P_f.

Utilizing FORM, this paper improves the decision analysis methodology proposed in Chapter 3 by including epistemic uncertainty associated with the limit state functions. The limit state functions are obtained using the SIMPLE-Design framework (Shahtaheri et al. 2018) by fitting a line to the points (alternative infrastructure design configurations) of equal utility assessed from the decision maker. By incorporating both aleatory and epistemic uncertainties in the decision analysis process, the sensitivity of the output results can also be assessed with respect to the model inputs. Integration of FORM, decision maker defined utility functions, epistemic uncertainties associated with the performance of the alternative infrastructure design configurations in the built environment, and aleatory uncertainties associated with finding the decision maker defined utility functions, leads to not only estimating the probability of meeting the decision makers' needs, but also assessing the reliability of the decision analysis results.

4. METHODOLOGY

In order to start the decision analysis framework under uncertainty the decision criteria and the types of uncertainties associated with the infrastructure life-cycle need to be identified. Each of the sources of uncertainty are additional decision variables that should be included in the decision analysis methodology and reliability assessment. Uncertainties associated with the nature of the built environment such as natural hazard events and climate change can be considered as aleatory sources of uncertainty. Moreover, since infrastructure design decisions are made by integrated design teams, assessing decision maker values, and combining individual decision maker preferences can be considered as an epistemic sources of uncertainty. Lack of accurate data on aleatoric uncertainties can also be considered as an additional source of epistemic uncertainty. In the proposed methodology, the natural variability of natural hazard events and the error associated with assessing decision maker values are respectively selected as aleatory and epistemic sources of uncertainty. Furthermore, individual decision maker preferences are combined in order to assess the reliability of alternative infrastructure design configurations in integrated design teams. In order to further demonstrate the decision analysis framework, mid-rise office buildings will be considered as an example.

4.1 Aleatory Uncertainties: Uncertainty of the Built Environment

The aleatoric uncertainties associated with the nature of the built environment can be found using available data on the natural variability of natural hazard events, natural hazard event frequencies, and climate change. It should be noted that the uncertainty of the built environment (e.g., natural hazard events) varies with respect to the infrastructure location. For example, Los Angeles, CA, where earthquake is the prominent natural hazard of the region, the frequency and severity of the earthquake hazard needs to be identified with respect to the region and infrastructure type. Available data on the natural hazard can be used to constrain the aleatory uncertainty on the resulting risk variables in the form of probability density functions for various alternative design configurations with respect to the decision criteria.

An example of a triple-bottom-line-based decision criteria can be initial cost, building damage and business interruption cost (C_d) and casualty cost (C_c) (due to the occurrence of the earthquake hazard), and CO_2 emission cost (C_e.). It should be noted that the initial cost can be considered as a deterministic number. However, building damage and business interruption cost, casualty cost, and CO_2 emission costs can be affected by the natural variability of natural hazard events. Once the decision variables are identified, the aleatory uncertainty of the earthquake risk can be integrated with the decision criteria. Assuming that the decision variables have a lognormal distribution (as recommended by Weidema 2013 and implemented in Chhabra et al., 2018) , the limit state function and solution space can be formulated as shown in Equation 7:

$$g\,(C_d, C_c, C_e) = \pm\, m_1 \ln (C_d) \;\pm m_2 \ln (C_c) \pm m_3 \ln (C_e) \;\pm\; b \leq 0 \qquad (7)$$

Where each decision criteria (C_d, C_c, and C_e) is in the form of a probability density function (decision variable); m_1, m_2, and m_3 are the weights (e.g., multipliers from polynomial fitting); and b is a constant.

4.2 Epistemic Uncertainties: Uncertainty of Decision Maker Preferences

Infrastructure design decisions are made by integrated design teams. For this reason, decision maker values should be assessed with respect to the probabilistic decision criteria. One of the most well established methods that can assess values and utilities from the decision makers is expected utility (Edgeworth 1881; Raiffa 1968; Hadar and Russell 1969). Indifference curve are a category of utility functions that have the ability to assess a one-time utility function from the decision maker, which can be applied to a range of alternative design configurations and shifted in parallel to the original indifference curve (e.g., in the case where additional alternatives are identified that are outside the original solution space). Shahtaheri et al. (2018), propose a modular preference assessment methodology (SIMPLE-Design) that utilizes indifference curves for assessing decision maker utilities with respect to a number of alternative infrastructure design configurations and decision criteria. Once the alternatives of equal utility are assessed from the decision maker, an indifference curve (with respect to two decision criteria) is fitted to the alternatives of equal utility. This fitting might lead to regression errors that might change the original utilities of the decision makers. In order to incorporate the deviations of the dependent variable observations from the fitted function in the decision analysis methodology, the residual values can be considered as an epistemic source of uncertainty.

4.3 Integration of Aleatory and Epistemic Uncertainty

In order to incorporate the deviations of the dependent variable observations from the fitted function in the decision analysis methodology, it is reasonable to assume that this source of uncertainty has a normal distribution with a mean of 0 and a standard deviation that is equivalent to the maximum of all residual values. Since the residual values might be different for various alternatives of equal utility assessed from the decision maker, the absolute maximum residual value can be considered as the standard deviation. In this case, the limit state function and solution space can be updated as shown in Equation 8:

$$g\,(C_d, C_c, C_e, \varepsilon) = \pm\, m_1 \ln (C_d) \;\pm m_2 \ln (C_c) \pm m_3 \ln(C_e) + N\,(\varepsilon) \pm\; b \leq 0 \tag{8}$$

Where each decision criteria (C_d, C_c, and C_e) is in the form of a probability density function (decision variable); m_1, m_2, and m_3 are the weights (e.g., multipliers from polynomial fitting); ε is the error (normal distribution with a mean of zero and a standard deviation that is equivalent to the maximum of all residual values); and b is a constant.

It should be noted that in this approach a frequentistic (statistical) representation is chosen to represent the epistemic uncertainty. An alternate approach is to collect further points of equal utility or value from the decision maker, in order to identify an indifference that is a closer fit to the original alternatives of equal utility assessed from the decision makers. However, in order to lower the cognitive load on the decision makers, three to four alternative of equal utility are assessed from each decision maker. Furthermore, in order to lower the computational expense and allow for integration with FORM, a frequentistic representation is chosen for the epistemic uncertainty.

4.4 Group Decision Making

Using the indifference curve development strategy, individual decision maker utilities can be assessed from each decision maker. Considering the decision criteria of initial cost, building damage and business interruption cost, casualty cost, and CO_2 emission cost, various alternative building design configurations can be assessed with respect to the decision criteria. In the SIMPLE-Design framework (Shahtaheri et al. 2018), twelve alternative design configurations are assessed with respect to the decision criteria. In this framework, a limited number of decision alternatives, i.e., five are presented to the decision makers for assessing their utilities. The decision makers are required to select one of the five alternative design configurations that presents the optimal allocation of initial costs, damage costs, casualty costs, CO_2 emission costs. Then, changes are made to the initial cost of the decision maker's original selection, by the aim of finding alternative design configurations that are of equal utility to the decision maker. Three to four alternatives of equal utility are assessed from each decision maker. Once the alternatives of equal utility are assessed from each decision maker, an indifference curve can be fitted to all the alternatives of equal utility assessed from all decision makers. Figure 1 shows an example of individual decision maker defined alternatives of equal utility and the line fitted to all decision maker alternatives of equal utility. It should be noted that different types of indifference curves can be utilized to represent the relationship between the alternatives of equal utility (Edgeworth 1881; Pareto 1971). However, a linear or perfect substitutes indifference curve is a sufficient representation of preferences that remain constant (constant line slope) within the performance range provided by the decision criteria. In the case of a perfect substitutes indifference curve, all decision criteria are important, however the relative important of the decision criteria might vary.

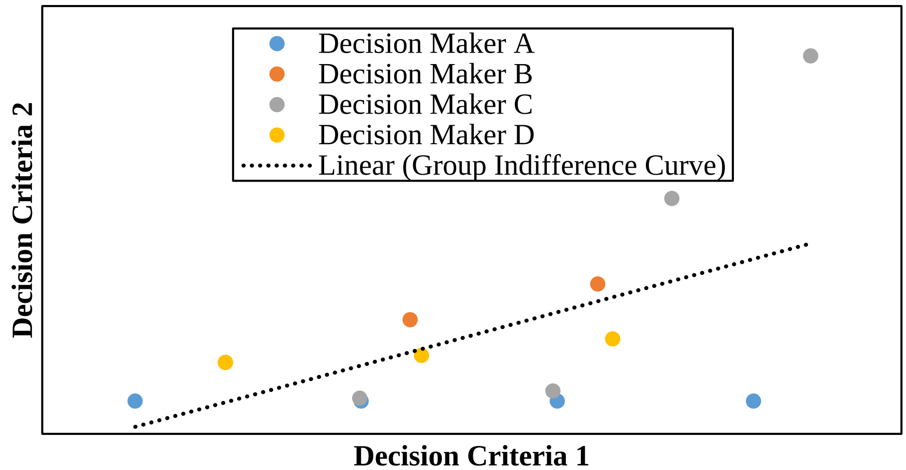


Figure 1: Combining Individual Decision Maker Utilities

4.5 Optimal Design Configurations

Once the decision criteria, sources of uncertainty, and decision maker utilities are identified, FORM can be utilized for finding the reliability of the alternative design configurations. In order to implement FORM, the correlation between the decision variables needs to be identified. Three types of correlations can exist with respect to the aleatory and epistemic sources of uncertainty. The three types of correlations can be categorized as the correlation between the aleatory variables, epistemic variables, and aleatory and epistemic variables. The probabilistic decision criteria such as building damage and business interruption cost and casualty cost are aleatory variables, which can be correlated. For example, if building damage and business interruption is increasing, it is also likely that casualty costs are also increasing. The two other types of correlations are the correlation between the epistemic variables, and aleatory and epistemic variables. The proposed methodology only considers one source of uncertainty in the decision analysis methodology, i.e., the indifference curve fitting epistemic error. In the case of the decision problem it is reasonable to assume that the regression error is not correlated with the probabilistic decision criteria. However, if additional sources of epistemic uncertainty are considered (e.g., climate change model error), they might be correlated to the aleatory decision variables and other epistemic decision variables. For this reason, the degree correlation between the decision variables is contingent on the nature of the decision variables and their corresponding sources of uncertainty.

5. PILOT IMPLEMENTATION

For the pilot implementation a nine-story office building located in Los Angeles, CA is considered with the decision criteria of initial cost, building damage and business interruption cost, casualty cost, CO_2 emission cost; epistemic uncertainty from fitting an indifference curve to decision maker utilities; and four individual decision makers (Wen and Kang 2001; Shahtaheri et al. 2018). It should be noted that the aleatory decision variables are considered as building damage and business interruption cost, casualty cost, CO_2 emission cost.

5.1 Aleatory Uncertainties: Uncertainty of the Built Environment

Although building design decisions are moving toward the consideration of probabilistic decision criteria, the inventory of such rigorous probabilistic performance assessments is still in the development phase. For this reason, deterministic decision criteria values will be transformed into probabilistic decision criteria. Table 1 shows twelve alternative design configuration of a nine-story office building.

Table 1: Alternative Design Configurations of a Nine-Story Office Building (Adapted from Wen and Kang 2001)

Design Alternative	Initial Cost ($)	Building Damage and Business Interruption Cost ($)	Casualty Cost ($)	CO_2 Emission Cost ($)	Sum of all Costs ($)	Death and Injury Rate (#People)
$1^{*\Delta}$	1,694,000	6,244,000	1,233,000	133,000	9,304,000	[7-8]
2	1,787,000	3,611,000	504,000	134,000	6,036,000	[3-4]
3^{Δ}	1,893,000	2,045,000	266,000	136,000	4,340,000	[1-2]
4^{*}	1,990,000	1,489,000	237,000	137,000	3,853,000	[1-2]
5	2,079,000	1,138,000	171,000	138,000	3,526,000	[1-2]
6^{Δ}	2,172,000	863,000	130,000	139,000	3,304,000	[0-1]
7^{*}	2,267,000	755,000	113,000	140,000	3,275,000	[0-1]
8	2,360,000	641,000	105,000	141,000	3,247,000	[0-1]
9^{Δ}	2,470,000	589,000	97,000	141,000	3,297,000	[0-1]
10^{*}	2,577,000	534,000	83,000	142,000	3,336,000	[0-1]
11^{Δ}	2,880,000	379,000	52,000	146,000	3,457,000	[0-1]
$12^{*\Delta}$	3,234,000	303,000	43,000	150,000	3,730,000	[0-1]

*used in the SIMPLE-Design preference assessment framework (Shahtaheri et al. 2018)

$^{\Delta}$used in the illustrations (Figure 4, Table 3, and Table 4)

In order to develop the probabilistic decision criteria with aleatory uncertainty, the deterministic values for the building damage and business interruption costs, casualty costs, and CO_2 emission costs are taken as the mean of a lognormal distribution with a coefficient of variation of 20% and 80%.

5.2 Epistemic Uncertainties: Uncertainty of Decision Maker Preferences

Using the preference assessment methodology presented in the SIMPLE-Design framework (Shahtaheri et al. 2018), decision maker preferences are assessed with respect to the alternative design configurations presented in Table 1. Equation 9 to 11 represents the indifference curve of the decision maker with respect to building damage and business interruption cost (C_d), casualty cost (C_c), and CO_2 emission cost (C_e). The individual alternatives of equal utility assessed from the decision maker are shown in Table 2 (i.e., decision maker D).

$$ln\ (C_c) = 0.02\ ln\ (C_d) + 82{,}000 \quad (9)$$

$$ln\ (C_e) = -\ 0.01\ ln\ (C_d) + 176{,}000 \quad (10)$$

$$ln\ (C_c) = -\ 2.03\ ln\ (C_e) + 442{,}000 \quad (11)$$

Linear indifference curves are fitted to the alternatives of equal utility assessed from the decision makers (e.g., Table 2). The maximum residual values respectively for the building damage and business interruption cost versus casualty cost, building damage and business interruption cost versus CO_2 emission cost, and CO_2 emission cost versus casualty cost indifference curves are respectively 4,500, 1,600, and 7,700. In this case Equation 9 to 11 can be updated as shown in Equation 12 to 14.

$$ln\ (C_c) = 0.02\ ln\ (C_d) + N(\ C_{\varepsilon_{cd}}) + 82{,}000 \quad (12)$$

$$ln\ (C_e) = -\ 0.01\ ln\ (C_d) + N(\ C_{\varepsilon_{ed}}) + 176{,}000 \quad (13)$$

$$ln\ (C_c) = -\ 2.03\ ln\ (C_e) + N\ (C_{\varepsilon_{ce}}) + 442{,}000 \quad (14)$$

Where, C_{ε} has a normal distribution of with a mean of zero and $C_{\varepsilon_{cd}}$, $C_{\varepsilon_{ed}}$, and $C_{\varepsilon_{ce}}$ respectively have standard deviations of 4,500, 1,600, and 7,700, and correlations of zero between all decision variables.

5.3 Decision Appraisal and Pilot Implementation Results

5.3.1 Integration of Aleatory and Epistemic Uncertainty

In order to assess the impact of all relevant uncertainties, constant probability of failure contours (probability of not meeting the decision maker's preferences (indifference curves in Equation 12 to 14)) are developed using FORM. For this purpose, an archetype building is generated for each of the building damage and business interruption cost versus casualty cost, building damage and business interruption cost versus CO_2 emission cost, and CO_2 emission cost versus casualty cost indifference curves. The archetype building is found by taking the average standard deviations of all the alternative design configurations (shown in Table 1 with a lognormal distribution and a coefficient of variation of 20%) with a correlation coefficient of zero between all the decision variables. As shown in Figure 2, the mean of the decision criteria distributions is shifted both in the x and y direction (creating a grid), covering the solution space. It should be noted that in a case study analyzed in Chapter 3, the effect of the correlation between the decision variables on the reliability of the alternative design configurations was found to be negligible for the decision variables with a low (20%) coefficient of variation. For this reason, a correlation coefficient of zero has been selected for the decision analysis methodology.

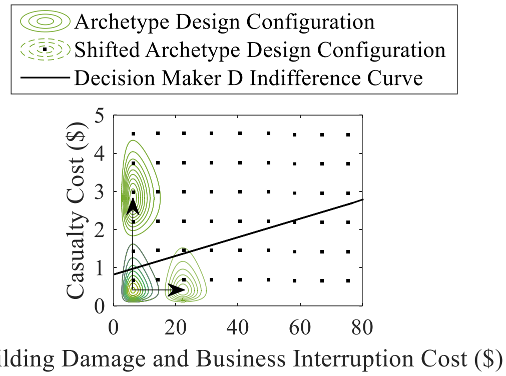
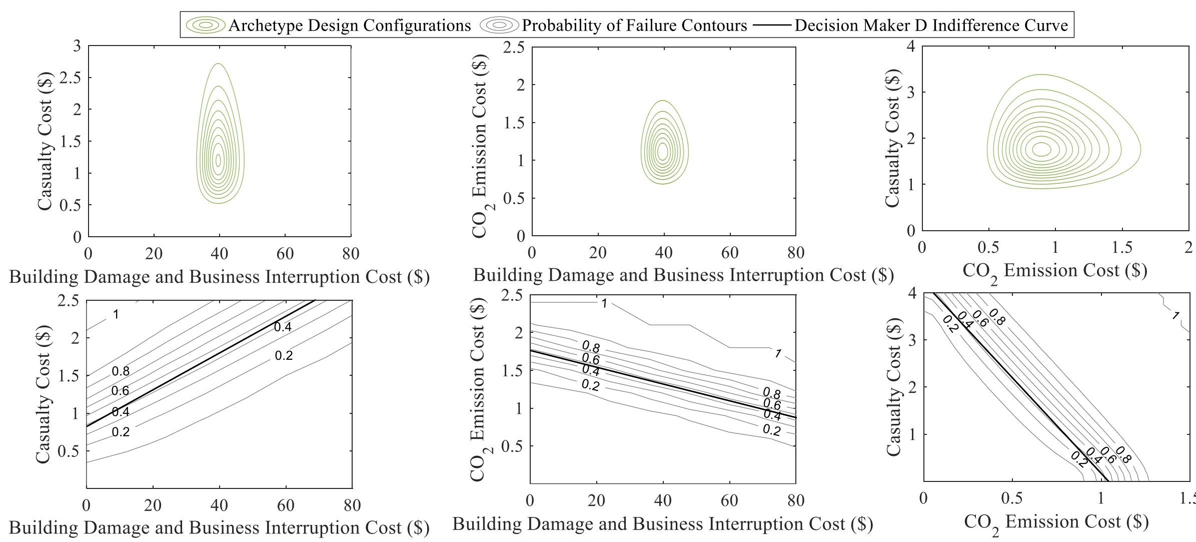


Figure 2: Archetype Design Configuration Shifts with Respect to the Building Damage and Business Interruption Cost vs. Casualty Cost Indifference Curve (all costs are presented in $100,000 USD)

The joint probability distribution of the archetype design configurations and the constant probability of failure contours for each indifference curve is shown in Figure 3.



(a) **(b)** **(c)**

Figure 3: Probability of Failure Contours and Archetype Design Configurations for (a) Building Damage and Business Interruption Cost vs. Casualty Cost, (b) Building Damage and Business Interruption Cost vs. CO_2 Emission Cost, and (c) CO_2 Emission Cost vs. Casualty Cost (all costs are presented in $100,000 USD)

The contours of constant probability of failure can be utilized to understand how various sources of uncertainty impact the probability of meeting the decision maker's preferences. A slower decay in the contours of constant of probability of failure means that there is a high uncertainty (variation) associated with the solution space, making design decision more complex. However, in the case of the decision problem, the decay in the contours are fast due to the consideration of a 20% coefficient of variation for each of the archetype buildings. Furthermore, the aleatory uncertainty from the indifference curve fitting (residual values) had a value between 1,600 and 7,700. This additional source of error had a negligible (or no) impact on the probability of meeting the decision maker's preferences with respect to the probabilistic decision criteria of building damage, casualty, and CO_2 emission (shown in Equation 7). Decision makers can utilize the constant probability of failure contours to guide their design decisions. A risk averse decision maker (attempting to lower uncertainty) is likely to select alternative design configurations that are on the contours with the lower probability of failure. Such as the 0.2 contour with a 20% probability of failure. A risk neutral decision maker (that is indifference between having their utilities met or not met), is likely to select alternative design configurations that are on the 0.5 probability of failure contours. Risk seeking decision makers (accepting greater uncertainty) might accept a higher probability of not meeting their preferences (e.g., 0.7 contour or 70% probability of failure).

5.3.2 Group Decision Making

Using the SIMPLE-Design framework (Shahtaheri et al. 2018), alternatives of equal utility can be assessed from decision maker with respect to a range of alternative design configurations. Table 2 represents the alternatives of equal utility assessed from four difference decision makers. It should be noted that the SIMPLE-Design framework recommends to normalize all the various types of costs (if the decision criteria are transformed into an equivalent cost value) for lowering the cognitive burden on the decision maker. For this reason, the alternatives of equal utility assessed from the decision makers have a total cost value of $4M in Table 2.

Table 2: Alternative of Equal Utility Selected by Decision Makers

Decision Makers	Initial Cost ($)	Building Damage and Business Interruption Cost ($)	Casualty Cost ($)	CO_2 Emission Cost ($)
A	3,468,000	325,000	46,000	161,000
	2,783,000	1,114,000	46,000	57,000
	2,098,000	1,799,000	46,000	57,000
	1,413,000	2,484,000	46,000	57,000
B	3,090,000	640,000	100,000	170,000
	2,405,000	1,325,000	110,000	160,000
	1,720,000	1,992,000	133,000	155,000
C	728,000	2,684,000	530,000	57,000
	1,414,000	2,199,000	330,000	57,000
	2,099,000	1,784,000	60,000	57,000
	2,784,000	1,109,000	50,000	57,000
D	3,090,000	640,000	100,000	170,000
	2,405,000	1,325,000	110,000	160,000
	1,720,000	1,992,000	133,000	155,000

In order to assess the reliability of the alternative design configurations (in Table 1), an indifference curve can be fitted to all the alternatives of equal utility assessed from the decision makers (Table 2). It is assumed that the preference of all decision makers remains constant in the performance range of the alternative design configurations. For this reason, the perfect substitutes (linear) indifference curve is selected to represent the combined utility of all decision makers.

Equation 15 to 17 represent the building damage and business interruption cost (C_d) versus casualty cost (C_c), building damage and business interruption cost (C_d) versus CO_2 emission cost (C_e), and the CO_2 emission cost (C_e) versus casualty cost (C_c) indifference curves (fitted to all the alternatives of equal utility from all decision makers presented in Table 2). Using a system reliability formulation (assuming series system formulation since all decision maker utilities should be met) shown in Equation 18, the reliability of the alternative design configurations can be computed for all decision makers with respect to the combined indifference curves.

$$p_{f,dc} = 0.11 \ln (C_d) - \ln(C_c) - 26{,}000 \leq 0 \tag{15}$$

$$p_{f,de} = -0.04 \ln (C_d) - \ln (C_e) + 173{,}000 \leq 0 \tag{16}$$

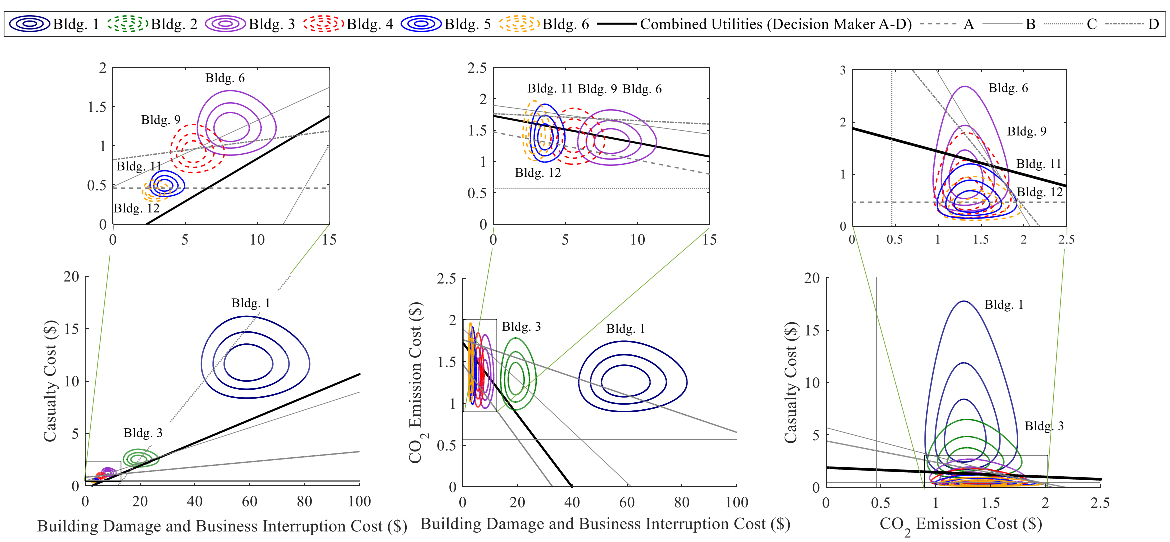
$$p_{f,ec} = -0.44 \ln (C_e) - \ln (C_c) + 188{,}000 \leq 0 \tag{17}$$

$$P_{f,System} = p_{f,dc} \cup p_{f,de} \cup p_{f,ec} \tag{18}$$

The coefficient of determination, R^2 for indifference curve 15 to 17 is respectively 0.3, 0.3, and 0.03. Which implies that the variability of the alternatives of equal utility is not accurately explained by the perfect substitutes indifference curve. In other words, the decision maker utilities are heterogeneous. In the case of a high R^2 value, the decision making group is homogenous and has an agreement on the alternative of equal utility.

5.3.3 Optimal Design Configurations

Utilizing FORM, the reliability of the alternative design configurations can be found with respect to the combined decision maker indifference curves. Figure 4 represents the joint probability density functions for alternative design configurations 1, 3, 6, 9, 11, and 12 with respect to the building damage and business interruption cost versus casualty cost, building damage and business interruption cost versus CO_2 emission cost, and the CO_2 emission cost versus casualty cost indifference curves. The indifference curves are shown for the individual decision makers A, B, C, D and the combined decision maker indifference curve. The joint probability density functions are plotted with respect to the distribution means shown in Table 1, for a coefficient of variation 20%; and a correlation coefficient of 0 between all the variables of building damage and business interruption cost, casualty cost, and CO_2 emission cost.



(a) **(b)** **(c)**

Figure 4: (a) Building Damage and Business Interruption Cost vs. Casualty Cost, (b) Building Damage and Business Interruption Cost vs. CO_2 Emission Cost, (c) CO_2 Emission Cost vs. Casualty Cost Uncorrelated Probability Density Function Contours with a Coefficient of Variation of 20% for Six Building Configurations with Respect to the Decision Maker Defined Indifference Curves (all costs are presented in $100,000 USD)

Table 3 shows the probability of not meeting the decision makers' preferences with respect to the combined decision maker defined indifference curves (Equation 15 to 17).

Table 3: Reliability of Alternative Building Configurations for Coefficient of Variation (CV) = 20% and 80%, and Correlation Coefficient (ρ) = 0

Bldg.	CV = 20%, ρ = 0 (for all variables)				CV = 80%, ρ = 0 (for all variables)			
1	$P_{f,system}$	1.00	$p_{f,dc}$	0.99	$P_{f,system}$	1.00	$p_{f,dc}$	0.74
			$p_{f,de}$	1.00			$p_{f,de}$	0.88
			$p_{f,ec}$	1.00			$p_{f,ec}$	1.00
3	$P_{f,system}$	1.00	$p_{f,dc}$	0.84	$P_{f,system}$	0.90	$p_{f,dc}$	0.62
			$p_{f,de}$	0.95			$p_{f,de}$	0.51
			$p_{f,ec}$	1.00			$p_{f,ec}$	0.70
6	$P_{f,system}$	0.99	$p_{f,dc}$	0.98	$P_{f,system}$	0.85	$p_{f,dc}$	0.73
			$p_{f,de}$	0.50			$p_{f,de}$	0.35
			$p_{f,ec}$	0.50			$p_{f,ec}$	0.33
9	$P_{f,system}$	1.00	$p_{f,dc}$	0.99	$P_{f,system}$	0.87	$p_{f,dc}$	0.80
			$p_{f,de}$	0.37			$p_{f,de}$	0.32
			$p_{f,ec}$	0.10			$p_{f,ec}$	0.21
11	$P_{f,system}$	1.00	$p_{f,dc}$	1.00	$P_{f,system}$	0.88	$p_{f,dc}$	0.81
			$p_{f,de}$	0.33			$p_{f,de}$	0.31
			$p_{f,ec}$	2×10^{-4}			$p_{f,ec}$	0.08
12	$P_{f,system}$	1.00	$p_{f,dc}$	1.00	$P_{f,system}$	0.90	$p_{f,dc}$	0.85
			$p_{f,de}$	0.34			$p_{f,de}$	0.32
			$p_{f,ec}$	6×10^{-5}			$p_{f,ec}$	0.07

$P_{f,system}$: series system probability of failure; $p_{f,dc}$: damage cost (d) vs. casualty cost (c) probability of failure; $p_{f,de}$: damage cost (d) vs. CO_2 emission cost (e) probability of failure; $P_{f,de}$: CO_2 emission cost (e) vs. casualty cost (c) probability of failure

From the results of the decision analysis methodology, it is evident that all the alternative design configuration have and 85% or higher chance of not meeting the preferences of the decision making group. It should be noted that the alternative design configurations can have up to an 80% probability of meeting the individual decision maker preferences (Chapter 3). However, combining decision maker utilities does not lead to a consensus on the optimal design configuration that meets the decision makers' needs (the decision makers have heterogeneous utilities). For this reason, further analysis is conducted on the importance vector, $\boldsymbol{\gamma}$, in order to identify the important decision criteria that have the highest impact on the reliability of the alternative design configurations. Table 4 shows the importance vectors for alternative design configurations 1, 3, 6, 9, 11, and 12 for a coefficient of variation of 20% and 80% and a correlation coefficient of zero for all the decision variables. In Table 4, the random variables with a corresponding γ_i value larger than 0.55 are considered as an important random variable.

Table 4: Importance Vectors for the Alternative Design Configurations for a Coefficient of Variation (CV) = 20% and 80%, and Correlation Coefficient (ρ) = 0

Bldg.	CV = 20%, ρ = 0 (for all variables)			CV = 80%, ρ = 0 (for all variables)		
	γ_{dc} [d, c]	γ_{de} [d, e]	γ_{ec} [e, c]	γ_{dc} [d, c]	γ_{de} [d, e]	γ_{ec} [e, c]
1	[**-0.72** **0.70**]	[**0.83** **0.56**]	[**0.97** 0.23]	[**-0.72** **0.69**]	[**0.84** 0.54]	[**0.98** 0.20]
3	[**-0.74** **0.67**]	[**0.58** **0.82**]	[**0.95** 0.32]	[**-0.75** **0.66**]	[0.55 **0.84**]	[**0.96** 0.28]
6	[**-0.78** **0.62**]	[0.26 **0.97**]	[**0.90** 0.43]	[**-0.80** **0.60**]	[0.21 **0.98**]	[**0.93** 0.37]
9	[**-0.81** **0.59**]	[0.17 **0.99**]	[**0.86** 0.51]	[**-0.83** **0.56**]	[0.14 **0.99**]	[**0.89** 0.45]
11	[**-0.86** 0.52]	[0.10 **0.99**]	[0.55 **0.84**]	[**-0.88** 0.48]	[0.08 **1.00**]	[0.46 **0.89**]
12	[**-0.88** 0.48]	[0.08 **1.00**]	[0.40 **0.92**]	[**-0.90** 0.44]	[0.06 **1.00**]	[0.31 **0.95**]

γ_{dc}: damage cost (d) vs. casualty cost (c) importance vector, γ_{de}: damage cost (d) vs. CO_2 emission cost (e) importance vector, γ_{ec}: CO_2 emission cost (e) vs. casualty cost (c) importance vector; **Bold**: more important decision criteria (sensitivity)

Considering design configuration 6, with the lowest probability of not meeting the decision makers' preferences, is it evident that the damage decision criterion in the damage versus casualty cost indifference curve is reducing the probability of not meeting the defined constraints (has a negative sign). However, all the remaining decision criteria have positive values in the $\boldsymbol{\gamma}$ vector, therefore are contributing to the probability of not meeting the preferences of the decision making group. With respect to design configuration 6, most of the decision variables have a high impact on the reliability of the alternative design configurations. For this reason, any of the decision criteria can be targeted for improving the reliability of the alternative design configurations. For a coefficient of variation of 20% and 80%, the CO_2 emission cost decision criterion has the highest impact on the reliability of the alternatives for the CO_2 emission cost versus casualty cost indifference curve. Alternative building materials can be proposed with a lower CO_2 emission in order to improve the reliability of the alternative design configurations. This feedback loop allows for finding the important decision variables with respect to the group indifference curve, which can be targeted for improving the reliability of the alternative design configurations. New alternative design configurations can then be proposed and re-assessed with respect to the decision criteria and the relevant sources of uncertainty, in order to maximize decision maker utilities (find design configurations that best meets the decision makers' needs).

6. CONCLUSIONS AND FURTHER RESEARCH

Infrastructure design decisions often include a number of conflicting design criteria, integrated design teams, and are made in an uncertain environment (i.e., the uncertainty associated with the built environment and the decision analysis methodology). Current practices and state of the art methods for infrastructure design decisions do not provide a systematic framework for finding infrastructure design alternatives that maximize decision maker utilities with respect to aleatory and epistemic uncertainties. In order to address the identified knowledge gap, this research proposed a holistic decision framework that integrates the First Order Reliability Method (FORM) with decision maker utilities, and aleatoric and epistemic uncertainties. The contribution to the body of knowledge is a decision analysis methodology that allows for full and consistent representation of all relevant uncertainties, multiple decision criteria, decision maker requirements, and decision variable correlations (i.e., correlations between aleatory and epistemic uncertainties). The presented decision analysis methodology also provides a meaningful feedback loop that allows the decision makers to improve the alternative design configurations with respect to their individual utilities, or the combined utilities for a group of decision makers. Furthermore, utilizing regression a systematic framework is provided for combining multiple decision maker utilities.

While the pilot implementation incorporated three decision variables with aleatory uncertainty (earthquake damage and casualty cost, and CO_2 emission cost), and one decision variable with epistemic uncertainty (utility function/indifference curve regression error), additional sources of aleatory and epistemic uncertainty can be added to the decision analysis methodology (e.g., climate change impact). Furthermore, the correlation between aleatory and epistemic uncertainties was taken as zero in the pilot implementation. Considering that the aleatory and epistemic sources of uncertainty were unrelated. However, in the case where the various sources of uncertainty are correlated, the correlation between the decision variables can be included in the decision analysis process. With regard to the decision maker defined indifference curves (utility functions), a linear indifference curve is chosen for representing the joint utility of all decision makers. In the case where the relative importance of the decision criteria might vary along the indifference curve, a non-linear indifference curve can be used.

Further extensions of the decision analysis framework can include the consideration of various sources of aleatoric and epistemic uncertainties and their relative correlations. Furthermore, using the feedback loop provided by FORM, the alternative design configurations can be tailored to better meet the preferences of the decision makers. The tailored alternative design configurations can be reanalyzed using the presented decision analysis methodology, in order the evaluate the updated reliability of the alternative design configurations.

Infrastructure design decisions can significantly benefit from a decision analysis methodology with a low computational expense that can incorporate the uncertainties associated with the built environment (aleatory uncertainties) and the decision analysis methodology (epistemic uncertainties) in the early design phase. To this effect, the First Order Reliability Method (FORM) is integrated with decision maker utilities and various sources of uncertainties (decision variables). The presented holistic decision analysis methodology allows for a full and consistent representation of aleatoric and epistemic uncertainties, decision maker utilities, alternative design configurations, and sensitivity assessment measures (feedback loop). Providing the decision makers with information on the impact of various sources of uncertainty on the decision criteria and the reliability of the alternative design configurations with respect to decision maker utilities, will lead to more informed infrastructure design decisions. Such holistic design decisions are a better representation of the uncertain environment that infrastructures are meant to serve.

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5. CONCLUSIONS

Infrastructures are the most fundamental facilities and systems serving the society. Due to the existence of infrastructures in economic, social, and environmental contexts, all lifecycle phases of such fundamental facilities should maximize utility for the designers, occupants, and the society. However, due to the uncertainties associated with the nature of the built environment, the economic, social, and environmental (i.e., triple bottom line) impacts of infrastructures must be described as probabilistic. Leading to a complex probabilistic decision problem, including a broad set of alternatives, a number of conflicting decision criteria and decision objectives (i.e., with respect to the triple bottom line), and multiple decision makers.

The state of the art probabilistic (stochastic) multi-criteria decision analysis frameworks are computationally expensive and do not provide means for conducting sensitivity assessment on the decision analysis results. Furthermore, due to the inherent complexity of stochastic optimization methods, integration of decision maker utilities with such complex optimization models has not been attempted. In order to address the identified knowledge gaps, this dissertation proposes a holistic, modular, probabilistic decision framework for a performance-based design of infrastructures. The proposed multi-criteria/multi-objective, probabilistic decision analysis framework consists of three modular phases. With respect to all three modules, an illustration is presented for a nine-story, 75×180 ft^2 office building located in Los Angeles, CA with the decision criteria of first costs, building damage and business interruption costs, casualty costs (due to the occurrence of natural hazard events), and CO_2 emission costs.

Module one (Chapter 2) develops a modular preference function development strategy, termed **S**ustainable **I**nfrastructure **M**ulti-Criteria **P**reference assessment of a**L**ternatives for **E**arly **D**esign (SIMPLE-Design). The proposed framework develops utility functions (indifference curves) for assessing decision maker preferences with regard to various tradeoffs of alternative design options, and leverages available data to provide decision makers with a consistent frame of reference for assessing alternatives. An illustration presented for a decision support tool using the Simple-Design strategy assesses decision maker preferences for commercial buildings with respect to initial costs, building damage and business interruption costs, casualty costs (due to the occurrence of natural hazard events), and CO_2 emission costs. The designed tool provides streamlined information to support preference assessment with reasonably low cognitive load and ensures that the preferences obtained are applicable to the full solution space through use of indifference curves. A post-survey instrument was used to assess the success of the pilot implementation in framing the problem and reducing the cognitive load. There was a general consensus (<30% coefficient of variation on numerical rankings) on the high usefulness of: allowing the decision makers to define alternatives of equal utility; and providing information on various cost categories (decision criteria).

Module two (Chapter 3) presents a novel utilization of the First Order Reliability Method (FORM), for integrating the individual capabilities of multi-criteria decision analysis models under uncertainty. The state of the art multi-criteria decision making models under uncertainty can significantly benefit from a holistic, computationally efficient, adaptive, reliability-based approach that also provides measures for conducting sensitivity assessments on the decision analysis results. FORM has the ability to 1) measure the effect of each decision criterion (e.g., life-cycle cost) on the reliability of alternative infrastructure configurations with regard to the decision maker defined utilities (preferences, requirements, and constraints), 2) include the correlation between the probabilistic decision criteria in the reliability analysis, 3) measure the correlation between the decision maker defined utility functions and solution spaces, and 4) include the full probability distribution of multi-criteria performance measures of infrastructure design configurations in the decision making process. The proposed probabilistic multi-criteria decision analysis model has the ability to analyze multiple and potentially conflicting probabilistic decision criteria for a number of decision alternatives with respect to a system of decision maker defined utilities, constrains, limits, and requirements. The results of the pilot implementation revealed that high-performing design configurations (with higher initial costs and lower failure costs) can be identified by having a higher probability of meeting the decision maker's preferences. This implies that combining decision maker utilities with multiple design options and probabilistic decision criteria (that are a better representation of the uncertain environment that infrastructures are meant to serve) can lead to finding high-performing infrastructure design configurations that also maximize decision maker utilities.

Module three (Chapter 4) tests the reliability of the output results (obtained in module two) under various sources of uncertainty. Although a number of models exist that consider the uncertainty associated with the nature of the built environment (aleatory uncertainty from a random process), they do not provide a systematic framework for including both aleatory and epistemic (due to lack of knowledge, e.g., decision maker utility assessment process) uncertainties in the decision analysis methodology. To this effect, module three (Chapter 4) presents an integration of the First Order Reliability Method (FORM) with uncertain limit state functions (utility functions/indifference curves) for finding the probability of various alternative infrastructure design configurations meeting the decision makers' preferences in an uncertain environment. The decision maker defined utility functions are subjected to epistemic uncertainty, in order to assess the sensitivity of the decision analysis methodology to various sources of certainty. The multi-criteria probabilistic decision analysis framework is tested on the nine-story office building with the probabilistic decision criteria (subjected to aleatory or external uncertainty) of building damage and business interruption cost, casualty cost, and CO_2 emission cost; twelve alternative design configurations; decision maker utility functions; and the epistemic uncertainty associated with assessing decision maker utilities (i.e., regression error) and combining a number of decision maker defined utility functions (i.e., group decision making). The results of the pilot implementation revealed that the errors associated with fitting indifference curves to the points of equal utility assessed from the decision makers does not change the reliability (probability of meeting the decision maker's preferences) of the alternative design configurations. It should be noted that the regression error or maximum residual error had a value of $7,700, which is a negligible with respect to the total summation of all costs (between $3M to $9M). Furthermore, combining decision maker utilities does not lead to a consensus on the optimal design configuration that meets the decision makers' needs, as the decision makers have heterogeneous utilities. This finding implies that the variability of various decision maker defined utilities might not be accurately explained by the linear (perfect substitutes) indifference curve (utility function). This is also evident in the low coefficient of determination, R^2 (between 0.03 to 0.3) of the indifference curve lines, fitted to the utilities of the decision making group. In the case of a high coefficient of determination, R^2 value, the decision making group is homogenous and has an agreement on the alternative of equal utility. However, for both homogenous and heterogeneous decision maker utility functions (indifference curves), the importance vector (sensitivity assessment measure) provided by FORM can be utilized to tailor the alternative design configurations with respect to decision maker utilities.

1. CONTRIBUTIONS

The contribution to the body of knowledge is a holistic, modular, multi-criteria, probabilistic decision analysis methodology, which can be categorized in three modules as shown in Figure 1.

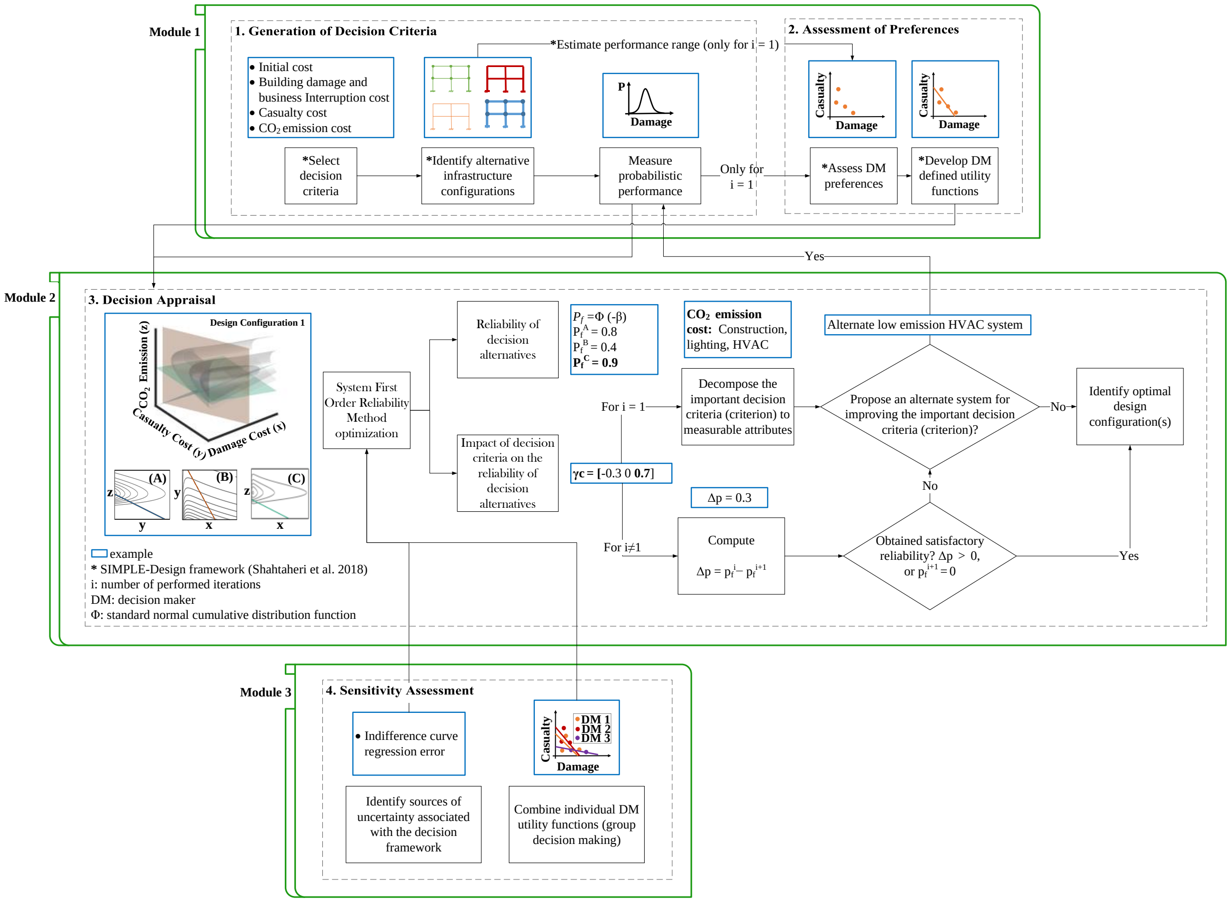

Figure 1: A Probabilistic Decision Support System for a Performance-Based Design of Infrastructures

Module one develops indifference curves (utility functions) for assessing decision maker preferences with regard to various tradeoffs of alternative design options, and leverages available data to provide decision makers with a consistent frame of reference for assessing alternatives. This module addresses the challenges associated with the lack of a systematic framework for presenting a large number of alternative design configurations to the decision makers and capturing their utilities with a low cognitive load in the initial design phase, while supporting subsequent optimization. The main contributions of module one of the decision analysis methodology are as follows:

- Communicate the performance of alternative infrastructure configurations to the decision makers and assess their preferences at an early design phase.

- Support subsequent optimization by using quantitative criteria to describe the triple bottom lines.
- Lower cognitive burden and avoiding bounded rationality by pre-selecting a limited set of alternatives that describe the possible tradeoffs between decision criteria and the performance range.
- Ensure that the preferences obtained are applicable to the full solution space through use of indifference curves.
- Reach a general consensus among the decision makers on the usefulness of the provided information.

Module two introduces the First Order Reliability Method (FORM) as an efficient optimization algorithm for finding the probability of various alternative infrastructure design configurations meeting the decision maker's preferences. Although stochastic optimization and multi-objective optimization are well developed in the field of operations research, their intersection (multi-objective optimization under uncertainty) is much less developed and computationally expensive. Furthermore, due to the inherent complexity of stochastic optimization methods, integration of decision maker utilities with such complex optimization models has not been attempted. In order to address the identified knowledge gap, the main contribution of module two is presenting a novel utilization of FORM in a system reliability approach, in order to allow for a computationally efficient, systematic integration of decision maker utilities; multiple probabilistic decision criteria; and alternative design configurations. The presented decision framework also adds an additional contribution to the body of knowledge, which is providing the decision maker with a meaningful feedback loop for understanding the decision analysis results. This allows the decision makers to tailor the original alternatives to better meet their individual or group preferences. The tailored alternative design configurations can be reanalyzed using the presented decision analysis methodology, in order the evaluate the updated reliability of the alternative design configurations. The main contributions of module two of the decision analysis methodology are as follows:

- Identify that the uncertainty associated with the performance of alternative infrastructure design configurations during early design is sufficiently important to be captured directly.
- Provide a systematic framework for integrating decision maker utility functions with the uncertainty associated with the performance of infrastructures.
- Formulate and frame a complex multi-objective decision problem by finding the probability of failure/success in terms of meeting the multi-criteria decision maker preferences.

Furthermore, operationalizing FORM in the context of early design engineering (under uncertainty) in a systems approach in order to:

- Measure the effect of all probabilistic decision criteria associated with the alternative design options on the probability of meeting the decision maker's preferences.
- Provide a consistent frame for including multiple decision criteria probability distributions, and the correlation between the decision criteria in the reliability analysis.

- Find the correlation between multiple utility functions and solution spaces.
- Provide a meaningful feedback loop that allows the decision makers to tailor the alternative design configurations with respect to their individual utilities, or the combined utilities for a group of decision makers.

Module three, develops a consistent framework for incorporating the uncertainty associated with the nature of the built environment (i.e., aleatory uncertainty), and the uncertainty associated with the decision analysis methodology (i.e., epistemic uncertainty) in the decision framework. This module addresses the challenge of a lack of systematic framework for incorporating both aleatory and epistemic uncertainties in the decision analysis methodology. In order to address this challenge, module three provides a systematic framework for incorporating uncertain limit state functions (utility functions or decision maker preferences) in the design of infrastructures and tests the robustness of the decision analysis methodology. Furthermore, in order to lower the complexity of group decision makings and combine all decision maker utilities, a method has been presented for combining various decision maker utilities (i.e., fitting a curve to all decision maker utilities), providing ease of use in the early design phase and allowing for subsequent optimization. The main contributions of module three of the decision analysis methodology are as follows:

- Allow for full and consistent representation of all relevant uncertainties (aleatory and epistemic).
- Provide a systematic framework for conducting sensitivity assessment on the decision analysis results.
- Provide an adaptable framework for quantifying aleatory and epistemic uncertainties.
- Include the correlation between aleatory and epistemic uncertainties in the decision analysis methodology.
- Provide a systematic framework for combining decision maker utilities with respect to alternative design configurations, and decision criteria.

A performance-based design of infrastructures is a complex decision problem involving a broad set of alternative design configurations, multiple conflicting decision criteria, multiple decision makers, and uncertainty. The state of the art infrastructure design models and stochastic optimization algorithms do not provide a systematic and holistic framework for addressing such complex decision problems. Although, considerable effort has been made in the development of multi-criteria stochastic (probabilistic) decision analysis models, due to the complexity of stochastic optimization methods, the probabilistic decision criteria, alternative design configurations, and decision maker utilities have not been integrated. The integration of all three modules of the proposed decision framework provide a consistent and systemic framework for capturing decision maker utilities at an early design phase with a low cognitive load, while assuring that the utility functions (indifference curves) are adaptable and scalable (eliminating the need for re-assessing preference when new alternative are added or removed); and find optimum design configurations that maximize decision maker utilities using a system reliability approach, while allowing for the incorporation of various sources of uncertainty in the decision analysis methodology.

2. LIMITATIONS OF RESEARCH

The limitations of the proposed decision support system are as follows:

a. All decision criteria are transformed to a dollar value and this transformation is not customized to the decision-maker, and therefore may not adequately reflect the value of global warming potential or human casualties.

b. The candidate alternatives are normalized to the same total life-cycle cost, implicitly assuming an expected-value decision maker. This normalization may penalize high-performing design options.

c. The initial cost is used as a basis for developing new alternatives, and while this basis is in line with the current state of practice, it may not best promote performance-based design solutions.

d. The perfect substitutes (linear) indifference curves is assumed, and may not accurately reflect the true form of a decision maker's utility function. In the case where the relative importance of the decision criteria might vary along the indifference curve, a non-linear indifference curve can be used.

e. The decision maker defined limit functions are assumed to have a series reliability formulation. This means that all limit state functions are equally important and violating one limit state function will impact the reliability of the alternative design options.

f. The pilot implementation incorporated three decision variables with aleatory uncertainty (earthquake damage and casualty cost, and CO_2 emission cost), and one decision variable with epistemic uncertainty (utility function/indifference curve regression error). Additional sources of aleatory and epistemic uncertainty can be considered in the decision analysis methodology (e.g., climate change impact).

g. The correlation between aleatory and epistemic uncertainties was taken as zero in the pilot implementation. However, in the case where the various sources of uncertainty are correlated, the correlation between the decision variables should be included in the decision analysis process.

h. The presented holistic decision analysis framework is data intensive and requires a rigorous probabilistic data collection with respect to the various alternative infrastructure design configurations and the decision criteria.

Limitations a, b, and c would be expected to significantly bias the results if they are not in agreement with decision maker beliefs. Additional work would be required to alter the current approach to measure decision maker utilities with respect to the original units of the decision criteria such as pounds of CO_2 emissions and number of expected death and injuries (by presenting the performance of the alternative design configurations to the decision makers and assessing decision maker utilities in their original units). Limitations d to g could be readily addressed with minor changes to the methodology, and are not expected to significantly bias the results. With respect to limitation h, the inventory of such rigorous performance assessment measures is in the development phase.

3. AREAS FOR FUTURE RESEARCH

The areas of future research with regard the proposed decision support system are as follows:

a. Incorporating the decision criteria weights in the regression model (e.g., orthogonal regression).

b. Utilizing the system reliability approach for combining multiple decision maker utility functions in group decision making problem.

c. Defining archetype utility functions by assessing the preferences of a larger number of decision makers in each category of stakeholder (e.g., owner, engineer).

d. Exploring further sources of uncertainty such as the epistemic and aleatory uncertainties (e.g., regression confidence interval from regression parameter uncertainty), their corresponding probability density functions, and correlations.

e. Tailoring the alternative design configurations using the feedback loop provided by the First Order Reliability Method (FORM) to better meet the preferences of the decision makers.

f. Reanalyzing the tailored alternative design configurations using the presented decision analysis methodology, in order the evaluate the updated reliability of the alternative design configurations.

4. BROADER IMPACT

Decisions made in the early design phase of infrastructures are more impactful (Basbagil et al. 2013) and address sustainability in a more effective way, making early design a prime target for the implementation of design analysis tools. However, lack of accurate data in the initial design phase (as the design has not been performed), the limited available time to make decisions, decision biases such as overconfidence bias (i.e., when the individual's subjective confidence is greater than the objective accuracy of the judgments) (Kahneman et al. 1982; Pallier et al. 2002), and the uncertainty associated with the built environment and the decision analysis process lead to poor infrastructure design configurations that do not maximize utilities for designer, occupants, and the society. Decision makers who are not aware of the uncertainty associated with the built environment, hazard-resilient designs, high-performing design options; and the environmental impact, natural hazard failure costs (or other unforeseen risk measures), life-cycle cost performance, and initial cost tradeoffs, are less likely to make informed decisions that consider the life-cycle performance of infrastructures at an early design stage. A risk and reliability-based decision analysis framework has the ability to greatly improve the initial design of infrastructures by finding the reliability of various infrastructure design alternatives with respect to unforeseen risk measures, decision maker preferences, and probabilistic decision criteria.

The holistic, modular, multi-criteria, probabilistic decision analysis framework presented in this dissertation, can capture the utilities of designers, occupants, and the society at an early design phase with a reasonably low cognitive load, and find optimum design configurations that maximize decision maker utilities with respect to unforeseen risk measures. Designers and decision makers can utilize this decision analysis framework and decision support tool to understand the tradeoffs of various alternative design configurations (i.e., economic, social, and environmental tradeoffs), and capture utilities with a low cognitive load. Decision analysts and designers can integrate decision maker utilities with the candidate alternative design configurations, and multiple conflicting, probabilistic decision criteria and decision objectives (e.g., minimize life-cycle cost and maximize safety in the occurrence of a natural hazard event), in order the find optimum design configurations that meet the needs of the decision makers. Furthermore, the decision makers can utilize the feedback loop in order to identify the important decision criteria and improve the reliability of the alternative design configurations (with respect to decision maker utilities). The presented decision analysis framework leads to performance-based infrastructure designs that optimize the economic, social, and environmental impacts of alternative design options with respect to decision maker utilities and the uncertain environment (i.e., uncertainty of the built environment and the decision analysis methodology), with a low cognitive load that makes tractable the complex nature of infrastructure design decisions given the limited time available time to make decisions.

4.1 References

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Kahneman, D., Slovic, P., and Tversky, A. (1982). *judgments under uncertainty: Heuristics and biases*, Cambridge University Press, UK.

Pallier, G., Wilkinson, R., Danthiir, V., Kleitman, S., Knezevic, G., Stankov, L., and Roberts, R. D. (2002). "The role of individual differences in the accuracy of confidence judgments." *The Journal of general psychology*, 129(3), 257-299.

APPENDIX A

In this section a broad literature review will discuss the various approaches that support (can support) a resilient design of infrastructures. Furthermore, since infrastructure design decisions include multiple decision criteria (e.g., initial cost and environmental impact), multiple decision makers, and are made in an uncertain environment (i.e., uncertainty associated with the built environment and the decision analysis methodology), the decision analysis methods are categorized with respect to the various sources of uncertainty (i.e., aleatory and epistemic). The decision making models under uncertainty are also categorized with respect to the models that find optimum design configurations with respect to decision maker requirements (utilities) and resilience criteria (e.g., initial cost and natural hazard failure cost), and the models that assess decision maker preferences. It should be noted that this review mainly focuses on the research areas that has not been covered in Chapters 2, 3, and 4 of the dissertation.

Figure A.1 represents the conducted search as nested sets and subsets; and the research areas that are able to assess resilience, such as information systems and decision support systems, as well as their interactions. While various research areas are presented in this Figure, the main focus of this research is the development of a decision support system. Figure A.2 provides an infrastructure asset resilience framework and depicts the link between the active areas of research. The geographic information system (GIS) based integrated asset management system is the main link between data collection, condition assessment, deterioration models, decision making, maintenance techniques, and the prioritization for future analysis. Each arrow represents a relationship between the two connected research areas. For example, inspection and data collection will affect the condition assessment of an infrastructure, and the condition assessment will affect the development of the deterioration model. Moreover, the size of each bubble represents the volume of literature found in each area.

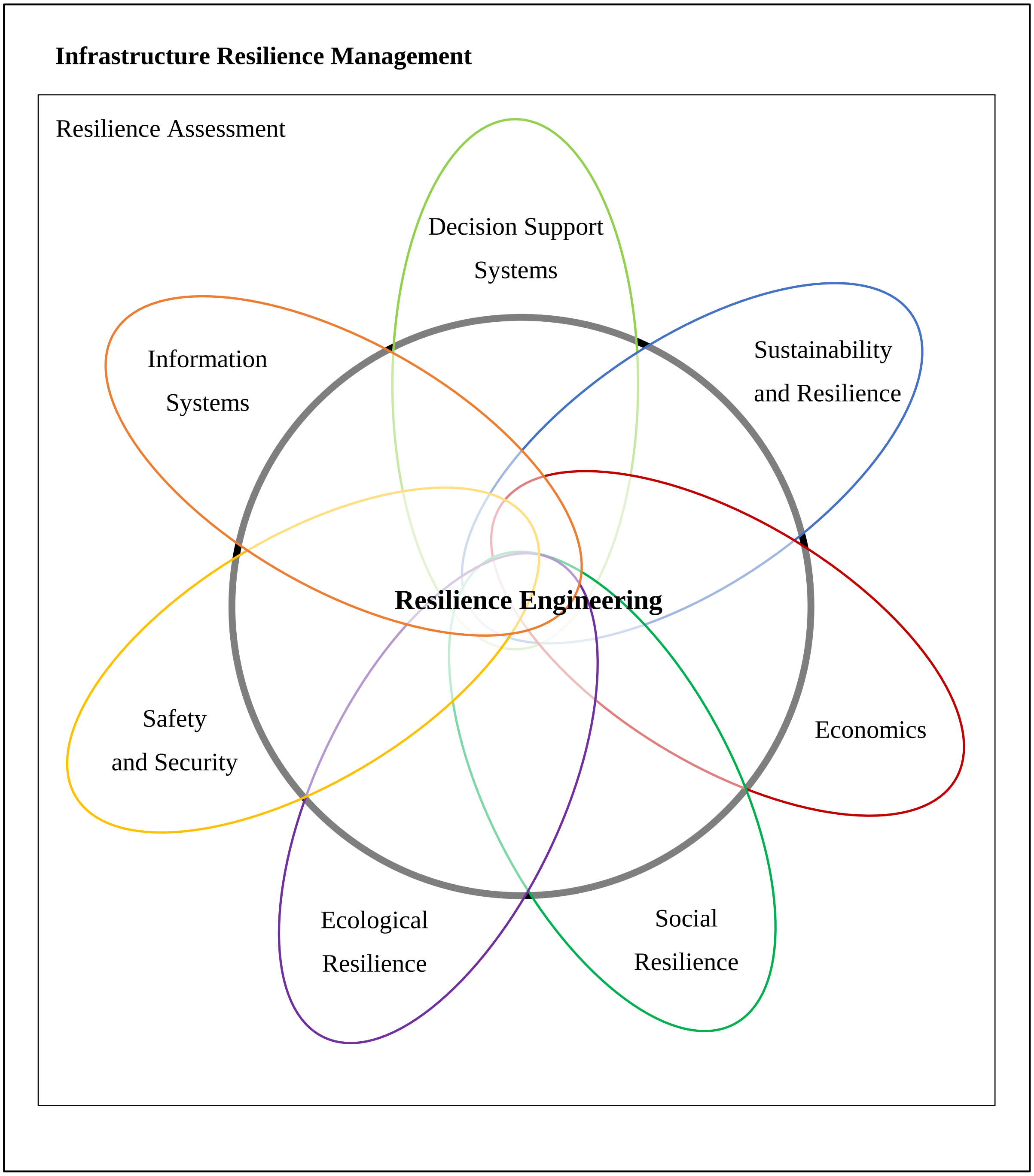

Figure A.1: Conducted Searches, Represented as Nested Sets and Subsets

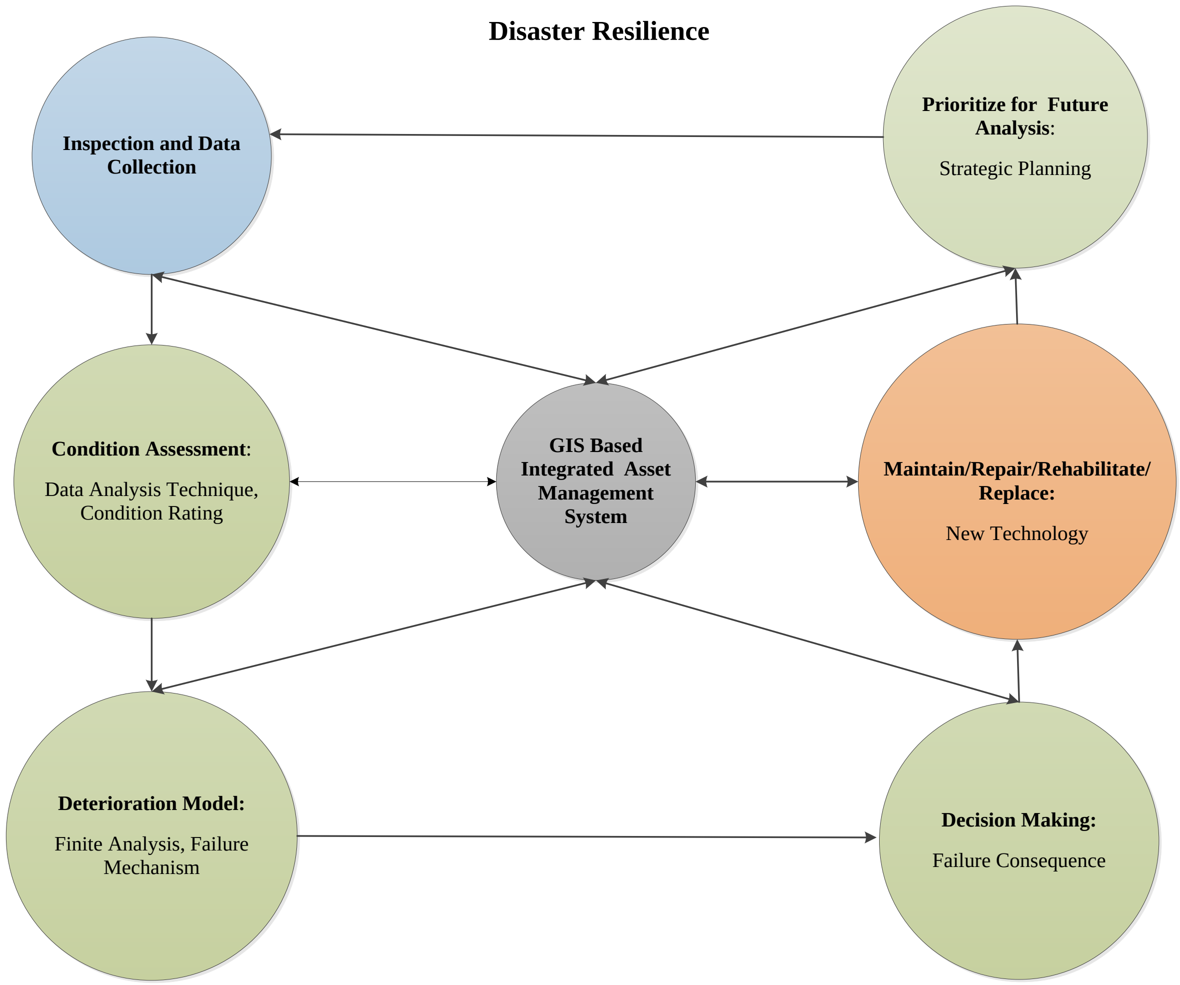

Figure A.2: Infrastructure Asset Disaster Resilience Framework

A.1 INTRODUCTION TO RESILIENCE

The concept of resilient, robust and recoverable systems has been studied since the 1980s by civil engineers, electrical engineers and computer scientists (Timmerman 1981; Aguilar 1984; Goldwasser et al. 1988; Leonhard 1990; Najjar and Gaudiot 1990). However, in the last decade this concept has started to evolve more quickly for building and maintaining a robust and recoverable community. Once a disaster strikes there is an expectation that the community will quickly bounce back to its initial condition. This expectation comes from the definition of resilience which is the capacity and capability of a structural system to recover back to normal or an improved normal (Bruneau et al. 2003). Performance and life-cycle standards are essential at a regional level to serve the needs of recovery. Standards are also required at a national level for new construction to withstand future risks and hazards. Achieving a resilient design does not mean mitigating all risks and predicting all future events. Rather it emphasizes a risk-based approach to absorption/mitigation, recovery, and adaption to potential hazard events (Ellingwood 2005; Li and

Ellingwood 2006; Tesfamariam and Saatcioglu 2008; Ellingwood and Kinali 2009; Dolšek 2012; Biondini and Frangopol 2016; Chen et al. 2016; Zhu and Frangopol 2016; Gardoni 2017; Xia et al. 2017; Fukutani et al. 2018; Sousa et al. 2018).

Structural resilience is a well-known term in seismic design and failure mode analysis, which has four different characteristics known as robustness, redundancy, resourcefulness, and rapidity (Bruneau et al. 2003). These characteristics could be further developed for additional hazards that may occur during the life time of a building, such as tsunami, hurricane, flood or combinations of different events (i.e. earthquake and tsunami). Robustness is described as the stiffness, strength, and stability of the structure during a natural hazard event. Redundancy relates to elasticity of the structure, and sub-structures in the occurrence of a natural hazard event. Resourcefulness is the capability to identify and correct the out-of-tolerance issues, misalignments, and other structural degradations which occur during a natural hazard event. Rapidity, is the process of minimizing the costs and risks of the repairs with respect to the project timelines. Moreover, a resilient system is one that reduces probability of failure, consequences from failure, and time to recovery. In a quantitative assessment and seismic resilience enhancement study by Bruneau et al, 2003, the conceptual definition of seismic resilience (quality of infrastructure) has been measured in terms of time which is shown in Figure A.3. This Figure represents the occurrence of an earthquake at t_0 which causes a reduction in the infrastructure quality, and the recovery time $(t_1 - t_0)$ for the infrastructure to recover and return back to its initial stage (Bruneau et al. 2003). Recovery curves allow the quantification of the building functional loss, and recovery time (Zobel and Khansa 2014; Burton et al. 2015).

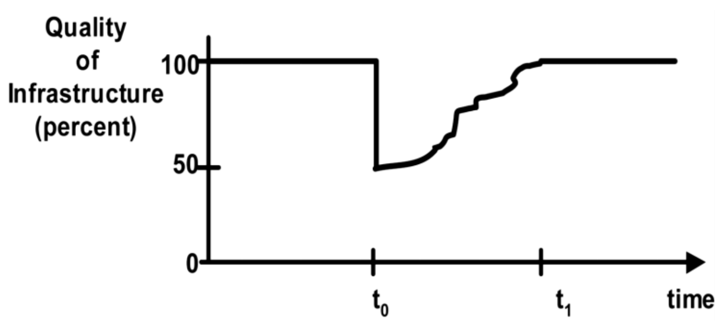

Figure A.3: Measure of Seismic Resilience (Bruneau et al. 2003)

Infrastructure and organizational resilience can also be correlated with business community management, crisis management, emergency management, legal compliance, and social resilience. Additionally, operational resilience is interrelated with facility management, technical infrastructure, organizations behavior, risk management, and supply chain systems (TISP 2012). It should be noted that hazard resilience can also be defined with respect to various infrastructure systems, resilience characteristics, cross-cutting and external communications, policy, social sciences, and economics. This has been well defined by the ASCE infrastructure resilience division and in shown in Figure A.4 (ASCE 2015).

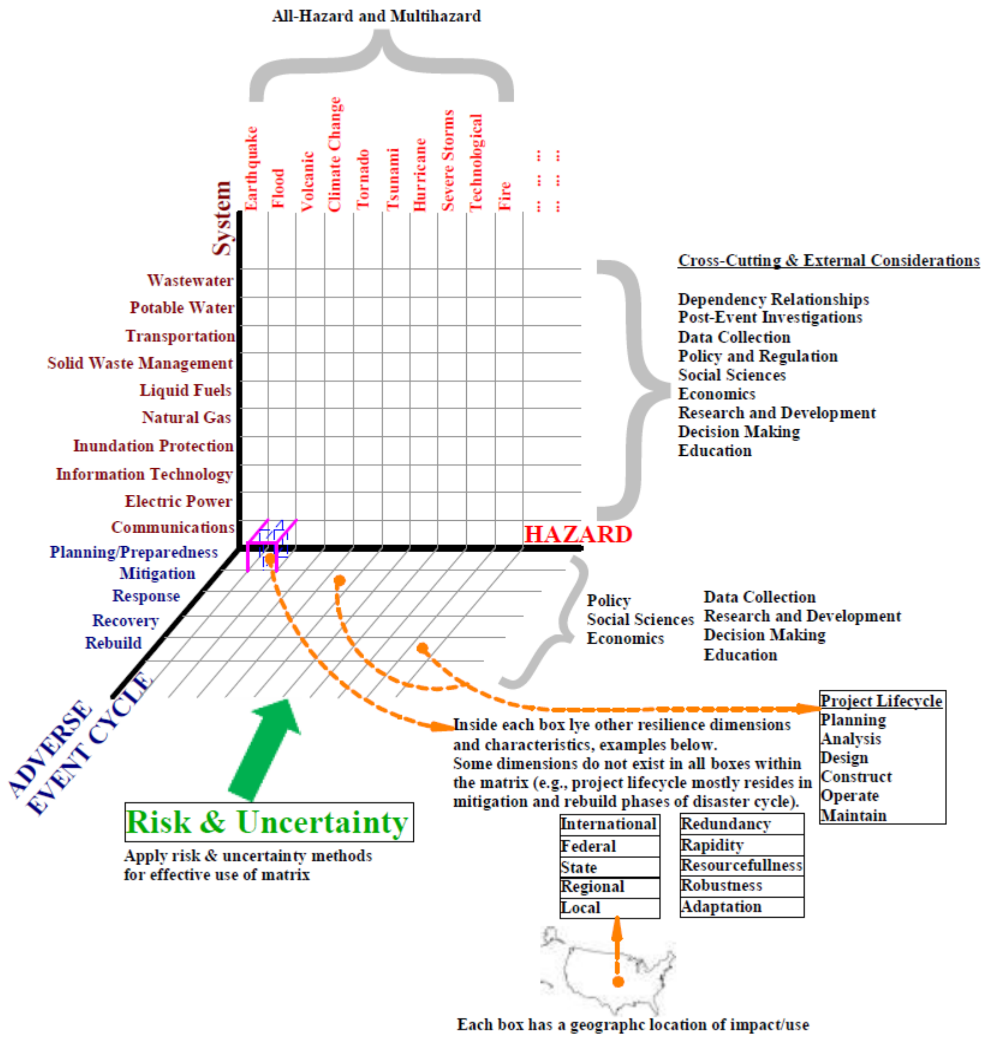

Figure A.4: Resilience Model (ASCE 2015)

A.2 IMPROVING RESILIENCE; A QUANTITATIVE APPROACH

In this section the frameworks that assess infrastructure resilience and provide means for assessing and understanding infrastructure resilience are described. In an earthquake loss evaluation model by Chang & Shinozuka (2004), two seismic retrofit methodologies have been compared in order to find the one that improves community resilience. This research quantifies expected losses in future earthquakes by addressing how much disaster mitigation and preparedness is required. This study also promotes community discussion for defining appropriate seismic performance standards for critical infrastructures. The resilience evaluation focuses on magnitude of damages and the recovery rapidity, in addition to technical, organizational, social, and economic interrelated resilience dimensions. This study aims to assist with comparing the effectiveness of various retrofit and emergency repose plans (Chang and Shinozuka

2004). McDaniels et al., 2008 have also developed a framework which addresses robustness and rapidity of hazard resilience. This framework uses flow diagrams for enhancing the decision making process in infrastructure systems with respect to the two mentioned dimensions of resilience. This research reveals that common decision settings appear in various infrastructures systems in the process of making the infrastructure more resilient.

Ouyang et al., 2012 proposed a performance-based multi-stage framework for analyzing the resilience in urban infrastructure systems. Annual resilience metric adequate for single and concurrent multiple hazards are stablished by identifying and combining the resilient-based improvement methodologies with the correlates of resilience. The results of this study reveal that the annual resilience is mainly affected by random hazards due to their higher frequency. Additionally, the recovery sequences have a significant impact on resilience improvement under limited resources. While under sufficient availability of resources, achieving redundancy and assuring the critical components and their rapid recovery are all effective responses. This framework is valuable for designing, maintaining, and retrofitting resilient infrastructure systems (Ouyang et al. 2012). Similar research has been done for evaluating the network resilience, survivability, and disruption tolerance by using analysis tools, topology generation, simulation, and experimentation (Sterbenz et al. 2011). Comparable research has been conducted with the aim of increasing the resilience of transportation systems. This has been done by defining a foundation for operational metrics in transportation security and resilience, and using performance measurement as a sustainability enhancement tool (Cox et al. 2011; Ramani et al. 2011).

Once the current state of the infrastructure disaster resilience models is identified, as a means of comprehensively determining the knowledge gap, the characteristics of the decision analysis problem are linked to the relevant literature. First, the current state of decision analysis models in construction engineering and management will be briefly reviewed. Second, the different types of decision analysis model uncertainties are identified. Then, the relevant decision analysis models are reviewed with respect to the different categories of uncertainty and the nature of the decision problem (i.e., including uncertainty, multiple decision criteria, and multiple decision makers).

3. CURRENT STATE OF DECISION ANALYSIS MODELS

Over the past 50 years (from 1960s to 2000s) in the journal of Construction Engineering and Management, about 25% of the total number of published research have been in the area of materials, procurement, performance, quality, and productivity. Moreover, about 60% of the subject areas have addressed construction management, project management, planning, estimation and control (Nik Bakht, and El-Diraby 2015). It should be mentioned that the proposed decision framework aims to improve sustainability and performance metrics of infrastructures. For this reason, it could fit in about 85% of the analyzed decision making publications in the Construction Engineering and Management journal in terms of its subject area. This confirms the importance of the development of such decision support systems. Moreover, about 25% of the mentioned decision support systems (from 1960s to 2000s) were similar to the described decision support system due their probabilistic nature. About 20% of them used stochastic analysis for their decision framework. It is also worth mentioning that from the 1960s to the 2000s the numbers of deterministic frameworks have decreased, conversely probabilistic models have increased (Nik Bakht, and El-Diraby 2015). In order to analyze probabilistic decision analysis models, first the different types of uncertainty in decision problems needs to be understood.

A.3 UNCERTAINTY IN DECISION ANALYSIS MODELS

Uncertainty in decision problems can be categorized as external uncertainty, related to the nature of the environment, and internal uncertainty, relating to the structure and analysis of the problem (French 1995; Friend et al. 2010). Uncertainty in the decision problem manifests itself in the natural variability of natural hazards (aleatoric uncertainty or statistical uncertainty). Epistemic or systematic uncertainty are associated with lack of knowledge regarding individual hazard probabilities and the response of the infrastructure system (e.g., soil, structure, foundation, and envelope systems) to each hazard type. Epistemic uncertainty can correspond to both internal uncertainty and external uncertainty, whereas aleatory uncertainty corresponds to stochastic behavior. It should be noted that aleatoric and epistemic uncertainties are not mutually exclusive, however as epistemic uncertainty can be reduced by searching for patterns or casualties, aleatory uncertainty cannot be reduced and can be managed using relative propensities (Brun et al. 2011). Table A.1 represents the distinguishing features of aleatory and epistemic uncertainty:

Table A.1: Distinguishing Features of Aleatory and Epistemic Uncertainty (Retrieved from Brun et al., 2011)

	Aleatory	**Epistemic**
Representation	Class of possible outcome	Single case
Focus of Prediction	Event propensity	Binary truth value
Probability Interpretation	Relative frequency	Confidence
Attribution of Uncertainty	Stochastic behavior	Inadequate knowledge
Information Search	Relative frequencies	Patterns, causes, facts
Linguistic Marker	"Chance", "Probability"	"Sure", "Confident"

Advancements in decision analysis under uncertainty and probabilistic assessment techniques have been an active area of research since the 1990s, and were identified as an important decision analysis methodology from 1990 to 2001 (Keefer et al. 2004). As this area of research has been evolving, the recent state-of-the-art techniques in Multi-Criteria Decision Making (MCDM) under uncertainty are mainly focused on unpredictable events (e.g. lotteries and uncertain tradeoffs) (Pratt et al. 1964; Massala and Tsetlin 2015), uncertainty in value of judgment and decision weights (Levary and Wan 1999; Hyde et al. 2005; Banuelas and Antony 2007; El Hanandeh and El-Zein 2010; Fan et al. 2010; Wang et al. 2013), and fuzzy decisions (Cetin et al. 2002; Wang et al. 2008; Zarghami et al. 2008; Dalalah et al. 2011; Liao et al. 2014).

Furthermore, based on Durbach and Stewart, five fields of uncertainty have been found with respect to MCDM referred to as probabilities, decision weights, explicit risk measures, fuzzy numbers and scenarios. Probabilities refer to joint performance outcomes across the alternatives and attributes. Decision weights look at how people transform probabilities into weights. Explicit risk measures categorize uncertain values into expected values or other central locations measures and risk components. Fuzzy numbers use the fuzzy set theory to model imprecision and external uncertainty. Lastly, "scenarios are incomplete descriptions of how the future might unfold". Using a chain of reasoning, the decision maker can find potential courses of action (Durbach and Stewart 2012).

Figure A.5 illustrates the state of the art decision making methods under uncertainty with respect to aleatory and epistemic uncertainties, and the capabilities of the decision analysis models.

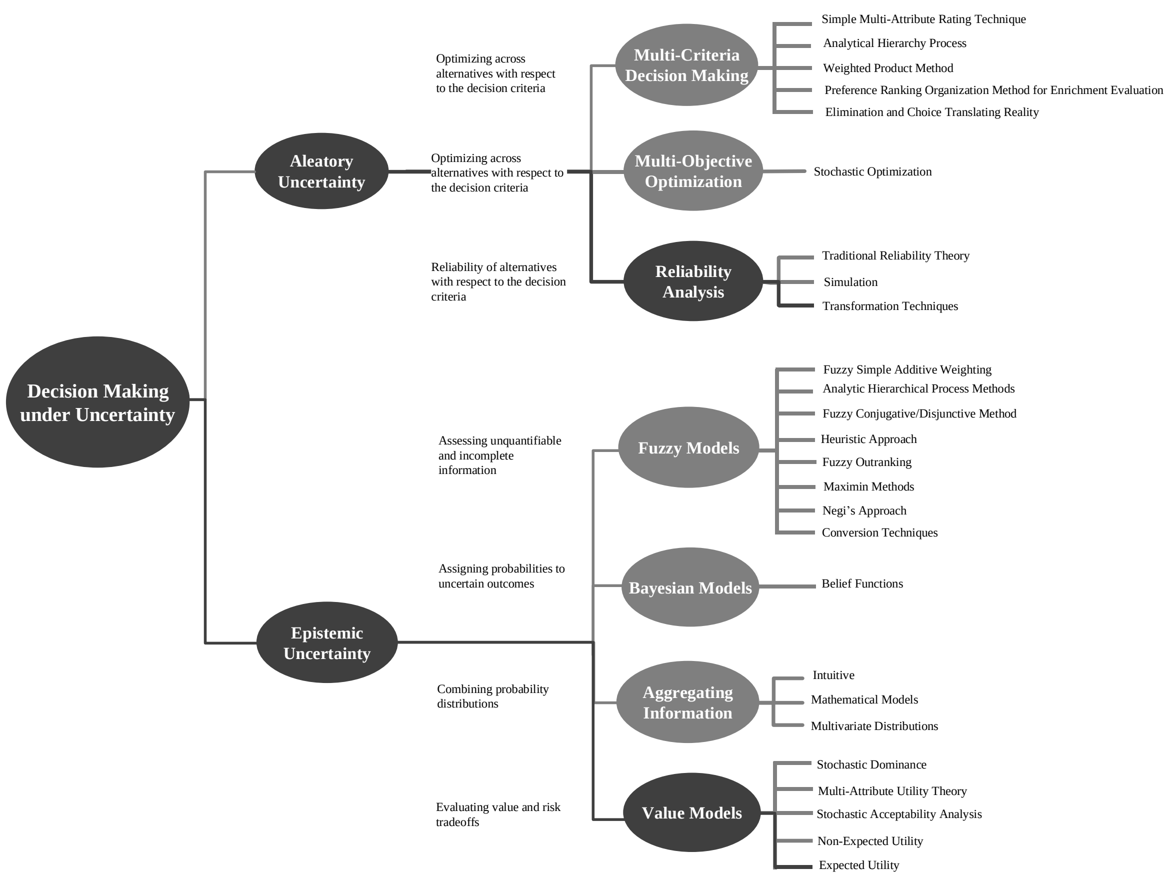

Figure A.5: Decision Making Methods under Uncertainty and the Proposed Approach for the Decision Problem

This review will describe the models that assess, frame, and combine decision maker preferences and the models that find optimum infrastructure design configurations with respect to decision maker requirements and the probabilistic decision criteria. Furthermore, since Bayesian models have been reviewed Section 3.3 in Chapter 4, they will not be reviewed here.

A.4 MODELS THAT ASSESS, FRAME, AND COMBINE DECISION MAKER PREFERENCES

4.1 Fuzzy Multi-Criteria Decision Analysis

Based on Chen and Hwang uncertainty can arise due to unquantifiable or incomplete information, non-obtainable information and partial ignorance (Chen and Hwang 1992b). Chen and Hwan have reviewed several models for including uncertainty in the form of fuzzy numbers in the decision framework. Among all the models, weighted additive models (Chen and Hwang 1992a), models based on ideas, aspiration-based models, and models based on rough set theory have received the most attention from researchers (Durbach and Stewart 2012). Moreover, choice, ranking and sorting methods are some of the decision analysis techniques used when information is given by interrelated points of view and a subset of sample alternatives (Figueira et al. 2005). It should be noted that missing or incomplete information can also be incorporated using stochastic simulation techniques that draw random values for criteria measurements and weights. This method is called the stochastic multi-criteria acceptability analysis and has solved many classes of decision making problem such as investment decisions and manufacturing decisions (Levary and Wan 1999; Lahdelma and Salminen 2001; Banuelas and Antony 2007).

Various MCDM methods have also been integrated with fuzzy logic. An additional category of fuzzy numbers are the models that use comparisons to ideal solutions such as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Hwang and Yoon 1981). Dalalah et al., capture the influential relationship between the evaluation criteria for supplier selection at a factory in Amman-Jordan using fuzzy MCDM. This model divides the criteria into a cause group and an effect group and uses a modified TOPSIS model in order to evaluate the criteria against the alternative. A fuzzy distance measure is also used for measuring the distance from the fuzzy ideal solutions (Dalalah et al. 2011). Analytic Hierarchy Process (AHP) is an additional MCDM method that has been integrated with fuzzy numbers. In a model developed by Yu, a group decision making problem was solved using goal programming and AHP for dealing with disagreements between two or more different rankings in group settings (Yu 2002). Similarly, Hopfe et al., used an adapted Analytic Hierarchy Process (AHP) for including uncertainty in the decision making process of two HVAC system designs. This was done using the classical AHP (Saaty 1980) for ranking the criteria by conducting pair-wise comparisons of the criteria and assigning importance weights. Once both design options are ranked based on the criteria weights, sensitivity analysis was conducted on the uncertainties associated with the performance indicators (e.g. thermal comfort) by having a range of numbers for building performance (i.e. worst performance to best performance) and different users. Then design options are analyzed with respect to an uncertainty range of performance indicators (Hopfe et al. 2013). As this method provides a framework for including uncertainty and parameter variations in MCDM, it is very important to note that adding a new option to the decision problem might lead to a change in the ranking of the previous alternatives.

Additional models exist that combine fuzzy numbers with rough sets. Rough set theory captures internal uncertainty arising from information uncertainty and vagueness (Pawlak 1982) and allows for missing data to be easily incorporated (Greco et al. 1999). Rough set theory methods for multi-criteria decision analysis have been introduced by Greceo et al. (2001) and can deal with both quantitative, qualitative, and inconsistent data. Belief functions are an additional tool for making decisions based on uncertain values. Such models are used to assess the belief of a decision maker to a specific proposition. Belief functions can be formed using the Dempster-Sahfer theory of evidence by assigning degrees of beliefs to collectively exhaustive and mutually exclusive hypotheses (Shafer 1976). It should be noted that degrees of belief should sum to less than one and the difference between degrees of belief represents the degree of ignorance regarding the beliefs. Belief functions have been applied to multi-criteria decision making models using first order stochastic dominance which employ beliefs rather than probabilities (Boujelben et al. 2009).

Some of the recent advancements in group fuzzy MCDM include interval-based fuzzy numbers integrated with a multiplicative form of the Multi-Objective Optimization by Ratio Analysis (MOORA) that was first introduced by Brauers and Zavadskas. The MULTIMOORA method uses an internal normalization, in addition to a ratio system and reference point (from MOORA) that treats all the objectives as equally important. In reality stakeholders might give more importance to an objective and in this case they could either multiply a dimensionless number in the internal normalization process that represents the response on an objective or split an objective into different sub-objectives. The ratio system of MOORA normalizes the data by comparing an alternative of an objective to all values of the objective. Then the reference point of MOORA finds the maximal objective reference point according the found ratios. The full multiplicative MULTIMORA embodies maximization and minimization of the multiplicative utility function. Interval-based fuzzy numbers are then used for splitting the criteria into different subsets. In order to use this method each decision maker needs to construct their own decision matrix by creating responses of alternatives with respect to the criteria. Then individual decision matrices are aggregated and the data is normalized (Brauers and Zavadskas 2006; Brauers and Zavadskas 2010; Baležentis and Zeng 2013).

As fuzzy numbers address uncertainty and prospect theory addresses the way that people choose between probabilistic alternatives which involve risk (Kahneman and Tversky 1979), Krohling and de Souza have combined prospect theory and fuzzy numbers for solving complex MCDM problems such as oil spill in the sea (Krohling and de Souza 2012). Fuzzy multi-criteria decision making models can also include intuitionistic fuzzy point operators which reduce the degree of uncertainty of the elements in an intuitionistic fuzzy set (Liu and Wang 2007). Intuitionistic fuzzy point operators can reduce the degree of uncertainty of the elements in an intuitionistic fuzzy set (Liu and Wang 2007).

As such methods treat internal information uncertainty and allow for the incorporation of missing data, they require a great deal of cognitive effort from the decision maker. Moreover, the scope of the decision making problem does not include any missing data, internal information uncertainty for this reason fuzzy multi-criteria decision making tools will not be used.

4.2 Aggregating Information

Based on Clemen et al. (2007), for decision models with probability distributions and multiple decision criterion, a systematic combination of distributions could bring clarity to the decision problem. In this case, in addition to intuitive aggregation, a number of mathematical models such as axiomatic approaches, median aggregation (Hora et al. 2013), and Bayesian approaches could be used for combing the probability distributions. Such methodologies present a summary of the ‘current state of information regarding the uncertainty on interest” (Clemen and Winkler 2007). An application of the presented method is aggregating probability densities from a number of seismic hazard experts for further analysis on the aggregated probability distribution (Edwards et al. 2007).

Multivariate distributions are also an additional distribution aggregation methodology, which consist of a number of univariate distributions combined in a multi-dimensional space. Multivariate distributions can be used for predicting the reliability of a system, which in the case of the research problem is a decision space (with a number of objectives and attributes). Multivariate distributions have been used since the early 1990s for finding the reliability of structural systems (Harr 1989; Rabi 1990). Such distributions have also advanced the risk-return decision making by forecasting time-varying portfolio risk (Arneric et al. 2009). Quality control of several correlated quality measures of chemical and process industries has also been addressed using multivariate distributions (Alt and Grimshaw 2013). Similarly, probabilistic hazard analysis has been conducted using hazard maps. Having two (or more) intensity measure distributions such as peak ground acceleration and magnitude of wind, intensity maps provide both marginal and correlated hazard information (Bocchini et al. 2016).

In the case of the research problem the probability distributions represent the probabilistic performance of each alternative infrastructure design configuration with respect to the various decision criteria, therefore the aggregation of probability distributions will be meaningless.

4.3 Value Models: Value Functions, Utility, and Risk Preferences

Value and risk tradeoff models with respect to epistemic uncertainty can be solved using stochastic dominance, multi-attribute utility theory, and expected/non-expected utility. Based on Keeney and Winterfelt (2007) decision analysis models can be categorized as consequence models that incorporate uncertainties inherent in decision problems to predict consequences of alternatives, and value models that incorporate value tradeoffs and risk tolerances. A value model can be referred to as an objective function (often single objective, e.g. minimize cost) in the field of operations research and a utility function, value function or preference function in the field of decision analysis (Edwards et al. 2007). As these terms may be used interchangeably it is important to note that a value function assesses decisions without uncertainty while utility functions assess decisions with uncertainty (such as gambles).

Utility functions can be used for investigating general rules of behavior and have been identified as a state-of-the-art technique for mathematical treatment of uncertainty in 2005 and 2012 (Figueira et al. 2005; Durbach and Stewart 2012). Utility functions are a category of value models that rank alternatives according to the utility of an individual. These alternatives could also be probabilistic in nature (e.g. chances of winning a game or chances of rain). This implies that the alternatives have an Expected Monetary Value associated with them. Expected Momentary Value suggests that if there are *i* possible courses of action (for lottery $\tilde{x}$) and *n* possible outcomes ($x_1, \dots, x_n$), and p_{ij} is the probability that action *i* leads to momentary outcome x_j, then one selects the action that maximizes $\sum_j p_{ij} x_j$ (Raiffa 1968). Furthermore, stochastic dominance proves that in a case where we have lotteries $\tilde{x}$ and $\tilde{y}$ with outcomes x_i and y_i that have a common probability p_i, then if $x_i \geq y_i$, no rational person would prefer $\tilde{y}$ over $\tilde{x}$ (Hadar and Russell 1969; Whitmore 1970; Edwards et al. 2007).

Pairwise comparisons of probability distributions has been presented as a tool for comparing alternatives without constructing the full utility function (Figueira et al. 2005; Durbach and Stewart 2012). In cases where many alternatives and many possible outcomes exist, utility theory can be used for assessing a one-time utility function with respect to the risk preference of the decision maker (Von Neumann and morgenstern 1947). In this case the stochastic dominance rules can be used for pairwise comparisons of the probability distributions of uncertain prospects. Stochastic dominance in the case of single-attribute decision problems can be analyzed using first, second and third degree stochastic dominance theories (Hadar and Russell 1969; Whitmore 1970). Considering *f* and *g* as probability functions of two prospects taking random values of x_i, $F(x_i)$ and $G(x_i)$ represent the cumulative distributions. In this case the stochastic dominance rules can be defined as follows:

1) First Order Stochastic Dominance: Prospect $F(x_i)$ is not preferred to prospect $G(x_i)$ if, and only if $F(x_i) - G(x_i) \geq 0$ for all $x_i \in [a, b]$.

2) Second Order Stochastic Dominance: Prospect $F(x_i)$ is not preferred to prospect $G(x_i)$ if, and only if $\int_a^{x_i} (F(y) - G(y))\, dy \geq 0$ for all $x_i \in [a, b]$.

3) Third Order Stochastic Dominance: Prospect $F(x_i)$ is not preferred to prospect $G(x_i)$ if, and only if $\int_a^{x_i} \int_a^{y} \big(F(z) - G(z)\big) dz dy \geq 0 \ and \int_a^{b} (F(y) - G(y))\, dy \geq 0$ for all $x_i \in [a, b]$.

In the case of multi-attribute utility functions, the stochastic dominance rules can be used for each individual criterion (Huang et al. 1978). Multi-attribute Utility Theory is an additional tool for assessing a number of alternatives over a number of attributes or criteria (von Neumann 1953). Expected Utility Theory was originated from a single attribute case developed in 1953 (von Neumann 1953) and extended to the Multi-attribute Utility Theory in the 1990s (Keeney and Raiffa 1993). The Multi-Attribute Utility Theory evaluates preferences for maximizing utility and has the ability to assess true preferences and descriptive decisions. Considering two decision criteria of life-cycle cost and environmental impact, the decision maker is likely to choose the alternative or the non-dominated alternatives that minimize both life cycle Cost and environmental impact and are not dominated by any other alternative. Wallenius et al. have looked at the advancements in Multi-Attribute Utility Theory (MAUT) and categorized the new application areas of MAUT and MCDM as data envelope analysis, negotiation science, multi-attribute auctions and shopping agents, geographic information systems and engineering applications (Wallenius et al. 2008). Multi-attribute utility functions can also be tailored to account for uncertainty in the outcome of an attribute for evaluating risky decisions. However such models may be subjected to assessment biases (Kirkwood 1992). Although MAUT has solved many classes on MCDM problems, it does not have the ability to analyze probabilistic decision criteria. As one of the main objectives of this decision problem is to analyze multiple probabilistic and potentially conflicting decision alternatives, MAUT cannot be used.

Non-expected utility has also been reviewed as an extension to utility theory for capturing the differences between descriptive and prescriptive decisions. Descriptive decision theory reflects how a decision maker makes decisions in real life by considering the behavior of decision maker, while prescriptive decision theory considers the decision maker as fully rational (which is not always true). Starmer (2000) has reviewed the developments in non-expected utility theory and descriptive choices under risk (Starmer 2000). Non-expected utility can address uncertainty in decision weights and capture the complexities of human mind and descriptive choices.

Uncertainty could also lie in the outcome of an attribute and in this case decision analysis methodologies will be based on explicit risk attributes and the value function can be formulated as (Durbach and Stewart 2012):

$$U_i^{(risk)} = \sum_{j=1}^{J}[w_j\, u_j(V_{ij}) - \sum_{k=1}^{K} w_{ij}^{R^k}\, R_{ij}^{(K)}] \tag{1}$$

Where V_{ij} and $R_{ij}^{(K)}$ are the value and risk measures, w_j is a swing weight (similar to utility function coefficients) representing the relative importance of one unit change in $U_i^{(risk)}$, and $w_{ij}^{R^k}$ is the risk weight. One of the earliest estimations techniques on deterministic multi-attribute evaluations was developed in the early 1990s by Kirkwood. The described framework estimates the impacts of uncertainty on multi-attribute evaluations prior to conducting a probabilistic multi-attribute utility analysis (Kirkwood 1992).

Although both value functions and utility functions are a valuable tool for assigning value (e.g. monetary value) to alternatives, finding the optimal alternative with respect to the criteria (Dees et al. 2013), and assessing the utility of an individual, they do not have the ability to deal with a stochastic behavior for alternatives (i.e. aleatory uncertainty). As the decision problem might include non-monetary criteria such as environmental impact and loss of resilience, assessing the risk profile of the decision makers with respect to the criteria will not be feasible unless the criteria are linked to monetary values.

4.4 Proposed Framework for the Assessment of Preferences

In a review of the role of environmental assessment tools in sustainable construction, the importance of sustainability index development by stakeholders is discussed. In the sustainability index, stakeholders have the opportunity to reflect on the level of importance of the criteria and sub-criteria during the feasibility stage of the project; therefore they make a positive contribution to the identification of optimum design solutions (Ding 2008). Similar models assess the willingness of stakeholders to pay for green building features and conduct life-cycle assessment for sustainable design options of commercial buildings (Chau et al. 2010; Wang et al. 2010).

Analysis on the perceptions of sustainability assessments in commercial buildings; supporting energy initiatives by linking visions with energy scenarios and multi-criteria assessment; and the conceptualization of stakeholder engagement in the context of sustainability (AlWaer et al. 2008; Mathur et al. 2008; Trutnevyte et al. 2011) have also provided clarity on assessing stakeholder preferences, perceptions, and perspectives with regards to sustainability measures. However, none of the described frameworks assess the utility or preference of the stakeholders with regards to economic, environmental, and social aspects of designs.

Although both value functions and utility functions are a valuable tool for assigning value (e.g. monetary value) to alternatives, finding the optimal alternative with respect to the criteria (Dees et al. 2013), and assessing the utility of an individual, they do not have the ability to capture the tradeoffs between multiple decision criteria. Indifference curves are a category of value functions that represent the different combinations of two goods providing equal utility to the consumer (Edgeworth 1881). Consumer indifference curves have the ability to solve consumer problems by creating input-output models of a combination of goods, information, services, etc. (Lancaster 1966; Reny 2015; Crown 2016). In cases where multiple indifference curves exist, equilibrium conditions are used for developing comprehensive trade-off strategies (Buchholz et al. 2015; Epple and Romano 2015). Complex fund-allocation decisions for a large number of assets has also been addressed by applying budgetary constraints to economic indifference maps and finding an equilibrium state at which equitable allocations are made (Saad and Hegazy 2015). Moreover, cost-benefit analysis in the form of indifference curves has been used for creating a benchmark for evaluation of the actual risk reduced by prohibiting nuclear power plant operation in China after the disastrous earthquake and tsunami in 2011(Higo and Pandey 2015). In the case of the research problem, indifference curves represent the preference of the decision maker with respect to a number of decision criteria such as life-cycle cost and loss of resilience after a natural hazard event.

The shape of the indifference curves will vary depending on the preference of the decision maker with respect to the two decision criteria. For example, in a case where both decision criteria are important (although the degree of importance may vary) a linear indifference curve can be used. In cases where one decision criterion can be substituted for another decision criterion, a logarithmic curve may represent the indifference curve of the decision maker. Indifference curves have been used to solve many classes of decision making problems such as conversion of multi-attribute consequences to a single attribute consequence using a reasonable value tradeoff curve (Edwards et al. 2007). With respect to the research problem, the shape of the decision maker defined indifference curves (or preference function) could be linear or non-linear. A linear indifference curve reflects the importance of all decision criteria with varying degrees of importance. A non-linear indifference curve (e.g. $x_2 = {}^{3}/_{x_1}$) could imply that the decision maker is willing to substitute one decision criteria (e.g., life-cycle cost) for the other (e.g., environmental impact), at a given substitution rate (e.g. environmental impact is three times more important than life-cycle cost). In this case, the indifference curve for the two criteria of x_1 and x_2 can be presented as:

$$V(x_1, x_2) = x_1 x_2 \text{ or } x_2 = {}^{c}/_{x} \qquad (2)$$

Indifference curves provide a systematic transformation of information into tradeoff strategies and preferences functions, and are scalable (adaptable). For this reason, indifference curves can serve as decision maker defined preference functions for a performance-based design of infrastructures.

A.5 MODELS THAT FIND OPTIMUM DESIGN CONFIGURATIONS

5.1 Multi-Criteria Decision Making Methods

Most complex decision making procedures are concerned with various levels of decision alternatives (DAs). Multi-Criteria Decision Making (MCDM) is one of the most frequently used tools for identifying these levels of preferred DAs over a number of criteria. MCDM allows the decision-maker to make favorable judgments with respect to the DAs and number of criteria. MCDM has been used since the mid-1700s by Benjamin Franklin, leading author, and political theorist as well as Joseph Priestley, English theologian, and natural philosopher. More recently a set of procedures has been developed, which allows for multi-criteria decision making and is consistent with the foundations developed in the mid-1700s (Keeney and Raiffa 1993).

One of the earliest applications of MCDM was proposed by Edwards in 1971 which was based on physiologically-oriented decision making and was named the Simple Multi-Attribute Rating Technique (SMART). This MCDM technique ranks a finite number of alternatives in the order of a finite number of preferences. Then, possibly considers the overall performance of the alternatives using numerical grade assignments (Edwards 1971). The general form of a multi-attribute decision making problem with *m* criteria and *n* alternatives has been described in Table A.2. In this table, $C_1, \ldots, C_m$ and $A_1, \ldots, A_n$ correspondingly represent the criteria and alternatives. Each column represents the performance of an alternative with respect to the assigned weights ($x_1, \ldots, x_n$); while each row represents a specific criterion with regards to the assigned weights ($\mathrm{w}_1, \ldots, \mathrm{w}_\mathrm{n}$). The a_{ij} score explicates the performance of alternative A_j against criterion C_j. While it is assumed that a higher score value will lead to a better performance, the minimization goal can be transformed into a maximization goal at any time. It should be noted that the criteria weights, w_i represents the importance of the criteria and are assumed to be positive. These weight factors represent the view of the decision maker(s).

Table A.2: Multi-attribute Decision Making Methodology

$$\begin{array}{ccc} & & \begin{array}{ccc} x_1 & \ldots & x_n \\ A_1 & \ldots & A_n \end{array} \\ \begin{array}{c} w_1 \\ \vdots \\ w_m \end{array} & \begin{array}{c} C_1 \\ \vdots \\ C_m \end{array} & \begin{bmatrix} a_{11} & \cdots & a_{m1} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \end{array}$$

The ranking value, x_j, of alternative, A_j, is the weighted algebraic mean of the corresponding value which is represented below:

$$x_j = \frac{\sum_{i=1}^{m} w_i a_{ij}}{\sum_{i=1}^{m} w_i}, \quad j = 1, \ldots n \tag{3}$$

In addition to the mentioned technique, Edwards presented a method for evaluating the criteria weights with respect to the relative importance of each decision (Edwards 1977). SMART is mainly used for effective decision making in asset management, and asset resource allocation (Blackwood et al. 2002), environmental management (Bakus et al. 1982), and supplier evaluation (Agarwal et al. 2011). The additional categories of MDCM tools include the Analytic Hierarchy Process (AHP), Weighted Product Method (WPM), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), and Elimination and Choice Translating Reality (ELECTRE). AHP has facilitated the decision making process by selecting the project delivery method (Mahdi and Alreshaid 2005), and conducting construction project risk assessment (Zeng et al. 2007). Similarly, WPM has enhanced the decision making process in construction contraction agreements (Mitkus and Trinkuniene 2006), building design (Mela et al. 2012), and facility management (Vilutienė and Zavadskas 2003). PROMETHEE facilitates similar construction management practices such as finding the critical path of a network (San Cristobel 2013), and selection of appropriate structural systems (Balali et al. 2014). ELECTRE has broad decision making implications in integrated management of municipal solid wastes, assigning priorities to activities in project management, and housing construction process (Karagiannidis and Moussiopoulos 1997; Rogers 2000; Mota et al. 2009).

MCDM techniques assess the preference of the decision maker with respect a number of alternative design configurations and decision criteria. In some cases (e.g., AHP), adding or removing alternatives might change the original ranking of the alternatives and require a re-assessment of preferences from the decision maker. The lack of adaptability and scalability of the MCDM methods does not allow for the development of a modular decision support system that is also easily implementable in the early design phase. For this reason, multi-objective optimization and reliability-based approaches will be reviewed next.

5.2 Multi-Objective Optimization under Uncertainty

Multi-objective decision making with *k* objectives, and *n* design variables can be defined as follows (Marler and Arora 2004):

$$E = \{E_1, E_2, \ldots, E_3\} \tag{4}$$

$$\text{Minimize } F(E^n) = [F_1(E^n), F_2(E^n), \ldots, F_k(E^n)] \tag{5}$$

Here E in an x-dimensional decision variable vector, and E^n vector is desired for minimizing the k objective functions. The objective function can be subjected to inequality constrains $(g_i(x))$, and equality constrains $(h_j(x))$:

$$g_i(E^n) \leq 0, \text{ and } i=1, 2, 3, \ldots, m \tag{6}$$

$$h_j(E^n) = 0, \text{ and } j = 1, 2, 3, \ldots, e \tag{7}$$

Where *m* and *n* are respectively the number of inequity and equality constrains.

The main goal of multi-objective optimization is to simultaneously optimize various asset management criteria (objectives) in order to find the best alternative between multiple and conflicting objectives. The search space in such problems has a high complexity with more than one solution (global minimum or maximum), which simultaneously optimizes all the objective (i.e., there is no superiority among the solutions). This will lead to having a set of solutions that are superior to the remaining solutions referred to as the Pareto front. Pareto optimal boundary, Pareto efficiency, or Pareto optimality represents a set of solutions which are superior to the other solutions. It is impossible to find a better individual solution outside this front without making at least one worse selection. This means that the Pareto set solutions satisfy all the objectives and are absolutely better than all the remaining (dominated) solutions. The solutions belonging to the Pareto optimal front or the Pareto optimal boundary are known as the non-dominated set of solutions, while the remaining solutions are the dominated solutions. It should be noted that the number of Pareto optimal solutions grows exponentially with the problem size, the number of objectives, and the degree of complexity between the objectives (Liefooghe et al. 2013).

MODM models have the ability to incorporate uncertainty in the decision objectives which is known as stochastic MODM. Although stochastic optimization and multi-objective optimization are well developed in the field of operations research, their intersection (multi-objective optimization under uncertainty) is much less developed (Gutjahr and Pichler 2016). Moreover as decision analysis frameworks are moving towards methodologies which allow for elaborations, sensitivity analysis, assessments of preferences, and trade-off strategies (Edwards et al. 2007; Howard and Abbas 2016; Wei et al. 2016), fewer decision models are analyzed using MODM techniques.

Nevertheless, multi-objective optimization under uncertainty is an active area of research that has the ability to solve different classes of decision making problems such as efficient budget allocations of infrastructure projects(Gabriel et al. 2006a). Gutjahr (2014) has linked variability in uncertain events to the risk preference of an individual for solving a three-objective optimization problem for cost effectiveness under uncertainty. In this framework, a risk-averse individual will prefer a choice with large uncertainty and small variability to a choice with small uncertainty and large variability. This framework generates a set of Pareto-Optimal solutions with respect to risk, cost and effect. Other scenario based problems such as multi-objective optimization under uncertainty of economic and life-cycle environmental performance of industrial processes, and bi-objective optimization for supply chain problems in uncertain environments have been solved using mixed integer nonlinear programming (Roghanian et al. 2007; Sabio et al. 2014; Pasandideh et al. 2015). Furthermore, in an attempt to simplify multi-criteria, stochastic optimization problems, Gutjaher and Picher (2016) review the non-scalarizing methods for reducing a multi-objective stochastic optimization problem to a single objective one.

Although the state of the art multi-objective optimization techniques provides a systematic framework for incorporating uncertainty, multiple decision criteria, and multiple alternative design configurations in the decision analysis methodology, the do not provide means for understanding the decision analysis results and improving the reliability of the alternative design configurations. For this reason, heuristic decision making methods and reliability-based decision analysis models will be reviewed next.

5.2.1 Decision Analysis and Heuristics

Multi-objective optimization under uncertainty can also be solved using heuristic and metaheuristic algorithms. Heuristics are partial search algorithms and metaheuristics are a higher-level heuristic algorithms for finding or generating a heuristic that may provide a sufficiently good solution by escaping from local optima (Blum and Roli 2003; Zitzler et al. 2003; Glover and Kochenberger 2006; Coelho 2015). In the field of decision analysis risky choice heuristics (as defined by Johnson and Payne (1985) are rules that systemically simplify the problem space search by disregarding some elements of the decision problem. This could be done by ignoring certain alternatives (Johnson and Payne 1985).

Due to the complexity of MODM problems, metaheuristics algorithms can be used as a tool for searching the decision space. These high level algorithms are mostly based on natural processes and aim to find optimal solution(s) using methods such as the behaviors of ants for finding the optimal path to food. These algorithms aim to reduce the chances of getting trapped in local optima. Simulated Annealing (SA) algorithms are a family of the MODM tools which have been used since the early 1990s for scheduling purposes, and resource leveling. Yeh, 1995 has developed an annealed neural network model adapted from SA and the Hopefield neural network for solving the construction-site layout problem (Yeh 1995). SA hyperheuristic techniques have also enhanced the generation of better-leveled construction resource profiles (Anagnostopoulos and Koulinas 2010). Similar studies have been conducted for addressing personnel-scheduling and personnel satisfaction problems in continuously operating organizations by developing a heuristic based simulated algorithm that generates feasible integer personnel schedules or utilizing combinatorial optimization (Brusco and Jacobs 1995; Thompson 1996; Asgari et al. 2012). Additional researchers have used SA to address job scheduling on parallel machines with sequence-dependent setup times; and distribution network design (Lee and Pinedo 1997; Jayaraman and Anthony 2003).

Evolutionary Algorithms (EA) inspired by biological evolution, are an additional category of the meta-heuristic MODM techniques that are used in the area of construction management and are mainly focused on large scale optimization (Elbeltagi 2007), site layout planning (Hegazy and Elbeltagi 1999), and scheduling of construction projects (Jaskowski and Sobokta 2006). EAs can be categorized as Genetic Algorithm (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Shuffled Frog Leaping (SFL). GAs have been used for purposes such as pipeline optimizations, construction resource scheduling, construction time-cost trade-off estimations, and resource allocation and leveling (Goldberg and Kuo 1987; Chan et al. 1996; Feng et al. 1997; Hegazy 1999; Leu and Yang 1999; Leu et al. 2001). ACO has enhanced the decision making process in the design of water distribution systems (Maier et al. 2003), and optimizing construction time and cost (Ng and Zhag 2008; Xiong and Kuang 2008). PSO is an additional category of the EAs which has been used in bicroterion time-cost trade-off analysis (Yang 2007), and multimode project scheduling (Zhang et al. 2006). Correspondingly, SFL is mainly used in water distribution network design optimization (Eusuff and Lansey 2010), and project management (Elbeltagi et al. 2007). Hybrid and comparison complex problems such as multiple project scheduling with multiple resource constrains have been addressed by a hybrid of GA and SA (Chen and Shahandashti 2009). Similar approaches have been taken for developing a multi-heuristic hybrid approach for resource leveling problems in construction engineering (Son and Skibniewski 1999). Moreover, several researches have been conducted on comparing various algorithms such as a comparison of SA, GA, and pair-wise swap algorithm in scheduling programs with repetitive projects (Shtub et al. 1996). Additional reviews has also been conducted on various metaheuristic algorithms that have enhanced the decision making process in project and construction management (Elbeltagi 2007; Liao et al. 2011).

Heuristics are partial search algorithms that may provide a sufficiently good solution by escaping from local optima. For this reason, in the case of computational feasibility, it is best to consider all the alternative design configurations available in the solution space. The basic reliability approach has the ability to utilize the underlying probabilistic models and addresses the limitations of the previously described decision making tools, for this reason it has been reviewed next as a decision analysis methodology.

5.3 Risk and Reliability Measures

A probabilistic MCDM problem could also lend itself to the reliability theory due to the stochastic nature of the decision variables. Most engineering risk and reliability based decision frameworks focus on finding probabilities of meeting or exceeding certain capacity, schedule, performance and/or availability requirements (Cornell et al. 2002; Winterfeldt 2007). Such frameworks address controversial decisions such as choosing a tritium supply technology for nuclear weapons. Similar decision analysis approaches have addressed the military systems acquisition process by conducting life-cycle cost-benefit analysis and finding an efficient frontier (Beccue and Stonebraker 2007). Moreover Bayesian belief networks, effective result communication, and game-theoretic ideas have aided with risk allocation and risk reduction strategies by conducting probabilistic risk analysis for engineered systems (Bier and Louis Anthony Cox 2007). Lifetime optimization methodologies have also provided optimal repair and design strategies for inspection, repair, and design of structures by estimating cost of failures (Wen and Kang 2001; Frangopol et al. 2004; Liu and Frangopol 2005). Further integer constrained decisions such as project funding decisions with multiple objectives and probabilistic considerations have been optimized using a combination of Monte Carlo simulation and the analytic hierarchy process, and cumulative prospect theory with set pair analysis (Gabriel et al. 2006b; Hu and Yang 2011).

Methods such as the unified reliability analysis also exist that utilize the underlying probabilistic models instead of conditional probabilities. Unified reliability analysis has been used for solving explicit time-dependent multi-hazard cost analysis based on parameterized demand models for optimum design of bridge structures (Haukaas 2008; Bisadi and Padgett 2015). Similar reliability based approaches exist, which analyze time-dependent failures of bridges and other structural systems (Stewart 2001). Such approaches have the capability to include different levels of detail in the form of probabilistic variables and parameters for single objective reliability problems.

Similarly, stochastic programming is a tool in the field of mathematical optimization for modeling optimization problems that involve uncertainty (Kali and Wallace 1994; Liu and Liu 2002). Based on Roubens and Teghem (1991), stochastic MCDM models are more precise for modeling uncertainty in the coefficients of the objective function, in contrast fuzzy MCDM models mainly focus on uncertainty in the constraints and limit state functions (Roubens and Teghem 1991).

Integer programming and capital budgeting are extensions to stochastic programming that have the ability to define goals in terms of desired probability levels (Keown and Taylor 1980):

$$p_f = p(g(\boldsymbol{X} = \boldsymbol{x}) \leq \beta) \geq \alpha \tag{8}$$

In this Equation, p_f is the probability of failing to meet the decision maker defined performance requirements, and $g(\boldsymbol{X})$ is a limit state function based on a vector of decision criteria values, $\boldsymbol{X}$, which take on values $\boldsymbol{x}$, β is the desired level of performance, and α is the desired probability of achieving such performance. Stochastic multi-criteria decision making models have the ability to solve problems with incomplete criteria weights and integrate decision makers risk preference with the decision making process (Fan et al. 2010; Wang et al. 2013). In the case where the criteria values and stochastic behavior of alternatives are can be found and the goal is to find the high-performing alternative design configurations that meet the decision maker defined constraints, Equation 8 can be re-written as:

$$p_f = p(g(\boldsymbol{X} = \boldsymbol{x}) \leq 0) \tag{9}$$

Where, P_f is the probability of failing to meet the decision maker defined performance constraints, $g(\boldsymbol{X})$ with respect to the stochastic behavior of each alternative design configuration and the designated decision criteria. In this case, each alternative design configuration will have a probability distribution associated with each decision criterion. The optimal alternative design configuration that best meets the requirements of the decision maker is the one with the highest probability of achieving decision maker utilities. Figure A.6 represents one alternative design configuration with a joint bi-variate distribution contour (e.g., life-cycle cost and environmental impact) and a given decision maker indifference curve (utility function) or the required performance level.

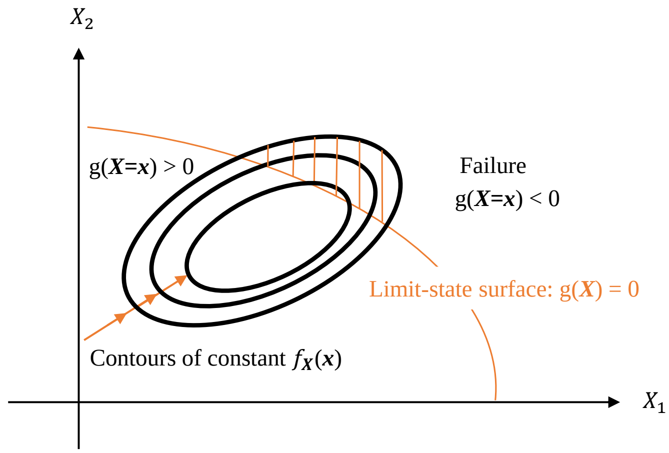

Figure A.6: Joint Probability Distribution, f_X, of Random Decision Criteria Variables X_1 and X_2 with Respect to the Probability of Achieving (or Failing to Achieve) the Required Performance, *g(X)*

p_f can be found using the stochastic MCDM making techniques (including optimization methods under uncertainty), traditional reliability theory (estimating the volume under the acceptable surface, First Order Second Moment Method, and Monte Carlo Simulation), simulation techniques (reducing the order of integration), response surface method (exploring the relationship between several variables), and transformation techniques (transforming the variables to standard normal variables). However, the main factor that separates the transformation techniques from other methods (i.e., stochastic optimization, and traditional reliability methods, and response surface method) is its ability to provide a number of different measures for conducting sensitivity assessments on the decision criteria, utility function uncertainty, and decision confidence probability (Cetin et al. 2002; Wei et al. 2016). The transformation methods include the First Order Second Moment (FOSM) method, First Order Reliability Method (FORM), and Second Order Reliability Method (SORM). The transformation methods are presented with respect to the complexity of each method (less complexity and more approximation to more complexity and less approximation) (Shinozuka 1983; Ang and Tang 1984; Bjerager 1988; Bucher 1988; Bjerager 1990; Ditlevsen and Madsen 1996).

As the stochastic behavior of the alternative design configurations can be found with respect to the decision criteria, it is best to incorporate the full distribution in the reliability analysis. For this reason, the traditional FORM will be used. It should be noted that FORM linearizes the limit state function in the transformation process and might lead to grossly inaccurate results in extreme situations. SORM uses a second order polynomial in the transformation process. However, this method is inherently more complex and might require numerical methods for solution (Melchers 1999). For this reason, SORM will be implemented only if FORM cannot generate sufficiently accurate results. The decision problem includes multiple probabilistic decision criteria (e.g., life-cycle cost, environmental impact, and loss of resilience due to natural hazard events), a number of alternatives, and requires sensitivity analysis on the performance criteria and decision analysis results. For this reason, FORM will be used for finding the probability of meeting certain performance requirements (in the form of utility functions/indifference curves) with respect to the alternative design configurations and the decision criteria. FORM has the capability to systematically combine the individual capabilities of different decision analysis tools and provide a meaningful feedback loop for the decision maker.

A.6 KNOWLEDGE GAPS AND EXPECTED CONTRIBUTIONS

A performance-based design of infrastructures involves multiple probabilistic criteria, multiple decision makers, and alternative design options. The state of the art decision making models under uncertainty do not provide a systematic integration of the uncertainty, multiple decision makers, and multiple decision criteria; are not adaptable and computationally efficient; and do not providing means for conducting sensitivity assessment on the decision analysis results. To this effect, this research proposes a holistic decision analysis model that integrates FORM with the utility of an individual and the designated probabilistic decision criteria.

The integration of FORM with the utility of an individual (decision maker defined utility functions/indifference curves) has the ability to 1) measure the utility of the decision makers, while allowing for subsequent optimization (i.e., indifference curves can be utilized as constraints in the optimization framework), 2) measure the effect of each decision criteria (e.g., life-cycle cost) on the reliability of each design configuration with respect to the decision maker utilities, 3) include the correlation between the probabilistic decision criteria in the reliability analysis, 4) measure the correlation between the decision maker defined limit sate functions, 5) allow for a full and consistent representation of all relevant uncertainties, 6) provide a meaningful feedback loop for understanding the impact of the decision criteria on the reliability of the alternative design configurations with respect to decision maker utilities, and 7) provide means for tailoring the alternative design configurations with respect to decision maker utilities using the feedback loop.

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