Decision-making under uncertainty for buildings exposed to environmental hazards

Hao Qin, Ph.D.

School of Engineering, The University of Newcastle,
Newcastle, NSW 2308, Australia.

School of Civil Engineering, The University of Queensland,
Brisbane, Qld 4072, Australia.

Abstract

Buildings are exposed to risks from environmental hazards such as earthquakes, windstorms and floods. Substantial uncertainties from various sources are inevitably involved in the risk estimation and decision-making for activities such as design and disaster risk mitigation for buildings. Decision makers seek to achieve economic efficiency while ensure building safety by managing the extreme tail risk that is typically a concern when facing low-probability, high-consequence events. Thus, risk preferences and tolerances play an important role in the decision process, which often vary among different decision makers. The conventionally used minimum expected life-cycle cost criterion (MELC) fails to adequately cope with large uncertainty and risk preferences. To this end, this paper presents the application of a set of decision models beyond the MELC to support decision-making under uncertainty for buildings exposed to environmental hazards. The objective is to provide risk-informed decision support for decision-makers with a wide range of risk appetites while taking into account uncertainties involved in the life-cycle cost. The features, strengths and weaknesses of these decision models are discussed from a practical point of view. The application and selection of the decision models are demonstrated by two practical decision problems: (i) seismic design of a high-rise commercial building, and (ii) wind hazard mitigation for a low-rise residential building. These examples illustrate how the decisions for choosing seismic design levels and wind mitigation measures vary when different decision models and model settings are applied.

Keywords: Decision-making, life-cycle cost, environmental hazards, uncertainty, risk preferences

1. Introduction

Buildings are exposed to risks from natural hazards such as earthquakes, windstorms and floods. The occurrence and intensity of these extreme events, the environmental loads imposed on buildings and the consequent performance, damage and loss of buildings are subjected to significant uncertainties, both aleatory and epistemic. Probabilistic risk assessment (PRA) for buildings provides a systematic way to account for associated uncertainties and estimate risks from environmental hazards. For a certain planning time horizon, the outputs of the PRA are typically probability distributions of life-cycle costs for buildings (e.g. [1-4]). Decision variables such as the net present value and benefit-to-cost ratio can also be obtained from the PRA (e.g. [3] [5-6]). These outputs can inform and support the decision-making for activities such as design and disaster risk mitigation for buildings. The decision-making process aims to achieve economic efficiency while limit extreme tail risks to ensure building safety, and therefore improve building resilience to natural disasters at an optimal cost.

Decision-making for buildings is conventionally based on the minimum expected life-cycle cost (MELC) criterion (e.g. [1] [7-8]), which represents a risk-neutral attitude to achieve long-term economic efficiency from a societal perspective. Substantial uncertainties are involved in the PRA and the low-probability catastrophic consequences are often the concern of many decision makers. Hence, it is not surprising that risk averseness is found to be prevalent in civil engineering decisions when facing environmental hazards [9]. The MELC fails to fully capture the large uncertainty and dispersion involved in the life-cycle cost distribution, and may downplay possible catastrophic losses because only the mean of life-cycle cost is taken into account. Moreover, the MELC is only adequate for risk-neutral decision makers but fails to cope with other risk preferences such as risk aversion.

To this end, there is a need for decision models to deal with large uncertainty as well as different risk preferences and tolerances of decision makers. This paper presents the application of a set of decision models to provide decision support for buildings exposed to environmental hazards beyond the decision-making solely based on expected life-cycle cost. The presented decision models in this paper include risk measures such as Value-at-Risk (VaR), Conditional-Value-at-Risk (CVaR) [10] and Range-Value-at-Risk (RVaR) [11-12], the utility theory (UT) [13], the stochastic dominance (SD) [14-15] and its extension almost stochastic dominance (ASD) [16]. To the best knowledge of the author, it is the first time that the ASD and RVaR are introduced to decision problems for buildings subjected to environmental hazards. The features, strengths and weaknesses of these decision models are discussed from a practical point of view. Two practical decision examples, i.e. seismic design of a high-rise commercial building and wind hazard mitigation for a low-rise residential building, are presented to compare and demonstrate the applicability of these decision models. It is anticipated that the practical examples given in this paper shed some light on the use and selection of decision models for buildings exposed to environmental hazards. The application of these decision models is expected to provide risk-informed decision support for decision-makers with a wide range of risk appetites while taking into account uncertainties involved in the life-cycle cost..

The remainder of the paper is organized as follows. First a set of decision models are introduced, and discussions are provided regarding their features, strengths and weaknesses from a practical point of view. Then practical examples of applying these decision models to the seismic design of a high-rise commercial building and wind hazard mitigation for a low-rise residential building are presented. Parametric studies and comparisons of the decisions based on these decision models are also included.

2. Decision Models

2.1. Risk Measure

A risk measure maps the random variable of interest (e.g. life-cycle cost, benefit-to-cost ratio) obtained from the probabilistic risk assessment (PRA) to real numbers, which explicitly quantifies the risk and provides the basis for choosing between different decision alternatives. Two most common risk measures in financial applications are the Value-at-Risk (VaR) and Conditional-Value-at-Risk (CVaR). For insurance industry and natural disaster management, VaR has also been adopted to represent the probable maximum loss (e.g. [17-18]). Consider that the probability distribution of life-cycle cost (LCC) is available from the PRA, then for a certain probability level α ($0 < \alpha < 1$), VaR_{α} (LCC) is

$$\mathrm{VaR}_{\alpha}(LCC) = Q_{\alpha}(LCC) \tag{1}$$

where Q_{α} (LCC) is the α-quantile of the random variable LCC. CVaR_{α} (LCC) can be viewed as an average of quantiles or VaRs for probability levels between α and 1, which is given by [19]

$$\mathrm{CVaR}_{\alpha}(LCC) = \frac{1}{1-\alpha}\int_{\alpha}^{1} \mathrm{VaR}_{\gamma}(LCC)d\gamma \tag{2}$$

The VaR and CVaR above a certain probability level (e.g. α = 90%) can be used to characterize the upper tail of the LCC distribution, which is of primary interest for low-probability, high-consequence hazards, and hence account for risk averseness in decision-making. The higher the considered probability level α, the higher the degree of risk aversion. The CVaR accounts for possible catastrophic losses in the upper tail exceeding the corresponding VaR [19], and hence may be more favoured by risk-averse decision makers in a decision context of extreme environmental events. CVaR also conforms some attractive theoretical axioms such as coherency and regularity [19]. However, compared to VaR, CVaR may be overly sensitive to outliers with extremely small probabilities in the upper tail [11]. In practice, it is often hard to tell if these outliers could really happen in reality or they are just caused by estimation errors of the risk assessment as no PRA models are prefect. Hence, CVaR may occasionally lead to costly decisions.

The Range-Value-at-Risk (RVaR) [11-12] offers a compromise between VaR and CVaR, which is less sensitive to extreme outliers than CVaR while can better capture the critical tail behaviour compared to VaR. At probability levels of α and β ($0 < \alpha \le \beta \le 1$), $\mathrm{RVaR}_{\alpha,\beta}$ (LCC) is given by

$$\mathrm{RVaR}_{\alpha,\beta}(LCC) = \begin{cases} \dfrac{1}{\beta-\alpha}\displaystyle\int_{\alpha}^{\beta} \mathrm{VaR}_{\gamma}(LCC)d\gamma & \alpha < \beta \\ \mathrm{VaR}_{\alpha}(LCC) & \alpha = \beta \end{cases} \tag{3}$$

The RVaR is closely connected to VaR and CVaR. When $\alpha = \beta$, $\mathrm{RVaR}_{\alpha,\beta}$ (LCC) is equivalent to VaR_{α} (LCC). When $0 < \alpha < \beta = 1$, $\mathrm{RVaR}_{\alpha,\beta}$ (LCC) equals to CVaR_{α} (LCC). Fig. 1 illustrates VaR_{α} (LCC), CVaR_{α} (LCC) and $\mathrm{RVaR}_{\alpha,\beta}$ (LCC) given the cumulative distribution function (CDF) of the life-cycle cost. It is indicated that, at a selected probability level, VaR cannot cope with extreme values of LCCs exceeding VaR_{α} (LCC). The CVaR_{α} (LCC) could be too sensitive to outliers with extremely small probability in the upper tail of life-cycle cost distribution. The RVaR serves as a risk measure that lies between VaR and CVaR.

The risk measures introduced here can also be used in conjunction with the minimum expected life-cycle cost criterion (MELC) by providing constraints on the maximum tolerable life-cycle cost. In other words, a decision alternative with lower expected life-cycle cost while satisfying the constraints specified by VaR, CVaR and/or RVaR would be preferred in the decision-making. The MELC leads to cost-efficient decisions while the constraints reflect the decision maker's tolerance of extreme losses and costs.

2.2. Utility theory

The utility theory (UT) is widely employed to explicitly factor risk preferences into the decision process (e.g. [20-21]), where utility functions are used to subjectively weigh possible consequences. In other words, utility measures the desirability of consequences. The UT provides a normative model that prescribes rational decisions by maximizing the expected utility associated with different risk preferences. For a random variable x of the consequence containing n outcomes, x_1, x_2, … , x_n, the expected utility (EU) of x is given by

$$\mathrm{EU}(x)=\sum_{i=1}^{n} p_i u(x_i) \tag{4}$$

where $u(x)$ is the utility function, and p_i is the probability of x_i. Note that $\sum_{i=1}^{n} p_i = 1$. The utility functions are used to reflect decision makers' risk preferences. When a linear utility function is adopted to represent the risk-neutral attitude, the decisions yielded by UT are equivalent to those dictated by MELC. Convex and concave nonlinear utility functions are used to characterize risk-seeking and risk-averse attitudes, respectively. Generally speaking, the more nonlinearity the utility function, the higher the degree of risk proneness or risk aversion. Consider a power utility function $u(x) = -(-x)^l$ where $x = -LCC$ is a negative value to frame the life-cycle cost as a loss, and to ensure $u(x)$ is a monotonic and increasing function. In other words, a lower life-cycle cost with a higher utility is preferred. The scaled shape of $u(x)$ with different l values is plotted in Fig. 2, where $l = 1$, $l < 1$ and $l > 1$ stand for risk-neutral, risk-seeking and risk-averse attitudes, respectively.

In practice, the elicitation of a widely accepted utility function is often not an easy task, which may hinder the application of UT. For example, decision makers often have difficulties in expressing their risk preferences quantitively via utility functions. It is also common that multiple decision makers with different risk preferences cannot reach an agreement, which could happen even when all decision makers are risk-averse but with varying degrees of risk-averseness.

2.3. Stochastic Dominance and Almost Stochastic Dominance

The stochastic dominance (SD) [14-15] provides an alternative approach for decision-making in civil engineering applications, for example, the selection of design levels for buildings and pipelines [2][22]. The SD conforms to the principle of maximum expected utility, and ranks two decision alternatives based on their distributional information without the need to specify any utility functions. In the context of this study, suppose F and G are two design candidates, or two mitigation/retrofit measures. Let $F(x)$ and $G(x)$ denote the cumulative distribution function (CDF) of x where $x = -LCC$ is a random variable associated with the life-cycle cost of a design or mitigation/retrofit measure. Then for any decision maker with a non-decreasing utility function $u(x)$ (i.e. $u'(x) \geq 0$), F dominates G by the first-degree stochastic dominance (FSD) if and only if $F(x) \leq G(x)$ for all values of x with a strong inequality for at least one value of x [23]. If F dominates G by FSD, F is always preferred to G, and the expected utility associated with F is always no smaller than that of G regardless of the risk preferences of decision makers (i.e. the implicit utility function of x can be linear, concave or convex). In other words, FSD provides a way to rank two decision alternatives for all decision makers who are expected utility maximizers without knowing their exact risk preferences and utility functions. Fig. 3a illustrates the CDFs of F and G when F dominates G by FSD. There are other higher degree SD rules that are narrowly applicable to either risk-averse or risk-seeking decision makers. These higher order SD rules are not included in this paper. See Levy [23] for details.

In practice, the SD often fails to fully rank all decision alternatives due to its rigorous rules that are frequently violated by some 'pathological' preferences [23], for example, extremely risk-averse or risk-seeking. Thus, SD is often used in an initial screen to exclude a small number of inefficient or suboptimal alternatives. For example, the FSD adopted by Goda & Hong [2] and Zhou & Nessim [22] failed to rank any design candidates, and only a few inferior designs were screened out by assuming risk aversion when higher degree SD rules were adopted. The almost stochastic dominance (ASD) is an extension of SD that provides a relaxation of SD's strict conditions [16][23]. Compared to SD, ASD has an improved capability to rank decision alternatives to satisfy most decision makers who are expected utility maximizers [23].

The almost first-degree stochastic dominance (AFSD) allows a relatively small portion of x at which the condition of FSD does not hold, i.e. $F(x) > G(x)$. Define S_1 is a subset of x that contains x values where $F(x) > G(x)$. For $0 \le \varepsilon < 0.5$, F dominants G by AFSD for all values of x if and only if [23]

$$\int_{S_1} [F(x) - G(x)]dx \le \varepsilon \int | G(x) - F(x) | dx \tag{5}$$

Fig. 3b illustrates the CDFs of F and G when F dominates G by AFSD. The ε value is calculated as the violation area enclosed between $F(x)$ and $G(x)$ when $F(x) > G(x)$ (i.e. $\int_{S_1}[F(x) - G(x)]dx$) divided by the total area enclosed under the two CDFs (i.e. $\int |G(x) - F(x)|dx$). Note that if there is no violation area ($\varepsilon = 0$), AFSD coincides with FSD. If F dominants G by AFSD and ε is sufficiently small, then F is preferred to G, and the expected utility associated with F is no smaller than that of G except for some 'pathological' defined utility functions [23], for example, overly convex or concave (i.e. extremely risk-averse or risk-seeking). In other words, the rank of alternatives dictated by AFSD would satisfy most expected utility maximizers with non-decreasing utility functions. The ε value in AFSD has a broad range, i.e. $0 \le \varepsilon < 0.5$, and therefore caution is needed when selecting the ε value in practice. The smaller the ε value, the stronger the dominance. It may need subjective judgement to determine the largest allowed violation area or ε value which may vary depending on the decision problem. The discretion of ε value in practical civil engineering decision problems is discussed in Section 3. Higher degree ASD rules are not included in this paper. Refer to Leshno & Levy [16] and Tzeng et al. [24] for more details.

2.4. Comparison of decision models

Table 1 presents a summary for different decision models in terms of their strengths and weaknesses in practical decision support applications. The application of these decision models are illustrated by two practical decision problems described in the next section.

3. Illustrative Examples

3.1. Seismic Design

In this example, the decision analysis was conducted to choose design spectral response acceleration and the corresponding return period for a high-rise commercial building in Vancouver, Canada. The building is described in detail by Goda & Hong [2]. It is a nine-storey office building with a floor area of 9406 m^2, which is classified as a moderately ductile moment-resisting steel frame.

The probabilistic risk assessment (PRA) and life-cycle cost analysis methods by Goda & Hong [2] were adopted considering a building service period of 50 years and a discount rate of 5%. The simulation-based PRA and life-cycle cost analysis include seismic hazard analyses, structural damage assessment and cost estimation. The seismic hazard analyses consider twelve seismic source zones including the Cascadia subduction zone that influence Vancouver as described in Adams & Halchuk [25]. The occurrences of seismic events from these source zones are modelled by stochastic processes (i.e. a renewal process for the Cascadia subduction zone and Poisson processes for the other source zones). The seismic magnitudes and ground motion parameters are obtained by relevant magnitude-recurrence relations and attenuation relations. The structural damage assessment simplifies the building as an elastoplastic single-degree-of-freedom system (natural vibration period is 1.0s and damping ratio is 5%) to obtain the probability of damage states related to the drift ratio and damage factor. The life-cycle cost includes the initial construction cost of a design candidate (C_0), and the damage and repair costs (C_{DR}) which cover the repair/reconstruction cost of the structural and non-structural components, loss of contents, business interruption and relocation expenses. The cost estimation empirically relates the initial construction costs to design levels, and the damage and repair costs are a function of the damage states (see [2] for details about empirical equations used for cost estimation). Note that injury and fatality costs can be regarded as an externality and it is assumed that the decision maker is only interested in the proposition of design, construction and ownership of the building [2][26]. Therefore, injury and fatality costs are not included in the life-cycle cost.

Table 2 lists nine seismic design candidates considered in the decision process including their design spectral response acceleration (S_{AEf}), design return period (T_R) and initial construction cost (C_0). The design candidates are from S1 to S9 with an increasing S_{AEf}, and thus increasing C_0 and seismic safety levels. Note that all the costs are presented in 2020 Canadian dollars (CAD). A total of 50,000 Monte Carlo simulations were conducted, and the random samples of life-cycle costs (LCC) corresponding to different design levels were then obtained for subsequent decision analyses. The major uncertainties involved in the life-cycle cost assessment are from seismic demands and the resulting building damage and losses. The expected damage and repair cost $E[C_{DR}]$, the expected life-cycle cost $E[LCC]$ and standard deviation of life-cycle cost σ_{LCC} derived from the simulation are also listed in Table 2. It suggests that the initial construction cost increases with seismic design levels, whereas the expected damage and repair cost as well as the standard deviation of life-cycle cost decrease with seismic design levels. This is expected as an increased initial expenditure in design and construction reduces potential seismic damage and the uncertainty associated with life-cycle costs. Based on the minimum expected life-cycle cost criterion (MELC), S6 (T_R = 3,000 years and S_{AEf} = 0.526g, where g is the gravitational acceleration) with the least expected life-cycle cost is the preferred design candidate among S1-S9.

For buildings exposed to seismic hazards, risk-averse decision makers may emphasize on the extreme life-cycle costs. The three risk measures introduced in Section 2.1 can be used to characterize the upper tail of life-cycle costs and provide decision support for risk-averse decision makers. Fig. 4 shows the Value-at-Risk (VaR), Conditional-Value-at-Risk (CVaR) and Range-Value-at-Risk (RVaR) of the life-cycle costs associated with different design candidates at five commonly used probability levels, i.e. 0.50 (median), 0.75, 0.90, 0.95 and 0.99. It suggests that the decision maker prefers a stronger design (i.e. larger T_R and S_{AEf}) as a higher probability level is specified. At the same probability level of α, VaR_{α} (LCC) $\leq$ $\text{RVaR}_{\alpha, \beta}$ (LCC) $\leq$ CVaR_{α} (LCC) for a given design candidate, and the CVaR yields the most conservative design selection as it fully accounts for the extreme tail risks. For example, at probability levels of 0.90, 0.95 and 0.99, the strongest design S9 is dictated by CVaR as shown in Fig. 4b. S9 is also preferred at probability levels of 0.95 and 0.99 based on VaR, whereas the second strongest design S8 would be preferred at the probability level of 0.90 as shown in Fig. 4a. S6 is preferred for $\text{CVaR}_{0.50}$, which is same with the decision based on MELC. A relatively weaker design S3 is dictated by $\text{VaR}_{0.50}$. As suggested by Fig. 4c, the RVaR may provide a middle ground between VaR and CVaR at a given probability level. For example, the seismic design selected based on $\text{RVaR}_{0.75,\ 0.90}$ is S6, while S5 and S7 are dictated by $\text{VaR}_{0.75}$ and $\text{CVaR}_{0.75}$, respectively.

As mentioned in Section 2.1, these risk measures can also be used as constraints in conjunction with the MELC to achieve a balance between economic efficiency and risk aversion. Such constraints reflect decision makers' tolerance of extreme tail risks. For example, the decision criterion may be set as: the best design among S1-S9 is the one with the minimum expected life-cycle cost while also satisfying the condition that $\text{VaR}_{0.90}$ (C_{DR}) $\leq C_0/2$. In other words, the VaR of damage and repair cost ($C_{DR} = LCC - C_0$) at a probability level of 0.90 is no greater than 50% of the initial design and construction cost C_0. Under this constraint, S6 with the minimum expected life-cycle cost among S1-S9 is still the preferred design candidate. If a more risk-averse constraint $\text{CVaR}_{0.90}$ (C_{DR}) $\leq C_0/2$ is used, then S7 with the second smallest expected life-cycle cost would be preferred as S6 no longer satisfies the constraint.

The decision analysis was further conducted by comparing the expected utility associated with the nine design candidates considering a variety of risk preferences. The power utility function described in Section 2.2 was used, i.e. $u(x) = -(-x)^l$, where $x = -LCC$ to ensure $u(x)$ is a monotonic and increasing function. The expected utilities were then evaluated for the l value ranging from 0.1 to 5.0 with an increment of 0.1 to represent a wide variety of risk preferences. For the risk-neural attitude (i.e. l = 1.0), the rank of design candidates based on the expected utility is equivalent to those based on the expected life-cycle cost (i.e. a design with a higher expected utility or lower life-cycle cost is preferred). Table 3 lists the preferred design among S1-S9 with different l values. A stronger design would be generally preferred as l increases. Fig. 5 shows the comparison of expected utility for l = 0.1, 1.7, 3.0, 4.0 and 5.0. The numerical value for utility in the vertical axis is not shown in the figure because only the rank of expected utility is of concern. It suggests that only for risk-seeking decision-makers with an extremely convex utility function (i.e. l = 0.1), a weaker design (i.e. S5) than that dictated by the MELC (i.e. S6) would be preferred. S6 is the preferred design for most risk-seeking decision-makers ($0.2 \leq l < 1.0$), mildly risk-averse decision-makers (($1.0 < l \leq 1.7$) and risk-neutral decision-makers (l = 1.0). For decision-makers with higher levels of risk aversion ($1.8 \leq l \leq 5.0$), a stronger design S7, S8 or S9 would be preferred. Recall the preferred design S7, S8 or S9 dictated by VaR and CVaR at relatively high probability levels (i.e. 0.90 or higher for VaR and 0.75 or higher for CVaR), which is consistent with that dictated by highly concave utility functions, and thus represents a high level of risk aversion.

Without specifying utility functions, the first-degree stochastic dominance (FSD) was used to select among the design candidates. Fig. 6 depicts the cumulative distribution functions (CDF) of $x = -LCC$ corresponding to the nine design candidates S1-S9. The CDF curves intersect with each other, and therefore no FSD relation is found for any designs. Besides a visual check, the FSD relation between any two design candidates can also be determined by the algorithm presented in Appendix A. The almost first-degree stochastic dominance (AFSD) with relaxed conditions was then employed. The ε value characterizing the area of violation can be assessed by the algorithm given in Appendix A. Table 4 shows if a design candidate in the first column dominates those in the first row by AFSD, and the corresponding ε value if AFSD relation exists. As shown in Table 4, S6 dominates the other design candidates by AFSD. However, in practice, S6 may not be viewed as the best design among S1-S9 that satisfies most decision makers because the ε values for some AFSD relations are very close to the maximum allowed value 0.5, which indicates a weak dominance relation. For example, ε = 0.48 for the AFSD relation between S6 and S7, and ε = 0.45 for the AFSD relation between S6 and S8. This is consistent with the utility analysis that S6 is not preferred by most decision makers that a considerable portion of risk-averse decision makers would choose S7 or S8. If the maximum allowed ε value is subjectively set as 0.30 in practice, then one design candidate would be chosen over the other only when the former dominates the later by AFSD with ε no greater than 0.30. In this case, S6 and S7 would be chosen over S1-S4, and S1 is screened out as most designs (S3-S9) would be chosen over S1. In this example, the AFSD fails to practically determine the best design option among S5-S9 but only screens out some inferior design candidates (S1-S4). If the selected threshold for ε is reduced, then less inferior design candidates will be screened out. On the other hand, increase of threshold for ε can better rank design candidates. However, caution should be exercised when increasing the threshold for ε as the resulting decision rank may not be preferred by a majority of decision makers who are utility maximizers.

3.2. Wind Hazard Mitigation

The second example presents a decision problem of wind hazard mitigation for a low-rise residential building in Brisbane, Australia. The building is a one-storey contemporary house with a complex hip-end roof. It has timber roof and wall frames. The exterior of wall is brick veneer. The roof cladding is corrugated metal sheeting attached to metal top-hat battens. This building is designed and constructed to a wind classification of N2 (a flat site with suburban terrain and partial shielding) according to AS 4055 [27] and AS 1684.2 [28]. The replacement values of the building and contents are estimated to be $375,000 and $75,000 Australian dollars (AUD) according to Australian housing cost guides ([29]), respectively. Refer to Qin [30] for more details about this low-rise residential building.

Brisbane is primarily under the threat of non-cyclonic windstorms such as severe thunderstorms and east coast lows. The economic losses for the contemporary house mainly arise from direct wind damage to the building envelope (e.g. roof cladding and windows) and subsequent rainwater intrusion through the damaged building envelope. Three mitigation measures are considered to reduce wind damage risks including (i) improvement of roof resistance by strengthening roof connections (RF), (ii) installation of window shutters (WS), and (iii) improvement of the design strength of windows (WR). See Qin & Stewart [6] for details of these mitigation measures and their influences on structural performance. Apart from these three mitigation measures, another decision alternative is to keep 'business as usual' with no mitigation (BAU). The life-cycle cost (*LCC*) includes a one-off cost for adopting a mitigation measure, and the damage, repair and replacement cost (inclusive of relocation and additional living cost) caused by severe windstorms. The base construction cost of the building is the same for the four decision alternatives and hence is excluded from the life-cycle cost. The mitigation measures applied at the initial design and construction stage are RF and WR, and the window shutters (WS) are also assumed to be installed at the beginning of the building service period. The mitigation cost additional to the base construction cost is 0%, 0.56%, 1.60% and 0.32% of the building replacement value, respectively, for BAU, RF, WS and WR. The damage, repair and replacement costs associated with the four decision alternatives are obtained from the probabilistic risk assessment (PRA) by Qin & Stewart [31] and Qin [30] for a building service period of 50 years and a discount rate of 4%. This simulation-based risk assessment consists of four major components, i.e. i) hazard modelling for extreme wind and associated rainfall, ii) reliability-based wind damage assessment for roof and windows, iii) evaluation of rainwater intrusion, and iv) loss estimation. See details in Qin & Stewart [31] and Qin [30].

A total of 100,000 Monte Carlo simulations were conducted, and the random samples of life-cycle costs corresponding to the four decision alternatives were then obtained for subsequent decision analyses. The major uncertainties involved in the life-cycle cost assessment are from wind hazards, building damage and loss modelling. Note that all the costs are presented in 2020 Australian dollars. The expected life-cycle costs for the 50-year building service period are \$8,609, \$10,218, \$6,285 and \$4,992 AUD for BAU, RF, WS and WR, respectively. Based on the minimum expected life-cycle cost criterion (MELC), implementing mitigation measures WR and WS would be preferred to ‘do nothing’ (BAU), and WR is the most cost-effective mitigation measure. Fig. 7 plots the histograms of the random samples of life-cycle costs corresponding to the four decision alternatives. It is indicated that mitigation measures WR and WS considerably reduce the extreme tail risks of the life-cycle cost distribution. Although WS is less cost-effective than WR according to MELC, it provides a significant reduction of uncertainty and extreme losses, which may be favoured by many risk-averse decision-makers. RF is not a cost-effective mitigation measure.

Wind mitigation decisions based on risk measures are then examined. The Value-at-Risk (VaR), Conditional-Value-at-Risk (CVaR) and Range-Value-at-Risk (RVaR) of the life-cycle costs associated with the four decision alternatives at five commonly used probability levels, i.e. 0.50 (median), 0.75, 0.90, 0.95 and 0.99 are compared in Fig. 8. RF is still not a viable mitigation measure based on all considered risk measures. WS would be preferred based on CVaR for all the five probability levels. This is expected as WS significantly reduces the extreme tail risks, though the expected life-cycle cost with WS is higher than that corresponding to WR. For mitigation decisions based on VaR, WR would be preferred at probability levels of 0.50 and 0.75, which is the same with the decision dictated by MELC and less conservative than that dictated by CVaR. The decision based on $\mathrm{RVaR}_{\alpha,\beta}$ is getting closer to that dictated by CVaR_{α} as β increases. For example, at a probability level α = 0.50, the preferred mitigation decision for $\mathrm{RVaR}_{0.50,\,0.75}$ is WR, which is the same with that for $\mathrm{VaR}_{0.50}$, while the mitigation decision dictated by $\mathrm{RVaR}_{0.50,\,0.90}$ is WS, same with that dictated by $\mathrm{CVaR}_{0.50}$.

The decision analysis was further conducted by comparing the expected utility associated with the four decision alternatives considering a variety of risk preferences. Same as the seismic design problem, the power utility function was used, i.e. $u(x) = -(-x)^l$, where $x = -LCC$. The expected utilities were then evaluated for the l value ranging from 0.1 to 5.0 with an increment of 0.1. It suggests that WS is preferred to BAU for most decision-makers except those with an extremely convex utility function (i.e. l = 0.1 for risk-seeking). WR is preferred to BAU for all the utility functions considered (i.e. $0.1 \le l \le 5.0$), whereas RF is not preferred to BAU. WR is preferred to WS for all considered risk-seeking, risk-neutral and a portion of risk-averse decision-makers (i.e. $1.0 < l \le 1.5$), which is consistent with the decision dictated by $\mathrm{VaR}_{0.50}$, $\mathrm{VaR}_{0.75}$ or $\mathrm{RVaR}_{0.50,\,0.75}$. WS is preferred to WR for a considerable portion of risk-averse decision-makers (i.e. $1.6 \le l \le 5.0$), which is the same decision with that based on CVaR at all the five probability levels as shown in Fig. 8b. This again shows CVaR is a more conservative risk measure than VaR and RVaR. The rank of the four decision alternatives with l = 0.1, 1.0, 1.6 and 4.0 is summarized in Table 5 to show the above findings.

The first-degree stochastic dominance (FSD) was then used for the mitigation decision-making. Using the FSD algorithm given in Appendix A, BAU, WS and WR are all found to dominate RF by FSD. It means that, for all decision makers with a non-decreasing utility function, RF is not preferred regardless of the decision makers’ risk preferences. This is consistent with the decision based on the three risk measures and the utility analysis which concludes RF is not a viable mitigation measure. BAU, WS and WR cannot be determined by FSD. The almost first-degree stochastic dominance (AFSD) was further adopted to identify the mitigation measure that would be preferred by most decision makers. Given the random samples of x ($x = -LCC$) associated with the mitigation options, the ε value for one dominating the other by AFSD can be calculated by Eq. (6) in Appendix A. Table 6 shows if a mitigation measure in the first column dominates those in the first row by AFSD, and the corresponding ε value if AFSD relation exists. Table 6 suggests that WR and WS dominate BAU by AFSD with ε = 0.02 and 0.21, respectively. These ε values are deemed to be small enough for most decision-makers to choose WR and WS over BAU. This is consistent with the decision analysis based on expected utility that WR is preferred to BAU for a wide range of risk preferences, and WS is preferred to BAU by most decision-makers except for those who are extremely risk-seeking. For these two viable mitigation measures, WR dominates WS by AFSD with ε = 0.36. This ε value may not be small enough to choose WR over WS for most decision-makers, which is consistent with the utility analysis that WS would be preferred to WR by a considerable portion of risk-averse decision-makers. By specifying a threshold for ε value (i.e. the maximum allowed ε value), the AFSD can be used to rank the mitigation options for most decision makers if the corresponding ε value does not exceed the threshold. This threshold value is somewhat determined by subjective judgement in practice and can vary depending on the decision problem of interest. For this wind mitigation problem, a threshold value around 0.25 might be appropriate. However, for the seismic design problem, it fails to find the best design candidate even with a larger threshold value (e.g. 0.30).

4. Conclusions

This paper presents the application of a set of decision models for buildings exposed to environmental hazards beyond the minimum expected life-cycle cost criterion (MELC), which can cope with large uncertainty and different risk preferences involved in decision problems for low-probability, high-consequence natural hazards. The decision models in this paper include risk measures such as Value-at-Risk (VaR), Conditional-Value-at-Risk (CVaR) and Range-Value-at-Risk (RVaR), the utility theory (UT), the stochastic dominance (SD) and its extension almost stochastic dominance (ASD), whereby the RVaR and ASD are newly introduced to a decision context for buildings exposed to environmental hazards. The features of these decision models were discussed from a practical point. The risk measures well capture extreme tail risks that are often of concern to risk-averse decision makers. The UT provides a full rank of decision alternatives for decision-makers with all possible risk preferences (risk aversion, risk proneness, risk neutral) that are encoded in utility functions. The SD and ASD have the advantage that a specific utility function is not required for decision-making as it is often difficult to elicit a widely accepted utility function in practice.

With the consideration of decision makers' possible risk preferences and tolerances, the selection and application of these decision models were illustrated by two practical engineering decision examples, i.e. seismic design of a high-rise commercial building and wind hazard mitigation for a low-rise residential building. It was found that, the decision based CVaR tends to yield a stronger seismic design or a more effective wind mitigation measure (e.g. installing window shutters) with high initial expenditures. CVaR is the most conservative risk measure that may suit decision makers with relatively high levels of risk averseness. The RVaR may give a decision in the middle ground between VaR and CVaR. The risk measures can also be used in conjunction with the MELC as a constraint for decision makers' risk tolerances. The seismic design example suggests that a higher design level may be selected when using a CVaR constraint rather than a VaR constraint. The utility analyses were conducted for a wide range of nonlinear utility functions. For most concave utility functions representing risk averseness, the seismic design and wind mitigation decisions yielded by UT are comparable to those based on risk measures at many commonly used probability levels. The first-degree stochastic dominance (FSD) and its extension the first-degree almost stochastic dominance (AFSD) with an improved capacity to rank decision alternatives were also adopted in these two examples. They failed to find the best seismic design candidate, and only a few inferior designs were screened out. For the wind mitigation problem, AFSD successfully selected mitigation measures that are worth adopting and satisfy most decision makers who are expected utility maximizers. The wind mitigation decisions by AFSD are consistent with those by the utility analysis.

The application and selection of decision models to adequately address the uncertainty involved in the decision problem as well as various risk preferences and tolerances can be challenging, and on a case-by-case basis depending on a particular decision context, whereby expert judgement is often required. This study attempts to make the decision-making process as objective as possible by applying quantitative decision models, however, a certain level of subjectivity is unavoidable in practical decision-making problems because decision makers will have different preferences and tendencies. It is anticipated that the two practical decision problems given in this paper shed some light on the application of decision models for buildings exposed to environmental hazards. The application of these decision models is expected to better support decision-making by providing decision options that meet different needs and risk appetites of decision makers while taking into account uncertainties involved in the life-cycle cost. The decision models introduced in this paper may also be extended to other civil structures and infrastructure systems subjected to low-probability, high-consequence events.

Appendix A: Algorithms for FSD and AFSD

Suppose F and G are two design candidates, or two mitigation/retrofit measures. $\boldsymbol{x}$ and $\boldsymbol{y}$, each containing n random samples, are the decision variables (e.g. $-LCC$) corresponding to F and G, respectively. Arrange the samples of $\boldsymbol{x}$ and $\boldsymbol{y}$ in a non-descending order (i.e. $x_1 \leq x_2 \leq \ldots \leq x_n$; $y_1 \leq y_2 \leq \ldots \leq y_n$), and assign a probability of $1/n$ to each sample.

The algorithm for FSD [23]: F dominates G by FSD if and only if $x_i \geq y_i$ for all i values (i = 1, 2, …, n), and $x_i > y_i$ for at least one i value.

The algorithm for AFSD [31]: The ε value characterizing the area of violation is calculated as

$$\varepsilon = \frac{\sum_{i:y_i > x_i} (y_i - x_i)}{\sum_{i=1}^{n} | y_i - x_i |} \tag{A1}$$

If $\varepsilon < 0.5$, then F dominates G by AFSD.

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Tables

Table 1. Comparison of decision models in practical application.

Decision model		Description	Strength	Weakness
Risk Measure	VaR	Quantile value of the decision variable (e.g. life-cycle cost)	Easy to use	May not well capture extreme tail risks
	CVaR	Average of quantiles beyond a certain probability level	Better capture extreme tail risks	May be too sensitive to outliners in the tail of probability distribution
	RVaR	Average of quantiles between two probability levels	Offer combined features of VaR and CVaR	More effort needed to determine the two probability levels
UT		Decision-making based on maximum expected utility.	Explicitly factor risk preferences into the utility function that measures the desirability of consequences	Elicitation of a widely accepted utility function is often not an easy task
SD		Rank two decision alternatives based on their distributional information without knowing risk attitudes; conform the principle of maximum expected utility.	No need to subjectively specify utility functions	Often fail to rank decision alternatives due to its rigorous rules that are frequently violated by some 'pathological' preferences
ASD		Select decision alternatives accepted by most decision makers; extension of SD.	No need to subjectively specify utility functions; a relaxation of SD's strict conditions; allow some extreme risk preferences as exemptions	May still not fully rank decision alternatives in practice

Table 2. Seismic design levels and statistical cost information.

design candidate	T_R (year)	S_{AEf} (g)	cost statistics (million CAD)			
			C_0	$E[C_{DR}]$	$E[LCC]$	σ_{LCC}
S1	250	0.178	19.5	9.3	28.8	12.7
S2	500	0.252	19.8	5.4	25.2	9.5
S3	750	0.303	20.1	3.9	24.0	8.2
S4	1000	0.343	20.3	3.2	23.5	7.4
S5	1500	0.405	20.6	2.4	23.0	6.1
S6	3000	0.526	21.3	1.4	22.7	5.0
S7	5000	0.635	21.8	1.1	22.9	4.0
S8	7500	0.736	22.4	0.7	23.1	3.4
S9	10000	0.829	22.9	0.6	23.5	3.1

Table 3. Preferred seismic design dictated by expected utility.

	$l = 0.1$	$0.2 \le l \le 1.7$	$1.8 \le l \le 3.1$	$3.2 \le l \le 4.6$	$4.7 \le l \le 5.0$
preferred design candidate	S5	S6	S7	S8	S9

Table 4. AFSD relations for the nine design candidates.

design candidate	S1	S2	S3	S4	S5	S6	S7	S8	S9
S1	N[a]	N	N	N	N	N	N	N	N
S2	$\varepsilon = 0.33$	N	N	N	N	N	N	N	N
S3	$\varepsilon = 0.26$	$\varepsilon = 0.42$	N	N	N	N	N	N	N
S4	$\varepsilon = 0.22$	$\varepsilon = 0.37$	$\varepsilon = 0.40$	N	N	N	N	N	N
S5	$\varepsilon = 0.18$	$\varepsilon = 0.28$	$\varepsilon = 0.32$	$\varepsilon = 0.42$	N	N	N	N	$\varepsilon = 0.42$
S6	$\varepsilon = 0.16$	$\varepsilon = 0.22$	$\varepsilon = 0.24$	$\varepsilon = 0.28$	$\varepsilon = 0.33$	N	$\varepsilon = 0.48$	$\varepsilon = 0.45$	$\varepsilon = 0.31$
S7	$\varepsilon = 0.16$	$\varepsilon = 0.25$	$\varepsilon = 0.27$	$\varepsilon = 0.30$	$\varepsilon = 0.39$	N	N	$\varepsilon = 0.42$	$\varepsilon = 0.34$
S8	$\varepsilon = 0.17$	$\varepsilon = 0.27$	$\varepsilon = 0.30$	$\varepsilon = 0.35$	$\varepsilon = 0.42$	N	N	N	$\varepsilon = 0.36$
S9	$\varepsilon = 0.19$	$\varepsilon = 0.36$	$\varepsilon = 0.41$	$\varepsilon = 0.49$	N	N	N	N	N

Notes: [a] N means no AFSD relation.

Table 5. Rank of decision alternatives based on the expected utility.

	rank based on expected utility			
	No.1	No.2	No.3	No.4
l = 0.1	WR	BAU	WS	RF
l = 1.0	WR	WS	BAU	RF
l = 1.6	WS	WR	BAU	RF
l = 4.0	WS	WR	BAU	RF

Table 6. AFSD relations for the four mitigation decision alternatives.

mitigation option	BAU	RF	WS	WR
BAU	N	ε = 0 (FSD)	N	N
RF	N	N	N	N
WS	ε = 0.22	ε = 0 (FSD)	N	N
WR	ε = 0.02	ε = 0 (FSD)	ε = 0.36	N

Figures

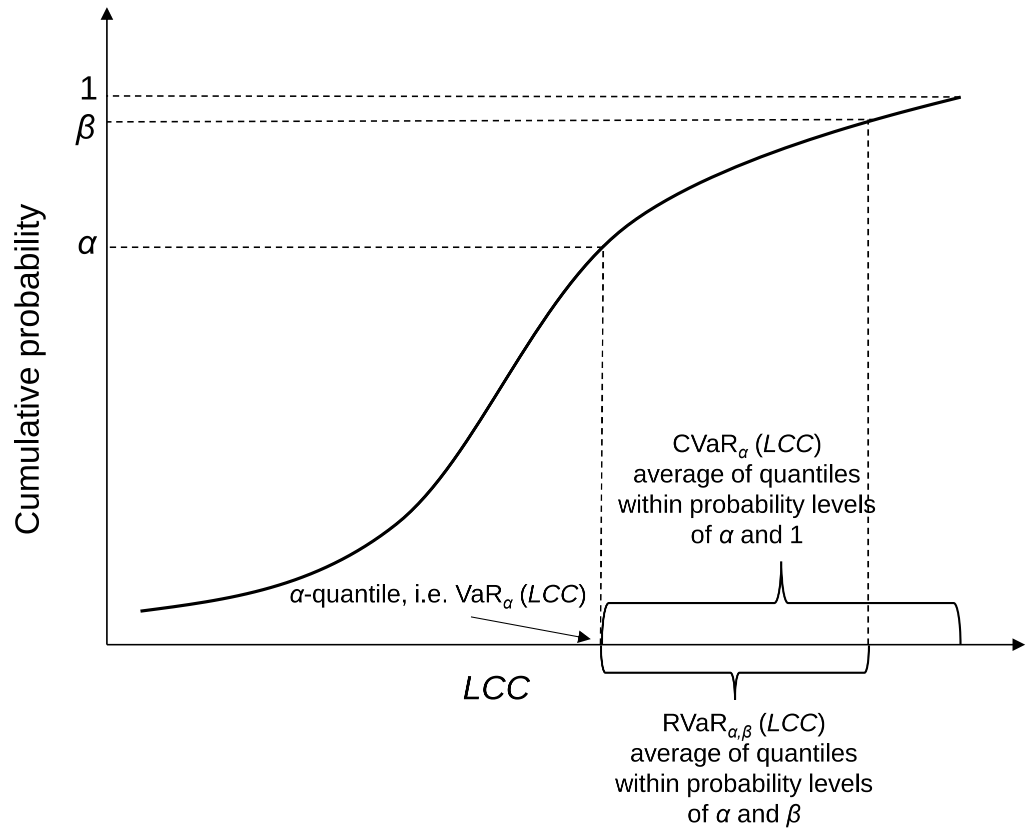


Fig. 1. Illustration of VaR, CVaR and RVaR using the CDF of life-cycle cost *LCC*.

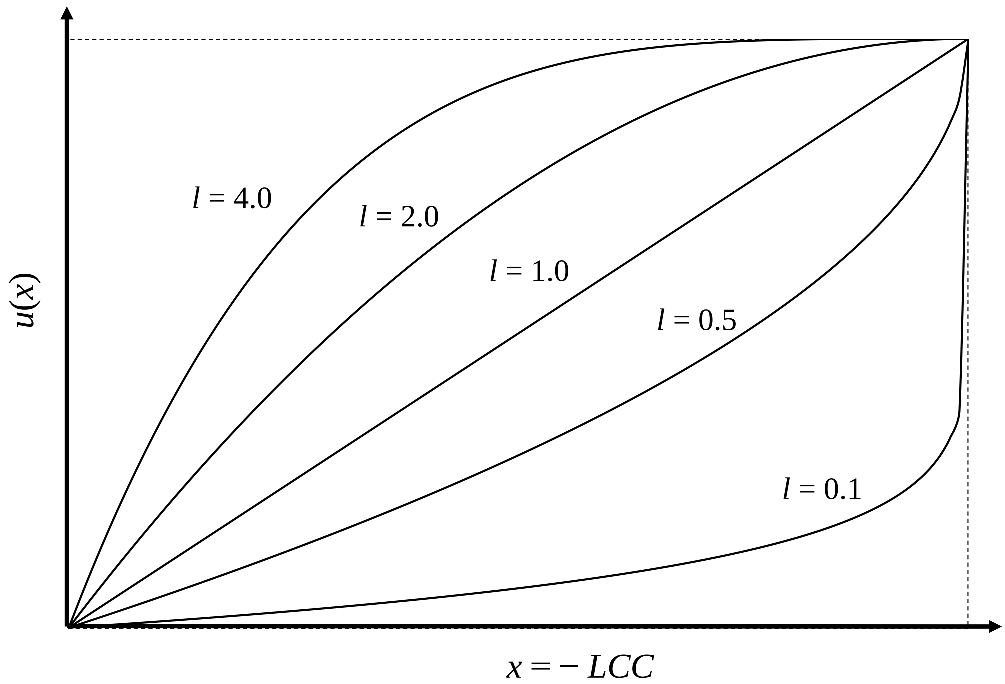


Fig. 2. Scaled power utility functions to reflect different risk preferences.

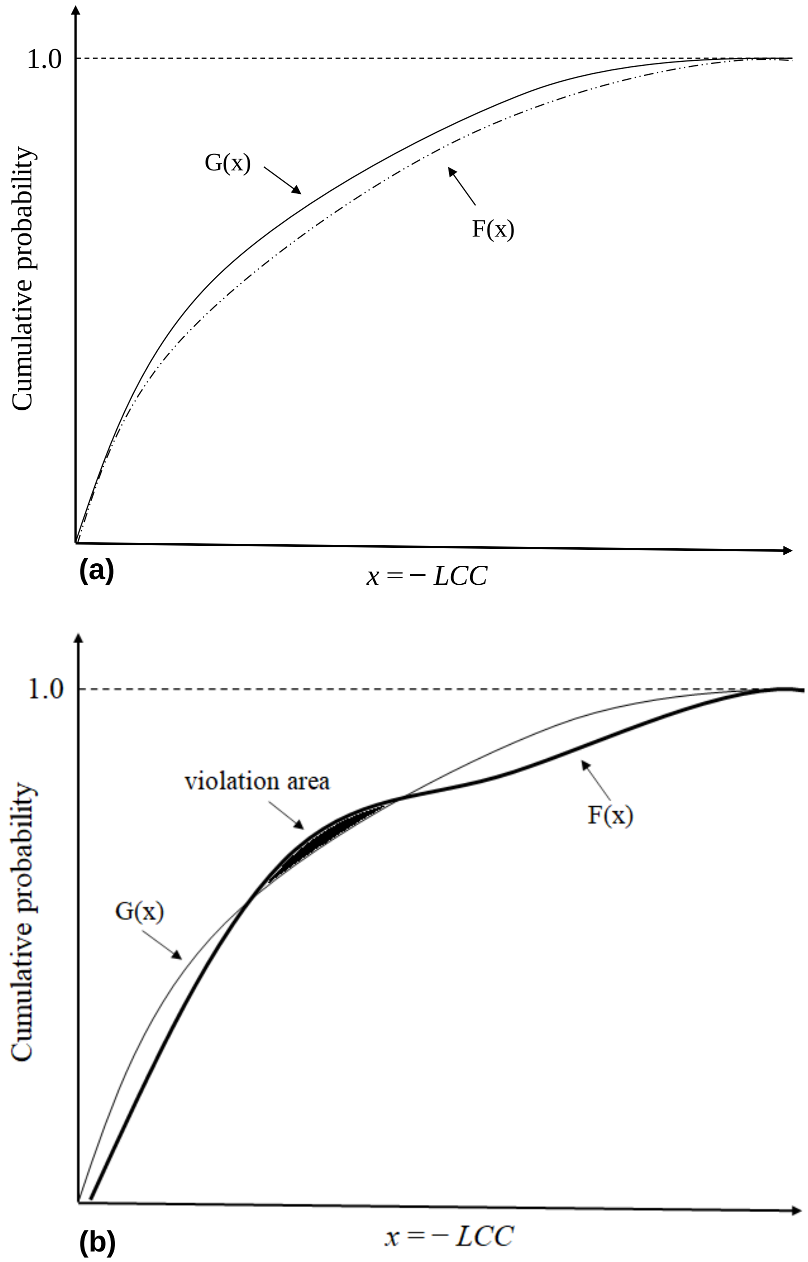
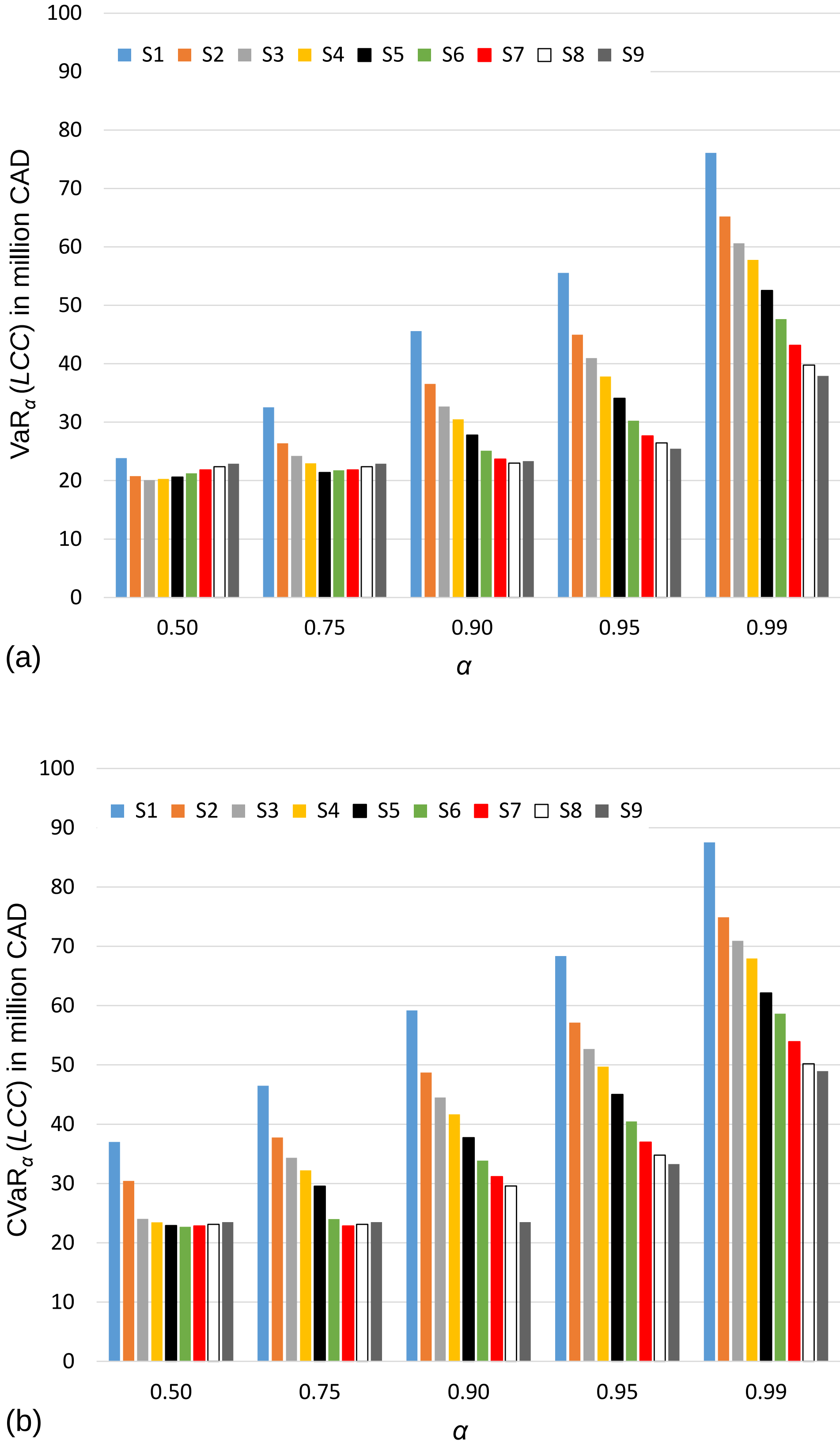


Fig. 3. Graphical interpretation of stochastic dominance: (a) FSD; (b) AFSD.


S1 S2 S3 S4 S5 S6 S7 S8 S9
100
90
80
70
60
50
40
30
20
10
0
VaR$_\alpha$(LCC) in million CAD
0.50
0.75
0.90
0.95
0.99
(a)
α
S1 S2 S3 S4 S5 S6 S7 S8 S9
100
90
80
70
60
50
40
30
20
10
0
CVaR$_\alpha$(LCC) in million CAD
0.50
0.75
0.90
0.95
0.99
(b)
α

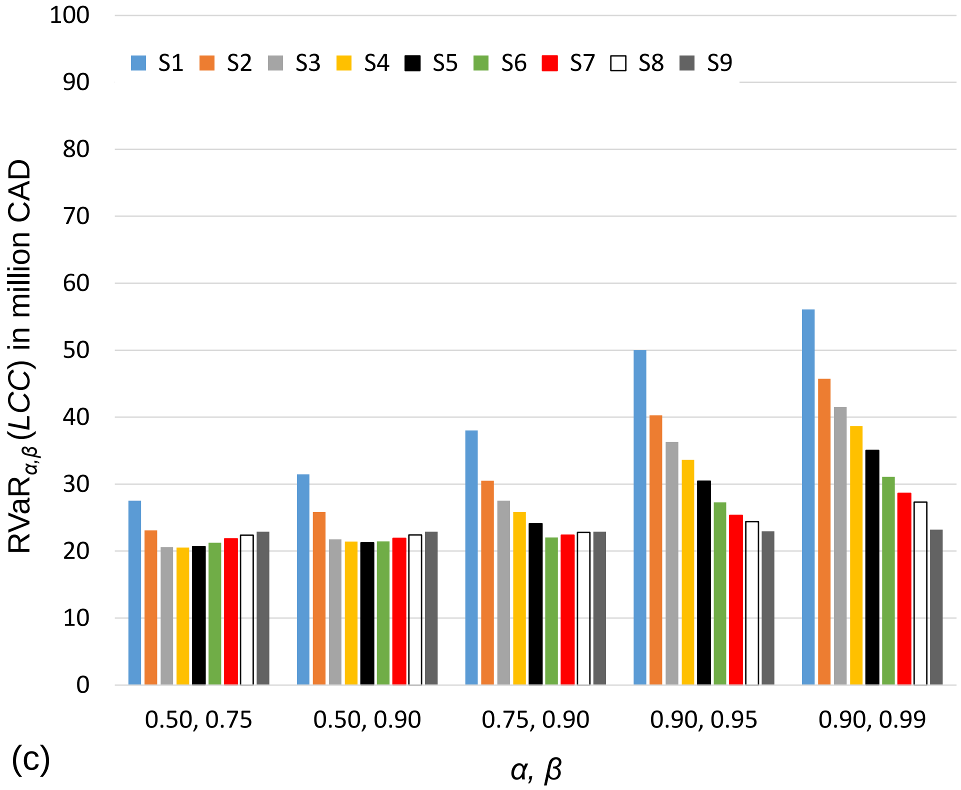
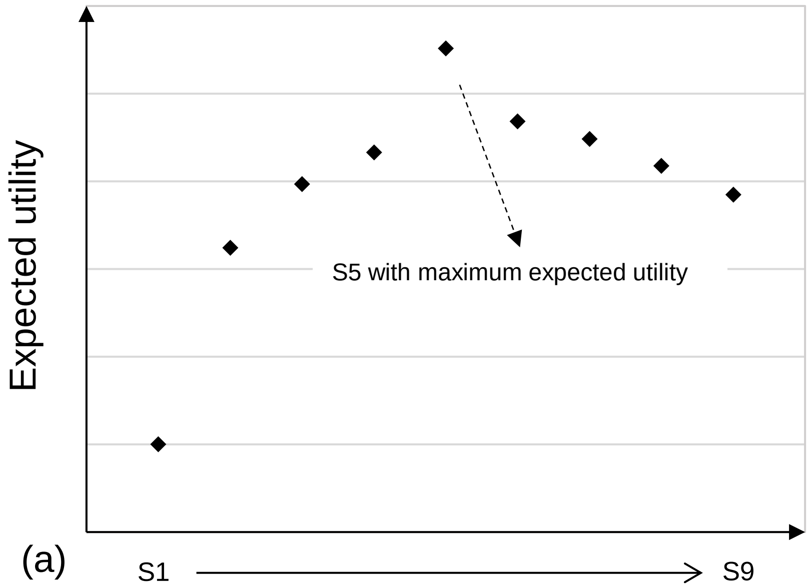
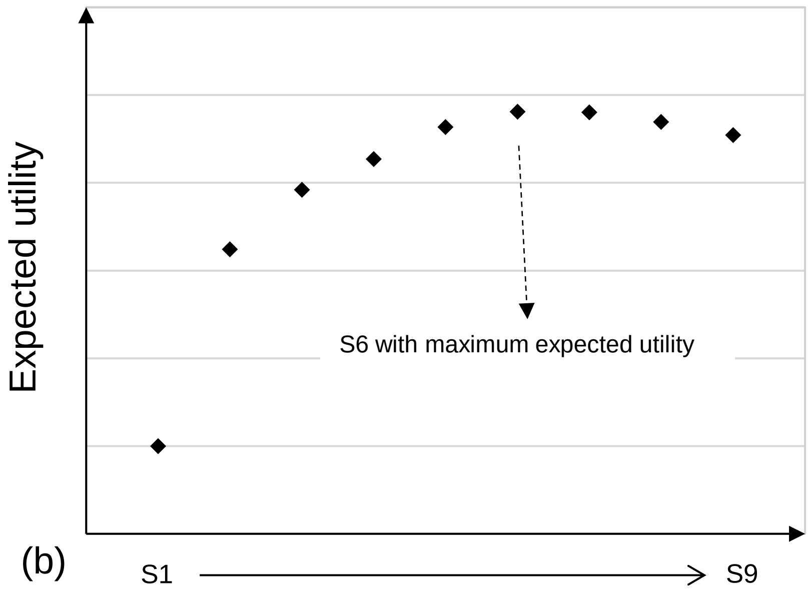


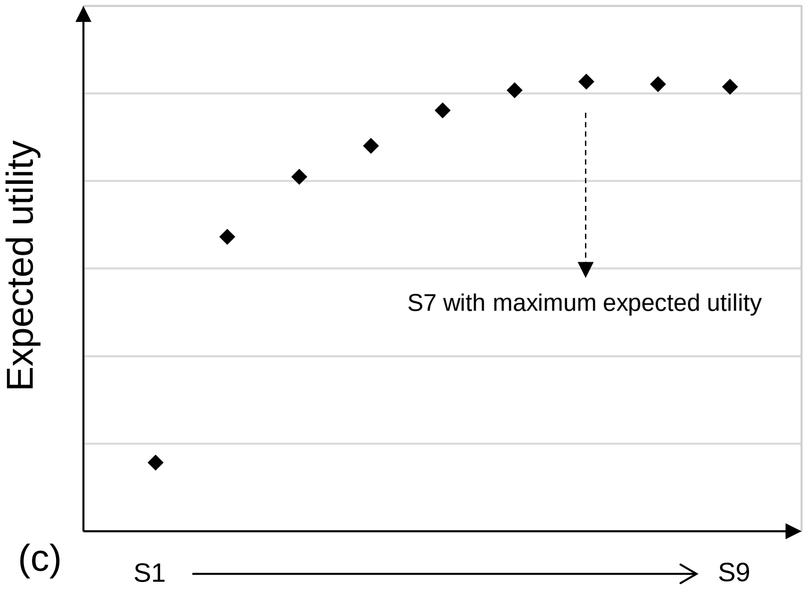
Fig. 4. Comparison of risk measures of life-cycle costs associated with the nine design candidates at different probability levels: (a) VaR; (b) CVaR; (c) RVaR.


Expected utility
S5 with maximum expected utility
S1
S9

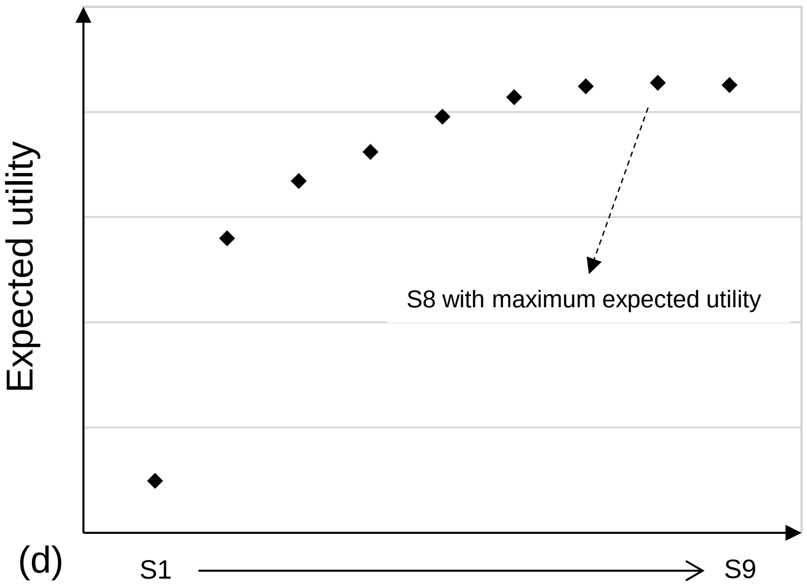
(a)


Expected utility
S6 with maximum expected utility
S1
S9

(b)


Expected utility
S7 with maximum expected utility
S1
S9

(c)


Expected utility
S8 with maximum expected utility
S1
S9

(d)

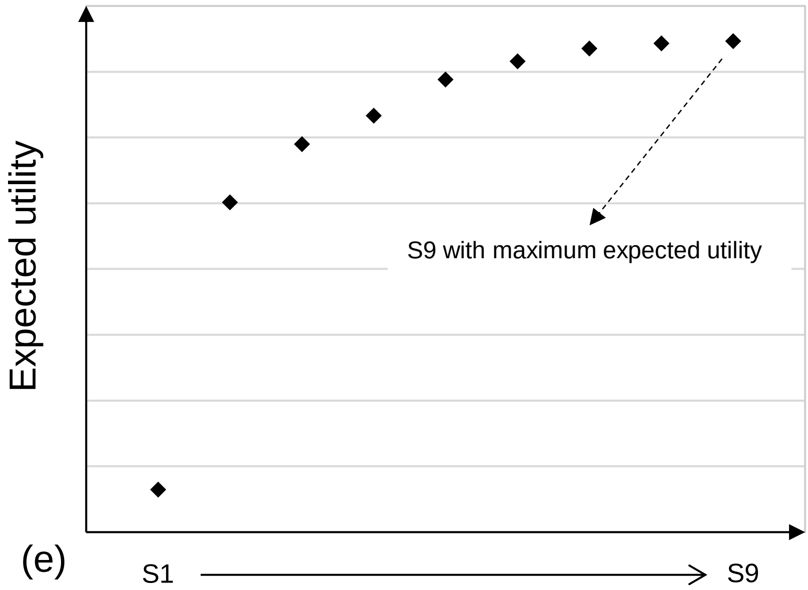


Fig. 5. Comparison of expected utility for the nine design candidates: (a) l = 0.1; (b) l = 1.7; (c) l = 3.0; (d) l = 4.0; (e) l = 5.0.

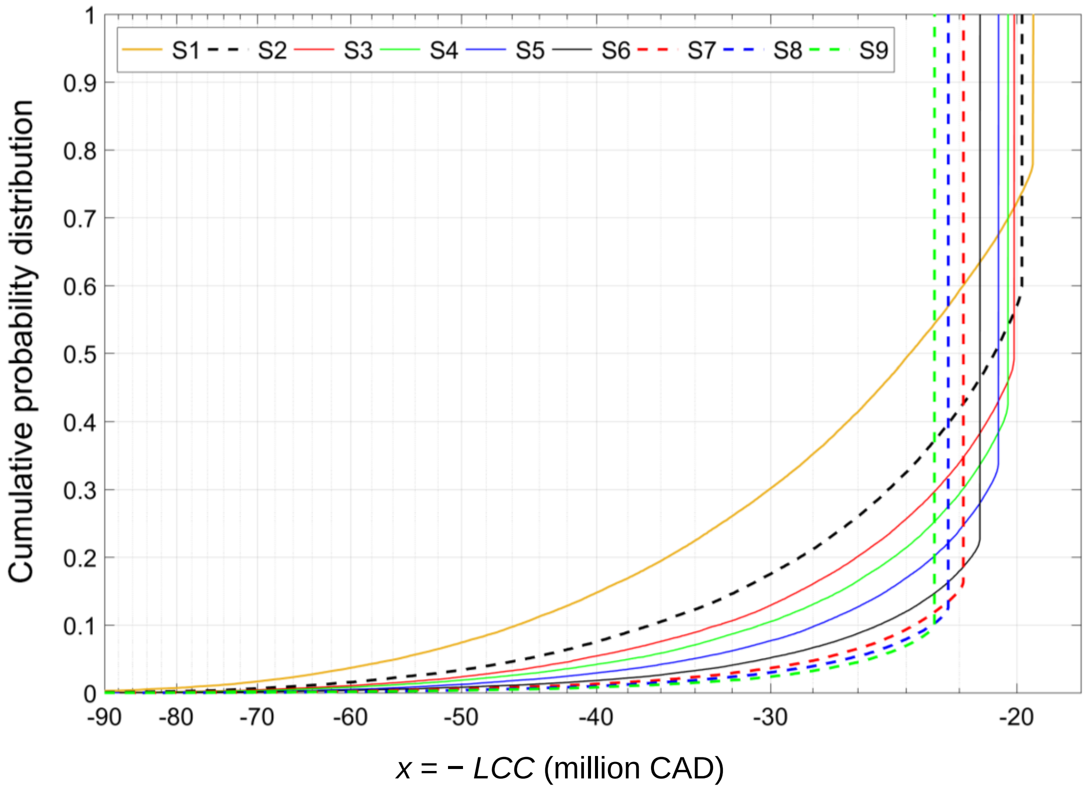


Fig. 6. CDFs of $x = -LCC$ corresponding to design candidates S1-S9.

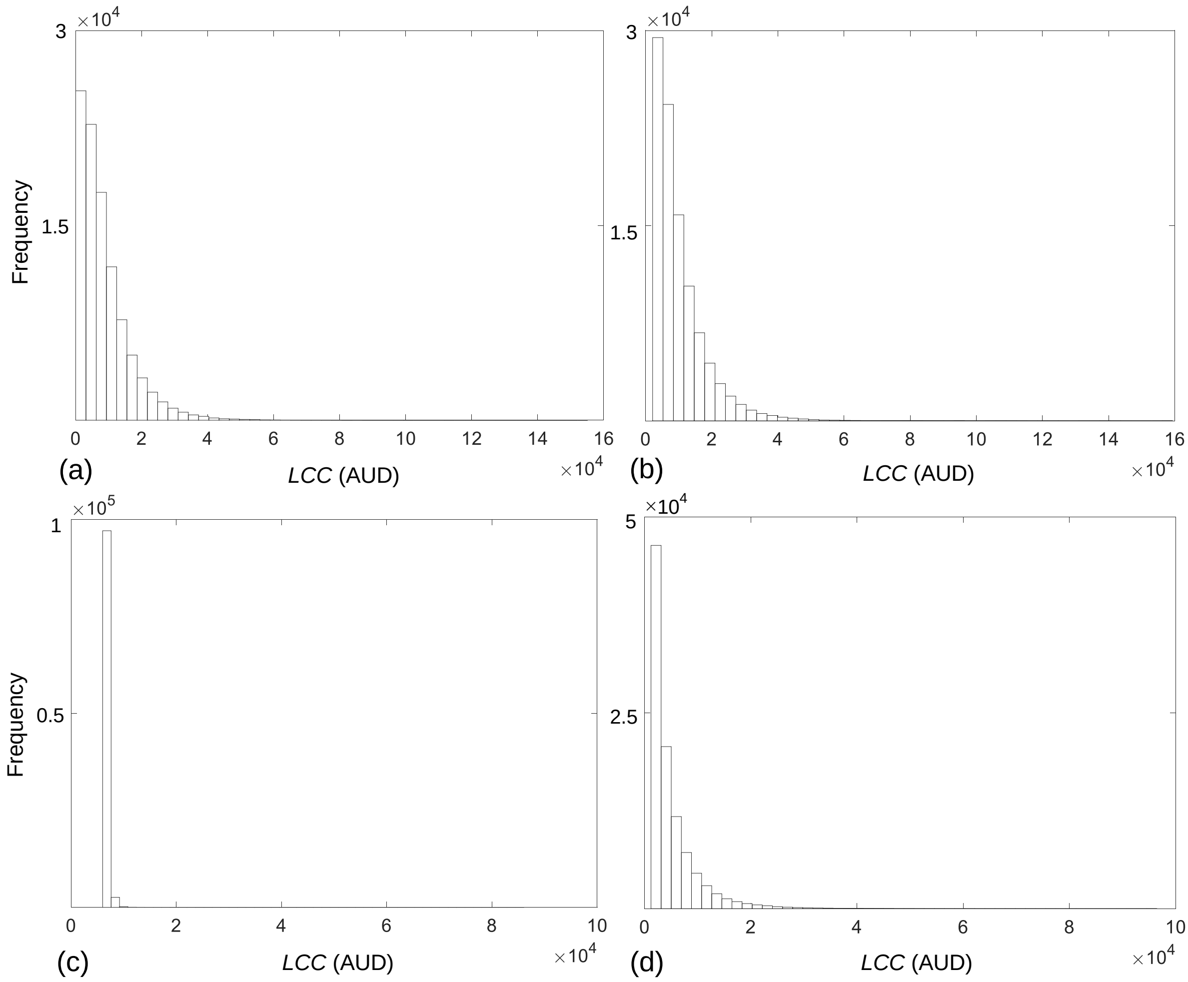
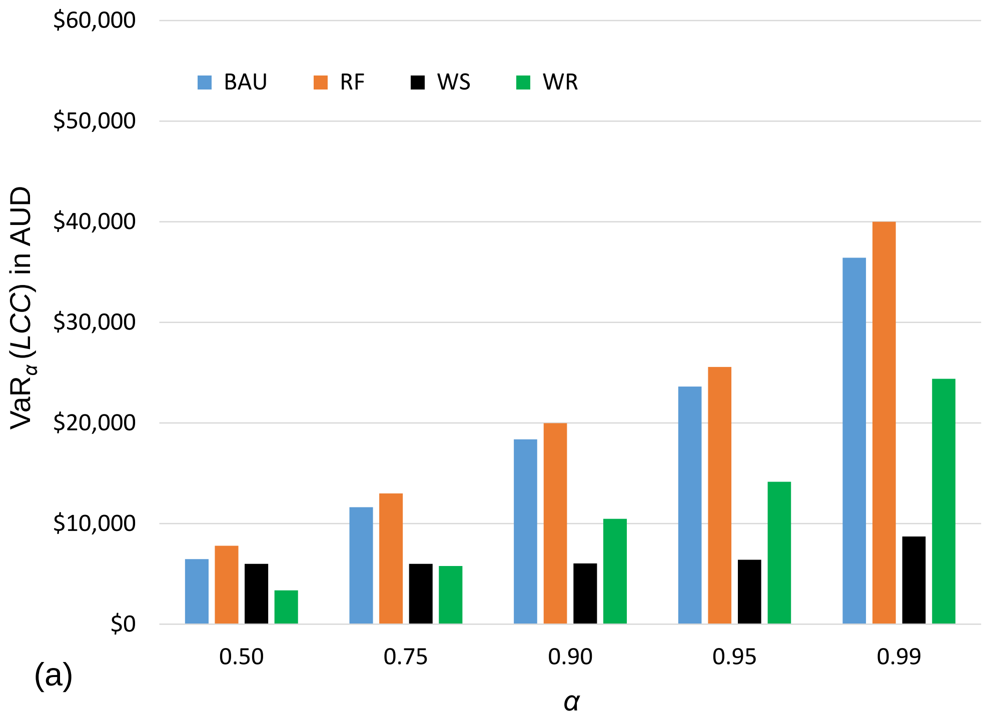
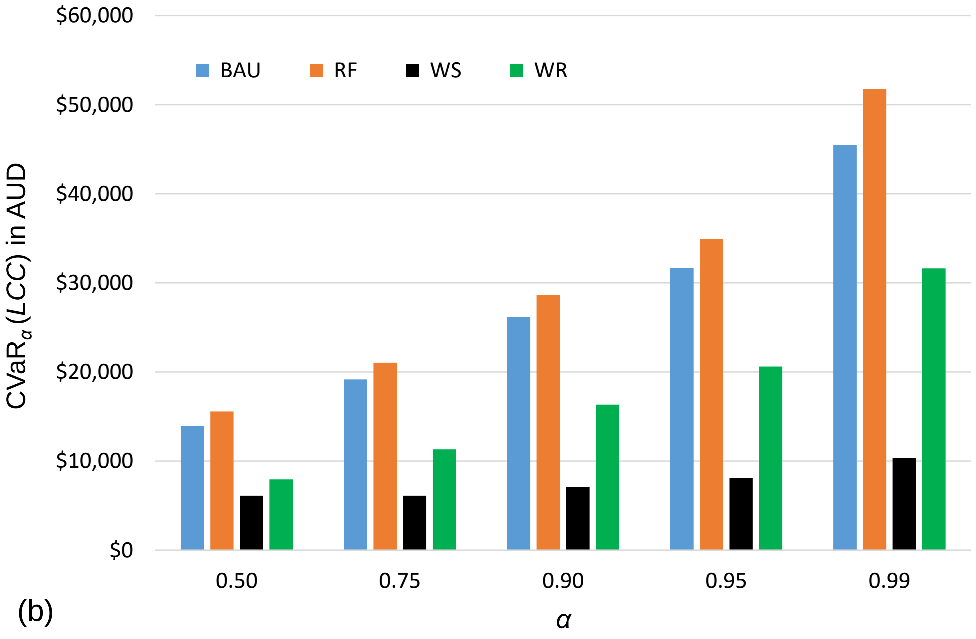


Fig. 7. Histograms of life-cycle costs corresponding to four wind mitigation decisions: (a) BAU; (b) RF; (c) WS; (d) WR.



BAU
RF
WS
WR
$60,000
$50,000
$40,000
$30,000
$20,000
$10,000
$0
$\mathrm{VaR}_{\alpha}(LCC)$ in AUD
0.50
0.75
0.90
0.95
0.99
α
(a)



BAU
RF
WS
WR
$60,000
$50,000
$40,000
$30,000
$20,000
$10,000
$0
$\mathrm{CVaR}_{\alpha}(LCC)$ in AUD
0.50
0.75
0.90
0.95
0.99
α
(b)

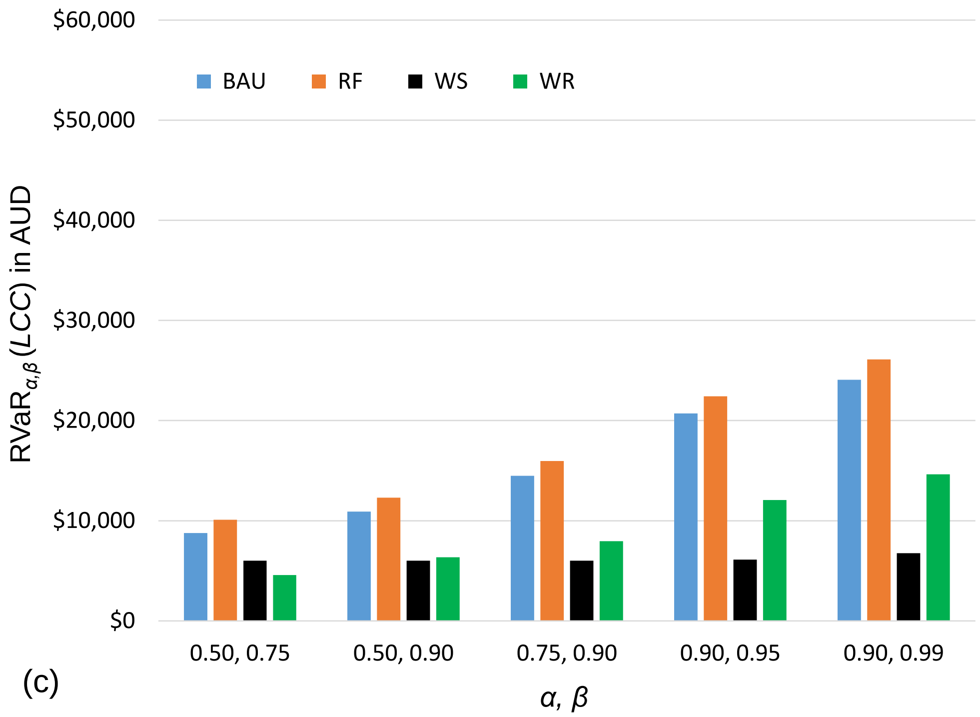


Fig. 8. Comparison of risk measures of life-cycle costs associated with the four mitigation decisions at different probability levels: (a) VaR; (b) CVaR; (c) RVaR.