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Economic risk analysis for sustainable urban development: validation of framework and decision support technique

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ABSTRACT

Sustainable urban development requires detailed assessment of economic, environmental and social impacts borne by major stakeholders. A framework to address these complex issues underpinning sustainable urban development is proposed to aid decision making in the face of uncertainties. An analytical approach is developed as a tool to assist decision makers by using an engineering approach, risk-based cost-benefit analysis model that encompasses concepts from "Life Cycle Costing", "Engineering Reliability Analysis" and "Risk Management". It aims to rank design options based on model outputs, such as rate of return, probability of loss and value at risk. This study presents the logic of this approach and tests the framework using a synthetic project formulated around the economic perspective of an investor in considering the implementation of various desalination plant technologies. Two alternative desalination plants were evaluated based on a collective of project information, and the results showed that the model output provided a clear indication of the preferred option using risk-based metrics.

Keywords: Cost-benefit analysis; Life cycle costing; Engineering reliability analysis; Risk management; Desalination

1. Introduction

Risk and uncertainty are of major consideration in appraising projects and issues are often raised concerning economic, environmental and social impacts of design options and their effects on different stakeholders. Risks may be defined as uncertain and unexpected events that may affect project elements such as scope, cost and quality [1], and their causes are often unforeseeable despite detailed planning [2]. Risk in investment is a significant factor in project evaluation. It is unavoidable; however, its impact on project goals can be reduced if it is well managed [3]. A variety of techniques to evaluate risk of building projects have been used in the past that enabled assessment of a range of facets of projects. Large infrastructure projects, like public private partnerships, explicitly consider risk and attempts are made to quantify the potential cost impact of such risks based on the likelihood of the event materialising, and the allowance to be made for the impact of

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the event. However, the accuracy of data used in these models is questionable leading to concerns over the value of these models to appropriately integrate the multiple uncertain variables involved in project appraisal. For instance, in desalination plants, uncertainty from factors such as water demand, water rates, energy prices and amount of rainfall will have an impact on decision making. Financial analysis would involve adding up construction and operational costs, and presenting it as a net present value and levelised cost per unit volume of water. In addition, certainty of construction risks of time and cost remain of ongoing concern. Often, investors are faced with the dilemma of choosing between a high yielding project with high risk, or a low return project with low risk [4]. The comparison of return with the amount of risk associated with different options can assist decision-makers in deciding the choice for optimal investment. This study presents an analytical approach to the extension of a risk component of cost-benefit analysis (CBA) and introduces risk management tools to aid investor decision.

Although uncertainty can be readily analysed using Monte Carlo Simulation (MCS) (approach generally adopted for major infrastructure projects) with the current capacity and accessibility of technology, there are shortcomings with the method. The fundamental technique involves sampling each random variable multiple times according to its probabilistic characteristics. Each sample represents a realisation that is solved deterministically in a given trial run. By simulating many trial runs, the probabilistic characteristics of the outcome can be obtained. However, this approach may be too time-consuming and become impractical in some cases [5]. The number of trial runs needed to achieve an acceptable level of accuracy may be very large, which could be problematic for computationally intensive deterministic systems and for those with multiple uncertain variables. While this paper uses MCS for some of the outputs, it also proposes an alternative method using engineering reliability analysis (ERA). MCS is often employed to verify the accuracy of new techniques and was used in this study. The proposed application reduces computational time as well as encompassing the distributional information of variables. The model is conceptually and mathematically based and developed from the economic perspective of engineering projects, where further inclusion of social and environmental aspects through future research is possible. Current practices primarily utilise traditional economic metrics such as benefit cost ratio as the basis for decision making, treating the analysis of risk separately [6]. While ERA has been applied to different engineering disciplines [7–9], only few literatures have been focused on reliability analysis and economics [10–12]. Implementation of ERA with CBA and financial analysis is relatively new. Moreover, value at risk (VaR), commonly employed in financial sectors, is introduced as one of the output metrics. Such a combination of economic and risk assessment has hardly been explored previously.

This study includes two sections with the results representing the initial development of a risk-based model to assist decision making. The first section addresses the background of the problem and introduces concepts of the model framework including CBA, life cycle costing (LCC), various risk management tools and ERA. Their functions within the framework are discussed. The second section presents a proof of the framework concept involving the study of two different desalination plants based in Victoria, Australia. The decision making capacity of the framework is demonstrated, and MCS is compared with the less computational intensive ERA for validation. Finally, the model outputs are discussed and the study concludes with suggestions for the direction of future research.

2. Research methodology

This study proposes a versatile risk assessment method as a decision-making tool for large engineering construction projects with a focus on economic impacts and implications to environmental and social factors. The framework overview is shown in Fig. 1. This will be a step forward to the quantification of social, economic and environmental impacts of sustainable infrastructure development that can be improved to increased sophistication for future consideration. The study presents a systematic methodology development together with a case study of desalination plants for model illustration.

3. Framework concept

Fig. 2 presents a systematic development of the framework. Step 1 instigates with the establishment of project scope and identification of infrastructure type. Step 2 identifies impact and involves recognising the variables included as benefit and cost. Step 3 gathers historical data related to variables identified in Step 2,

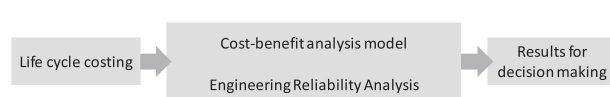

Fig. 1. Conceptual overview of model framework.

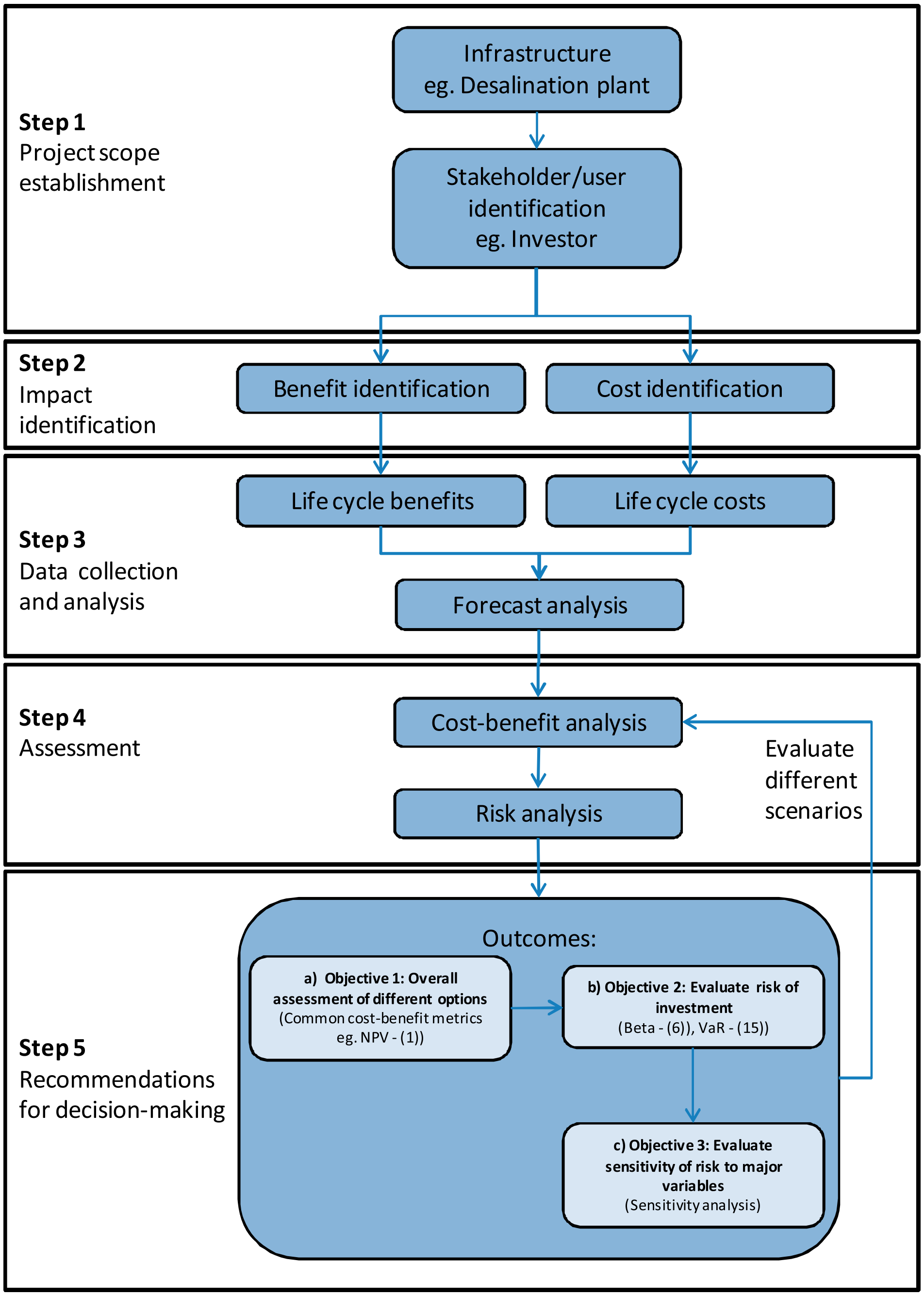

Fig. 2. Steps of the framework.

and projects the benefit and cost into future periods. This step also classifies the variables into the various phases of LCC. Step 4 discounts benefit and costs back to present values. Step 5 assesses the risk and uncertainty of variables using various risk-adjusted return tools and ERA. This final step also presents outcomes of the analysis in a form that is easily understandable to decision makers. To evaluate alternative scenarios, Step 4 is repeated to produce different sets of outcomes for comparison. Details of each model step are further addressed below and illustrated by the desalination plant case study.

Step 1: Project scope establishment

Involves determining the project context and identifying stakeholders of interest for the analysis. The boundaries and assumptions are also defined.

Step 2: Impact identification

Two methods to identify and examine benefit and cost variables include desktop research and/or evaluation of existing projects.

Step 3: Data collection and analysis

LCC is an expansion of life cycle assessment (LCA) to include economic issues that were originally utilised in USA in the 1960s [13]. LCA, part of the ISO 14000 Environmental Management Standards, assesses all stages of a product's life beginning from raw materials through disposal. It is a widely used framework in industries including materials production, manufacturing/construction and government organisations with the results used for analysis in business strategies, research and development, and inputs into product designs [14]. LCC is essential as ongoing costs of an engineering project can account for a significant proportion of its total cost during the entire project life. Data for the variables identified in Step 2 are acquired in this step. However, data related to uncertainty may not be readily available. Furthermore, it is especially challenging to forecast benefits and costs to a high degree of accuracy.

Step 4: Assessment

CBA is a technique used to examine economic relevant impacts and commonly applied to assess engineering projects by discounting costs to a net present value (NPV). NPV is the sum of discounted future cash flows of the entire project life and is shown in Eq. (1) [15]:

$$\mathrm{NPV} = B - C \tag{1}$$

where B = present value of all benefit, $\sum B_j(1+i)^{-t}$; C = present value of all cost, $\sum C_j(1+k)^{-t}$; t = time of the cash flow in years; i = discount rate for benefit; k = discount rate for cost; B_j = benefit variables, where $j = 1, 2, 3, \ldots$; C_j = cost variables, where $j = 1, 2, 3, \ldots$

Aside from NPV, other common indicator metrics are sometimes utilised that are specific to the type of infrastructure. For instance, levelised cost per unit volume of water is used for desalination plant assessments. This is later discussed in the case study.

CBA alone does not adequately evaluate project uncertainty. As such, this study introduces risk analysis to complement CBA. Two methods are introduced: MCS and ERA. As discussed, MCS uses random numbers to simulate uncertainty. While MCS is a useful technique to assess uncertainty, it can be computationally time consuming if the deterministic structure is complex or if the number of random variables are large. ERA may then be used alternatively to address this shortfall. ERA is a risk-based design concept to incorporate uncertainties into the design framework. It summarises the probability of events generated by computationally intensive models [16]. Different types of uncertainty can be captured by the analysts assessment of input variables relating to a systems specification, design and operation parameters for different scenarios. While MCS is able to reduce statistical uncertainty through multiple runs, ERA captures this variety by computing the probabilistic distributions of the output and summarised as a probability. Furthermore, sensitivity analysis can be used to compare different scenarios of critical parameters. As employed in a study by Lee and Kim [17], MCS was used to verify the results of ERA. Fig. 3 shows a simple case of benefit, B and cost, C, adapted from Haldar and Mahadevan [5]. Both are assumed to be statistically independent normally distributed random variables described by their means μ_B and μ_C, standard deviations σ_B and σ_C, and probability density functions $f_B(b)$ and $f_C(c)$. Feasible design conditions require satisfaction of $C_N < B_N$, where N represents the nominal values. The shaded area represents a qualitative measure in the probability of loss (PoL).

Taking NPV as defined in (1), PoL can be expressed with the following equation adapted from Haldar and Mahadevan [5]:

$$P_f = P(\text{loss}) = P(\mathrm{NPV}<0) = \int_0^\infty F_B(c) f_C(c)\,dc \tag{2}$$

where $F_B(c)$ is the cumulative distribution function of B calculated at "c". The PoL is dependent on the following factors:

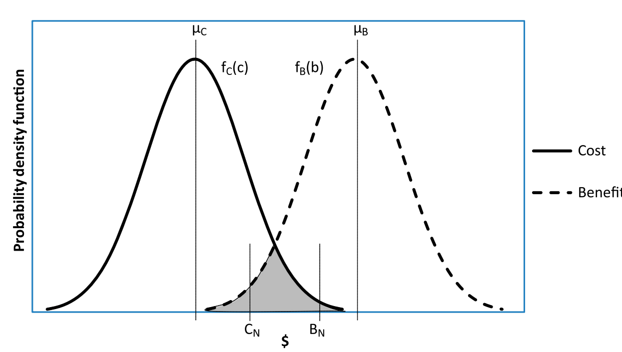

Fig. 3. Concept of ERA where C_n and B_n represents nominal values of cost and benefit respectively. The shaded area represents the PoL.

- position of curves, denoted by their means μ_B and μ_C,
- dispersion of curves, represented by their standard deviations σ_B and σ_C,
- shape of curves are characterised by their density functions $f_B(B)$ and $f_C(C)$.

The optimal design approach aims to find the smallest overlapping area. Suppose B and C are normal distributed variables, where $B \sim N(\mu_B, \sigma_B^2)$ and $C \sim N(\mu_C, \sigma_C^2)$. NPV is also a normal random variable as B and C are statistically independent. That is, $\mathrm{NPV} \sim N\left(\mu_B - \mu_C, \sqrt{(\sigma_B^2 - \sigma_C^2)}\right)$. The performance function can be further described by the following, adapted from [5]:

$$\mathrm{NPV} = g(X) = g(X_1, X_2, \ldots, X_n) \tag{3}$$

where X_i are the benefit and cost variables and X is the vector of variables. When NPV = 0, it is defined as the limit state or failure surface. ERA involves evaluating the limit state equation. The PoL thus becomes the integral defined as [5]:

$$P_f = \int \ldots \int_{g()<0} f_X(X_1, X_2, \ldots, X_n)\mathrm{d}X_1\mathrm{d}X_2 \ldots \mathrm{d}X_n \tag{4}$$

where $f_x(X_1, X_2, \ldots, X_n)$ signifies the joint probability density function for the random variables of $X_1, X_2, \ldots, X_n$. The integration is calculated for the failure region where $g() < 0$ in which the product of the individual probability density function could be used instead of the joint probability density function if the random variables are statistically independent [5]. The Eq. (4) is named the full distributional approach. The joint probability density function is hard to compute due to the difficulty in evaluating multiple integrals. Furthermore, information on variables is not always practically available. Instead, first-order reliability methods (FORM), a method to obtain analytical approximations of the integral utilising the means and standard deviations of variables, is applied [5,16]. FORM is used when the limit state function involves linearly uncorrelated normal variables. Where the limit state function is nonlinear, a first-order approximation of equivalent normal distributed variables is applied. For this study, the cost and benefit variables are assumed to be normal distributed, uncorrelated and exhibit a linear limit state function. The model uses the first-order second-moment, a type of FORM. The PoL is given by the evaluation of $B < C$, or NPV < 0 and could then be represented as [5]:

$$p_f = P(\mathrm{NPV}<0) = \Phi\left[\frac{0 - (\mu_B - \mu_C)}{\sqrt{\sigma_B^2 + \sigma_C^2}}\right] = 1 - \Phi\left[\frac{\mu_B - \mu_C}{\sqrt{\sigma_B^2 + \sigma_C^2}}\right] \tag{5}$$

where Φ is the cumulative distribution function of the standard normal variate. Hence, the PoL is dependent on the ratio between the mean and standard deviation of variable NPV. The ratio is known as the safety index or reliability index and it is represented by β [5]:

$$\beta = \frac{\mu_{\mathrm{NPV}}}{\sigma_{\mathrm{NPV}}} = \frac{\mu_B - \mu_C}{\sqrt{\sigma_B^2 + \sigma_C^2}} \tag{6}$$

The PoL from (5) can thus be re-expressed in terms of the safety index [5]:

$$p_f = \Phi(-\beta) = 1 - \Phi(\beta) \tag{7}$$

The performance function from (3) expanded into a Taylor series about the mean values produces [5]:

$$\mathrm{NPV} = g(\mu_X) + \sum_{i=1}^{n} \frac{\partial g}{\partial X_i}(X_i - \mu_{X_i}) + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{\partial^2 g}{\partial X_i \partial X_j} \times (X_i - \mu_{X_i})\left(X_j - \mu_{X_j}\right) + \ldots$$

where μ_{X_i} is the mean value of X_i and the derivatives are calculated based on the mean values of the random variables $X_1, X_2, \ldots, X_n$. To obtain the first-order approximation of the mean and variance of NPV, the series is shortened into linear terms [5]:

$$\mu_{\mathrm{NPV}} \approx g(\mu_{X_1}, \mu_{X_2}, \ldots, \mu_{X_n}) \tag{8}$$

$$\sigma^2_{\mathrm{NPV}} \approx \sum_{i=1}^{n}\sum_{j=1}^{n}\frac{\partial g}{\partial X_i}\frac{\partial g}{\partial X_j}\mathrm{Cov}(X_i, X_j) \tag{9}$$

where $\mathrm{Cov}(X_i, X_j)$ describes the covariance of X_i and X_j. If the variables are not correlated, the variance could be simplified to [5]:

$$\sigma^2_{\mathrm{NPV}} \approx \sum_{i=1}^{n}\left(\frac{\partial g}{\partial X_i}\right)^2 \mathrm{Var}(X_i) \tag{10}$$

The safety index β in (6) is the ratio between the mean and standard deviation of NPV and could be used to find the PoL in a few special cases. That is, when X_i are statistically independent normal variables and NPV is a linear combination of these values, which implies that NPV is also normal distributed. The limitation of this approach is that in cases where the variable is not normal or not statistically independent, or when NPV is not a linear function of the variables X_i, the safety index cannot be applied directly to determine the PoL. In such cases, the safety index could only be used as an indication of the risk level or reliability. Furthermore, in situations where the variables are correlated and non-normal distributed, or when the limit state function is non-linear, FORM cannot be applied [5]. This is important as many real life applications may not follow a normal distribution.

Step 5: Recommendations for decision-making

This final step involves the presentation of risk results in an understandable format to stakeholders of various backgrounds.

VaR is a single statistical measure of losses in response to the consequence of economic uncertainties [18]. It is commonly used in financial sectors to analyse portfolio risk of an asset [19,20] and was formulated as a response to fluctuations in interest rates, exchange rates and commodity prices [18]. It was selected for use as a benchmark for analysing risk in capital requirements by the Basel Committee on Banking Supervision [19]. VaR corresponds to a quantile of the loss distribution over a period of time at a specified confidence level [19]. As VaR combines the risk of potential losses into one number, it is a useful tool to signify market risk [21]. Adapted to this model, VaR provides information with the most probable worst-case scenario return experienced over a given time at a specified confidence level. Losses beyond the VaR occur at a specified probability [18]. In this study, it is employed to fit engineering project returns by drawing random samples from statistical distribution that subsequently allows the VaR to be determined. The derivation of VaR is given in Eqs. (11)–(15) adapted from Krause [22]. It represents the percentage return at 95% confidence level [22]. This indicates that the return is expected to be below the VaR value at 5% of the time. Alternative investment options can thus be ranked according to the values. A high VaR is favourable as the worst scenario return would still be a relatively high return.

$$\mathrm{Prob}(W \leq W^*) = \int_{-\infty}^{W^*} \mathrm{d}F(W) = 1 - \mathrm{Cl} \tag{11}$$

where Cl = confidence level; W = investment value; W^* = investment value with which the value falls below with a probability of $1-\mathrm{Cl}$.

$$\mathrm{VaR}^{\mathrm{Mean}}_{\mathrm{Cl}\cdot\Delta T} = E[W] - W^* \tag{12}$$

where ΔT = time horizon for the possible losses.

$$W^* = (1 + R^*)W_0 \tag{13}$$

$$E[W] = (1 + \mathrm{ER})W_0 \tag{14}$$

where R^* = returns; W_0 = current investment value; ER = expected return.

$$\mathrm{VaR}^{\mathrm{Mean}}_{\mathrm{Cl}\cdot\Delta T} = -W_0(R^* - \mathrm{ER}) \tag{15}$$

A second risk metric, the safety index β, is defined in Eq. (6). A higher β represents a more favourable investment. β can be used to derive the probability that an investment falls below \$0 NPV, denoted PoL. The risk metrics selected for the model are calculated using a combination of MCS and ERA. This is summarised in Table 1.

4. Case study

Droughts are not infrequent in Australia. In Victoria, Australia, water restrictions were in effect four times since its introduction in 1975 [23]. In the recent drought that began in 1997 and lasted for more than a decade, water storage levels dropped to 16% in the Thomson Reservoir [24]. With Australia's steady population growth, the drought prompted alternative sources of potable water to relieve the water-stressed reticulation system, such as the construction of desalination plants. Desalination processes can be categorised into membrane-based or thermal-based processes, and be used to treat different types of water. There are now several major desalination plants in Australia including the Gold Coast Desalination Plant in Queensland and the Perth Seawater Desalination Plant in Western Australia, both of which are operated by reverse osmosis. At the time that this study was written, the Wonthaggi Desalination Plant

Table 1
Set of results calculated employing various combinations of MCS and ERA

Indicator metrics	MCS	ERA
NPV	$\surd$	–
Expected return	$\surd$	–
Return standard deviation	$\surd$	–
VaR	$\surd$	–
PoL	$\surd$	–
β	$\surd$[a]	$\surd$[b]

[a,b]Used for comparison of MCS and ERA.

in Victoria was under construction. High rainfall since 2009 have caused some of the desalination plants in Australia to unexpectedly reduce its production capacity and potentially mothballed to save costs, as is the case for the Gold Coast Desalination Plant. Furthermore, unforeseeable construction problems and delays could increase project costs. It is, therefore, evident that construction of such large infrastructures is fraught with risk and uncertainty. Investors also have to consider the possibility that the plant may not be required to run at full production capacity during the entire duration of the investment given the inconsistent nature of Australia's climate, hence affecting the expected revenue. The risk model developed in this study is illustrated with two synthetic desalination plant alternatives, as formulated using background data from each of the above projects, differing in technology and operational requirements. A common desalination process involves the use of multi-stage flash (MSF) technology, which is being used extensively in the Middle East region [25]. Another popular process is reverse osmosis (RO) that is comparatively less expensive and achieves similar levels of water quality and reliability [26]. The framework steps outlined in Fig. 2 is applied in this section.

Step 1: Project scope establishment

Two desalination plants were identified for investigation in this study from Schliephake et al. [27], which was a study to examine the advantages and disadvantages of thirteen potential desalination technologies from different countries that may be suitable for Victoria's needs. Details of each plant are briefly summarised in Table 2 with data sourced and adapted from the report for this study. The two plants were selected based on diversity and comparability of plant production capacity. The report provided information on capital costs, energy costs, operation and maintenance costs and labour costs discounted to 2005 Australian dollars with a discount rate of 10%. Furthermore, this study also includes water rates and the uncertainty of reducing production capacity. The assumptions for the case study are outlined in Table 3. Appendix provides the cost data for the plants.

Step 2: Impact identification

Impacts were largely pre-identified through Schliephake et al. [27]. In addition, water rates and reduced production capacity were considered.

Table 2
Details of desalination plants

Plant	Desalination process/ technology	Water type processed	Potable water produced	Daily production capacity (m^3)[a]	Advantages	Disadvantages
Brownsville, USA	Reverse osmosis, membrane-based	River	Yes	100,000	• Low- energy consumption • Low- investment cost • Plant remains functional during maintenance	• High costs for membrane replacement • Sensitive to feed water quality • Life expectancy of membrane about 5–7 years minimum
IDE technologies	Multi-stage flash distillation (MSF), thermal-based	Sea	Yes	100,000	• Reliable technology • Long operating life • High quality product water	• High capital cost • High energy consumption • Necessary to shut entire plant for maintenance

[a]Rounded to the nearest capacity for simplicity.

Table 3
Desalination plant assumptions

Parameters	Assumptions
Currency	All costs and benefits in AUD, kept consistent with Schliephake et al. [27]
Discount rate	10%, kept consistent with Schliephake et al. [27]
Base year	2005, kept consistent with Schliephake et al. [27]
Full production capacity	100 mL/day, approximate average capacity of the two plants taken from Schliephake et al. [27]
Reduced production capacity	30% of full production capacity. For simplicity all ongoing operational costs are reduced by 50% on the assumption that costs cannot be fully eliminated even when plant is not in use. The duration of the reduced production capacity period is uncertain and is assumed to begin in 2009 to coincide with increased rainfall levels in Australia during that time. It is assumed to last for 5 years normally distributed with standard deviation of 2 years
Energy price forecast	Energy price from 2013 to 2025 = 551 n (CO_2 price)–135 [28] CO_2 price trajectory sourced from the treasure core scenario (medium) [29] Historical energy price from 2002 to 2012 [30]
Water price forecast	$P_t = P_{t-1} \times \mathrm{CPI}_t \times (1 + \mathrm{PPM}_t)$ [31,32] CPI assumed to be 2.43% [31] Average of business-water annual service charge from City West Water, South East Water, and Yarra Valley Water [33]
Length of investment for investor (different from plant life)	20 years
VaR confidence level	95%
Tax rate	30%

Step 3: Data collection and analysis

Desalination plants have significant ongoing costs and as such, LCC is appropriate. The models used to forecast energy prices are from [28,29]. Water rates were forecasted from [31–33] and were listed in Table 3. The variables that were analysed stochastically were water rates, energy price and duration of reduced production capacity. All other variables such as annual operation and maintenance cost, capital cost and labour cost were treated deterministically.

Step 4: Assessment

Apart from calculating NPV in the CBA, levelised cost per unit water is a common metric for desalination plant assessment. It accounts for the capital and operational costs over the production capacity of the plant, as shown in Eq. (16) adapted from Fane et al. [34]. Clearly, a more favourable investment is reflected by a low levelised cost per unit volume of water.

$$\text{Levelised cost} = \frac{\frac{\text{cap}\times i}{1-(1+i)^{-t_c}} + \text{op}}{\text{Annual yield}} \tag{16}$$

where cap = capital cost; op = annual operation cost; t_c = life time of asset; i = discount rate.

5. Results and discussion

Step 5: Recommendations for decision-making

The model outputs, from an investor's point of view, for the two desalination plants are listed in Table 4. Referring to Step 5 in Fig. 2, the case study illustrated the interpretation of the model outcomes. The uncertain variables were water rates, energy price and duration of reduced production capacity.

Objective 1: Overall assessment of different options

NPV and levelised cost of water are common indicator metrics used to compare between desalination plants. IDE Technology MSF is favourable as it exhibits the higher NPV of $103,666,382 over a 20-year period discounted at 10%, which indicates

Table 4
Model outputs with common CBA metrics

Plant location	Brownsville, USA	IDE technologies
Process	RO	MSF
Commission year	2005	2005
Final year	2025	2025
NPV ($)	62,018,145	103,666,382
Levelised $ per mL	1,055	868

that the plant has the higher difference between discounted benefit and cost. Likewise, it also possesses the lower levelised cost, producing water at $868 per ml. This further suggests that it is the least expensive option in generating potable water. The least favourable is Brownsville with the lowest NPV and highest levelised cost of water. These results compare favourably with the expert opinions used in the original project appraisals [27]. However, these commonly used indicator metrics do not shed light on the risk associated with each plant. The outcomes are calculated deterministically and thus ignore the uncertain nature of the variables. Therefore, while NPV and levelised cost of water are useful in providing the overall view of the options, it is inadequate to convey risk information.

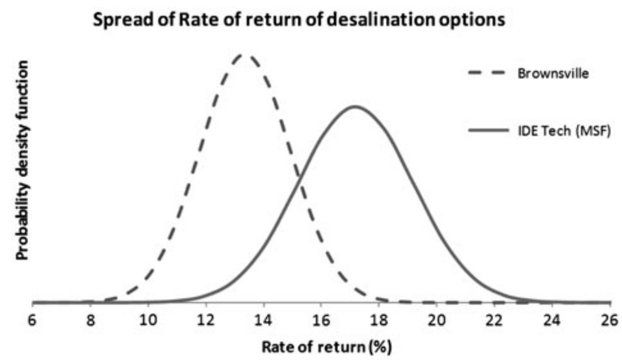

Fig. 4. IDE technology MSF has a larger return but higher return standard deviation (investment risk) than Brownsville.

Objective 2: Evaluate risk of investment

Rational investors seek projects that have high return with low risk. Table 5 shows the expected return and its standard deviation. The expected return is based on the internal rate of return. The standard deviation measures the variability of returns and is often associated with the extent of risk for a project. In examining the IDE Technology MSF, it has a high return of 17.18%, but also a high risk with return standard deviation of 2.01%. Brownsville has a low return with a lower risk. Fig. 4 illustrates the rate of return and standard deviation of the plants. It is evident that the risk of investment increases as the expected rate of return increases.

Without a clear set of guidelines, it is difficult for investors to decide which investment is more favourable. Two different risk indicator metrics are introduced: VaR and β. VaR holds information on return, and β examines probability. Firstly VaR, a commonly used measure in the finance sector, is suitable for this study as desalination plants that are large infrastructures with potential for large losses. Referring to Table 5, the VaR sheds light on a specific percentile of return, in this case 5% which may be considered a worse-case scenario. The interpretation of VaR is that return will be less than 10.9% for 5% of the time for the Brownsville plant. A lower VaR value is undesirable as the tail end of the NPV distribution will include a higher number of low returns. Secondly, β is an indicator for the PoL where NPV falls below $0. For instance, a β of 1.21 for the Brownsville investor suggests that the PoL will be 11.3%, indicating a 11.3% chance that NPV will fall below $0 given the set of assumptions. A higher β indicates lower PoL, implying a favourable investment. Comparing VaR and β in Table 5, IDE Technologies MSF is a better investment option over Brownsville as it exhibits a higher VaR of 14.2% and β of 2.12.

Table 5
Model outputs with risk indicator metrics

Plant location	Brownsville, USA	IDE technologies
Process	RO	MSF
Commission year	2005	2005
Final year	2025	2025
Expected return (%)	13.35	17.18
Return standard deviation (%)	1.59	2.01
VaR (%)	10.9	14.2
β	1.21	2.12
PoL (%)	11.3	1.7

VaR and β present risk from two perspectives depending on the type of information stakeholder needs. In cases, where the discount rate equals the weighted average cost of capital (WACC), β could be interpreted as the probability of obtaining a value that is lower than an investor's or company's required return. A low β or high PoL implies a risky investment as it suggests a large proportion of return will fall below the WACC. Investors would be keen to avoid such an investment.

Objective 3: Evaluate sensitivity of risk to major variables

Objective 3 examines the response of risk to major variables. For this case study, the major variables are water rates, energy price and the production capacity, when the desalination is not needed at full capacity during times of high rainfall. Under Objective 2, IDE Technology MSF was identified as a superior investment compared with Brownsville, when uncertainty had been taken into account. Hence, IDE Technology MSF is used to demonstrate objective 3. Fig. 5 shows the percentage change of VaR, when the three variables vary from −30 to 30% and suggests that water rates, and production capacity have the highest effect on the risk adjusted return. Similarly, Fig. 6 illustrates the percentage change of β when the variables vary from −30 to 30%, and shows that production capacity and water rates have the highest effect on β. The difference in ordering of the most influential variable could be attributed to the probability density profile of the IDE Technology MSF. Given that VaR's confidence level is set at 5% and β's corresponding probability lies below the VaR value, with a PoL of 1.7% probability, the β sensitivity in Fig. 6 reflects the change in very low tail events. That is, the extent that reduced capacity production effects risk is highest for extreme tail events. The VaR sensitivity suggests water rates and reduced capacity affects risk by around the same amount at the 5% worse-case scenario.

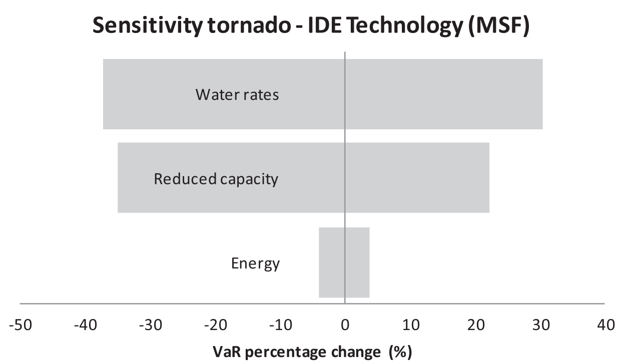

Fig. 5. Sensitivity analysis on major variables (−30 and 30%) of IDE Technology MSF plant shows that water rates and the extent of reduced production capacity have the highest effect on VaR.

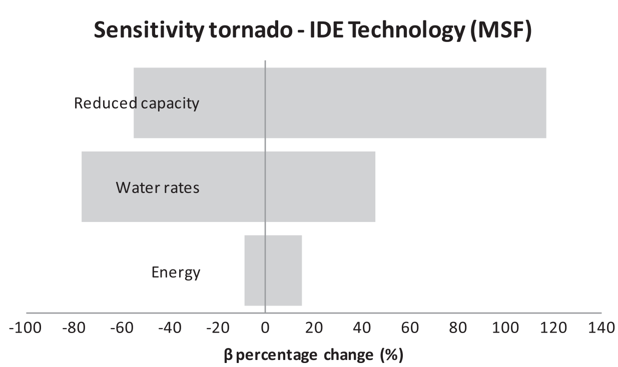

Fig. 6. Sensitivity analysis on major variables (−30 to 30%) of IDE Technology MSF plant shows that the extent of reduced production capacity and water rates have the highest effect on β.

The model generated β by two methods: MCS using 1,000 simulation runs, and ERA. The difference between β evaluated by using MCS and ERA is minimal, as shown in Table 6. The difference in percentage is also shown. However, ERA uses much less computational time than MCS. MCS takes approximately 1.5 min to run two sets of data on Excel. Given a set of either return and return standard deviation, or a set of benefit, cost and their standard deviations for each case, ERA produces the result instantly. This illustrates the computational efficiency in using ERA over MCS especially if the number of variables increases or if model variables become increasingly complex.

The adoption of a reliability approach that incorporates VaR and explicit computation of the uncertainty of the analysis enables critique and judgements to be made on the accuracy of the risk based model. This ability to appraise the uncertainty within the risk modelling provides a mechanism to sensibly assess the risk-based model rather than simply accepting the single point output from typical MCS analyses. The framework encourages analysts to identify variables of high uncertainty from the life cycle of a project and employ as inputs to the economic appraisal system. The reliability approach aims to collate and summarise the uncertainty systematically such that conclusions could be drawn for better decision-making.

Further, it has been demonstrated that the proposed framework is useful for evaluating risk in large infrastructure projects using VaR and β. In reality, investors and other stakeholders have higher interest in the downside risk than upside risk [35]. That is, losses are often viewed more heavily than gains. This is especially important for projects where the financial contingent for risk is small, particularly if

Table 6
Comparison of β values from MCS and ERA

Plant location	Brownsville, USA	IDE technologies
Process	RO	MSF
MCS	1.21	2.12
ERA[a]	1.21	2.10
Percentage difference	−0.22%	0.85%

[a]Standard deviation inferred from MCS.

an investment is privately-funded. Further research can improve on the model by introducing risk metrics that accounts for this assymmetric response to risk. In this model, the forecasting of variables have been formulated from pre-determined equations and government estimations. However, variables are often not well defined in future projections. The model could thus be improved by incorporating statistical forecasting techniques for variables that do not have clear forecasting guidelines. While the framework in this study has been built based on financial impacts, it is beneficial that future works be expanded to include social and environmental impacts. Monetary values are often obtainable for financial data, but becomes complicated and may be unavailable for non-monetary items. This may be explored using a range of non-monetary valuation techniques such as travel cost method, replacement costs and environmental benefits transfer [36]. Another challenge is the determination of an appropriate discount rate to evaluate the present value of future cash flows. This study uses 10% which is consistent with Schliephake et al. [27]. Issues surrounding the intergenerational fairness of discount rates have been raised in the literature [37]. Market rates are often applied as the discount rate however, it has been argued that present values of distant future cash flows would be valued too low when effects could in fact be momentous in future years.

6. Conclusions

The lack of a comprehensive system for assessing project risk has led to the development of a risk-based CBA model for economic appraisal to assist in decision-making. This study presented an analytical approach in developing the framework for the decision making, which enables the assessment of multiple uncertain variables. The model employs concepts from LCC, ERA and risk management tools including VaR and β. The result is to aid common CBA metrics, such as NPV, with risk outcomes that are easily understood by a wide range of stakeholders. The study used the synthetic project of two desalination plants to illustrate the model from an investor's financial point of view. It has been shown that VaR and β can be used to rank different investment options. Other additions to the model is suggested by including risk metrics that takes into account the asymmetric behaviour of investors to risk, utilising better statistical forecasting techniques, incorporating social and environmental factors, and by studing the effects of discount rate on risk economic appraisals.

Symbols

B	—	present value of all benefit, $\sum B_j(1+i)^{-\tau}$
B_j	—	benefit variables, where $j = 1, 2, 3, \ldots$
C	—	present value of all cost, $\sum C_j(1+k)^{-\tau}$
cap	—	capital cost
C_j	—	cost variables, where $j = 1, 2, 3, \ldots$
Cl	—	confidence level
Cov	—	covariance
ER	—	expected return
$f_B(c)$	—	cumulative distribution function of B calculated at c
f_x	—	joint probability density function
i	—	discount rate for benefit
k	—	discount rate for cost
NPV	—	net present value
op	—	annual operation cost
R^*	—	returns
t	—	time of the cash flow (year)
t_c	—	life time of asset
VaR	—	value at risk
W	—	investment value
W^*	—	investment value with which the value falls below with a probability of $1-$Cl
W_0	—	current investment value
X	—	vector of variables
X_i	—	benefit and cost variables
β	—	safety index or reliability index
ΔT	—	time horizon for possible loses
μ	—	mean
μ_{Xi}	—	mean value of X_i
σ	—	standard deviation
Φ	—	cumulative distribution function of standard normal variate

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References

[1] E.S. Chia, Risk assessment framework for project management, in: 2006 IEEE International Engineering Management Conference, Bahia, September 17–20 (2006) 376–379.
[2] N. Gil, B.S. Tether, Project risk management and design flexibility: Analysing a case and conditions of complementarity, Res. Policy 40 (2011) 415–428.
[3] A. Nieto-Morote, F. Ruz-Vila, A fuzzy approach to construction project risk assessment, Int. J. Project Manage. 29 (2011) 220–231.
[4] K. Dowd, Adjusting for risk: An improved Sharpe ratio, Int. Rev. Econ. Finance 9 (2000) 209–222.

[5] A. Haldar, S. Mahadevan, Probability, Reliability and Statistical Methods in Engineering Design, Wiley, New York, 2000.
[6] Infrastructure Australia, Infrastructure Australia's Reform and Investment Framework. Australian Government, 2012, Canberra, Australia.
[7] G. Lemming, P. Friis-Hansen, P.L. Bjerg, Risk-based economic decision analysis of remediation options at a PCE-contaminated site, J. Environ. Manage. 91 (2010) 1169–1182.
[8] W. An, W. Zhao, H. An, Reliability analysis of stochastic structural system considering static strength, stiffness and fatigue, Sci. China Ser. G 50(3) (2007) 357–369.
[9] B.M. Ayyub, I.A. Assakkaf, J.E. Beach, W.M. Melton, N.J. Nappi, J.A. Conley, Methodology for developing reliability-based load and resistance factor design (LRFD) guidelines for ship structures, Naval Eng. J. 114(2) (2002) 23–41.
[10] P. Zhang, W. Li, Boundary analysis of distribution reliability and economic assessment, IEEE Trans. Power Syst. 25(2) (2010) 714–721.
[11] E. Stoker, J.B. Dugan, Economic reliability forecasting in an uncertain world, in: 17th European Simulation Multiconference, Nottingham Trent University, Nottingham, England, 2003, pp. 217–221.
[12] Y.T. Yoon, M.D. Ilić, A possible notion of short-term value-based reliability, in: Winter Meeting of the IEEE-Power-Engineering-Society, New York, NY, 2002, pp. 772–778.
[13] J.B. Guinée, R. Heijungs, G. Huppes, A. Zamagni, P. Masoni, R. Buonamici, T. Ekvall, T. Rydberg, Life cycle assessment: Past, present, and future, Environ. Sci. Technol. 45(1) (2011) 90–96.
[14] J.S. Cooper, J.A. Fava, Life-cycle assessment life-cycle assessment: Summary of results, J. Indust. Ecol. 10(4) (2006) 12–14.
[15] N. Hanley, C.L. Spash, Cost-Benefit Analysis and the Environment, Edward Elgar, Cheltenham, 1993.
[16] D. Straub, A. Der Kiureghian, Bayesian network enhanced with structural reliability methods: Methodology, J. Eng. Mech. 136(10) (2010) 1248–1258.
[17] O.S. Lee, D.H. Kim, The reliability estimation of pipeline using FORM, SORM and Monte Carlo simulation with FAD, J. Mech. Sci. Technol. 20(12) (2006) 2124–2135.
[18] T.J. Linsmeier, N.D. Pearson, Value at risk, Financ. Anal. J. 56 (2) (2000) 47–67.
[19] Z. Cai, X. Wang, Nonparametric estimation of conditional VaR and expected shortfall, J. Econo. 147 (2008) 120–130.
[20] J.C. Escanciano, P. Pei, Pitfalls in backtesting historical simulation VaR models, J. Banking Finance 36 (2012) 2233–2244.
[21] D. Hendricks, Evaluation of value-at-risk models using historical data, Econ. Policy Rev. 2(1) (1996) 39–70.
[22] A. Krause, Exploring the limitations of value at risk: How good is it in practice? J. Risk Finance 4(2) (2003) 19–28.
[23] Melbourne Water. History of Managing Drought in Melbourne (2012) [cited 2012 21/10/2012]; Available from: <http://www.melbournewater.com.au/content/water_conservation/drought_management/history_of_managing_drought.asp>.
[24] Melbourne Water. Thomson Reservoir (2012) [cited 2012 21/10/2012]; Available from: <http://www.melbournewater.com.au/content/water_storages/water_supply/water_distribution/thomson_reservoir.asp?bhcp=1>.
[25] L. Yang, S. Shen, H. Hu, Thermodynamic performance of a low temperature multi-effect distillation experimental unit with horizontal-tube falling film evaporation, Desalin. Water Treat. 33 (2011) 202–208.
[26] D.L. Owen, Towards sustainable desalination, Desalin. Water Treat. 35 (2011) 10–13.
[27] K. Schliephake, P. Brown, A. Mason-Jefferies, K. Lockey, C. Farmer, Overview of Treatment Processes for the Production of Fit for Purpose Water: Desalination and Membrane Technologies, 2005, report to the Department of Sustainability and Environment for the project entitled Desalination and Membrane Technologies.
[28] J. Burgess, Low-Carbon Energy Evaluation of New Energy Technology Choices for Electric Power Generation in Australia, Australian Academy of Technological Sciences and Engineering, Melbourne, 2010.
[29] R. Jackson, 2012 Scenarios Descriptions, Australian Energy Market Operator, Sydney, 2012.
[30] Average Price Tables. 2012 [cited 2012 20/10/2012]; Available from: <http://www.aemo.com.au/Electricity/Data/Price-and-Demand/Average-Price-Tables>.
[31] Synergies Economic Consulting, Australian water prices, Gladstone Area Water Board, Brisbane, 2010.
[32] Metropolitan Melbourne Water Price Review 2009 Final Decision: Yarra Valley Water Determination (2009), Essential Services Commission: June.
[33] Fact Sheet 3 – Metropolitan Water Price Review Final Decision – Tariff Elements, Essential Services Commission, 2009.
[34] S. Fane, J. Robinson, S. White, The use of levelised cost in comparing supply and demand side options, Water Sci. Technol.: Water Supply 3(3) (2003) 185–192.
[35] J.F. Bacmann, S. Scholz, Alternative performance measures for hedge funds, AIMA 1 (2003) 1–9.
[36] D. Hadley, J. D'Hernoncourt, F. Franzén, G. Kinell, T. Söderqvist, Å. Soutukorva, R. Brouwer, Monetary and Non Monetary Methods for Ecosystem Services Valuation—Specification Sheet and Supporting Material: Spicosa Project Report, University of East Anglia, Norwich, 2011.
[37] S. Stagl, SDRN rapid research and evidence review on emerging methods for sustainability valuation and appraisal, University of Sussex, Brighton, 2007, p. 70.

Appendix. Cost data of plants taken from Schliephake et al. [27]

Plant location	Process	Capital cost (AUD million)	Energy (kWh/m^3)	Annual membrane replacement (AUD/m^3) (if reported separately)	Annual O&M (AUD/m^3)	Labour (AUD/m^3)
Brownsville, USA	RO	197.2	3.68 (total kWh/total annual production)	All operations and maintenance costs have been reported in O&M, no separate reporting of membrane replacement or maintenance	AUD 0.15/m^3 (generated by dividing total O&M costs by total production). O&M includes chemicals, site maintenance and miscellaneous costs	AUD 0.05/m^3 (generated by dividing total labour costs by total production)
IDE Technologies	MSF	148.5	3.5	All operations and maintenance costs have been reported in O&M, no separate reporting of membrane replacement or maintenance	AUD 0.16/m^3 calculated by dividing total cost by annual output (includes chemicals and spare parts)	AUD 0.02/m^3 (calculated by dividing total labour cost by annual output)