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Comparisons of Risk-based Decision Rules for the Application of Water Resources Planning and Management

Hsin-Ting SU · Yeou-Koung Tung

Abstract Water resources planning and management are plagued with various uncertainties in that any chosen management alternative always has the possibility to be inferior to other competing alternatives. To facilitate risk-based decision making, the minimax expected opportunity loss (*EOL*) rule is applied for alternative selection. Two existing risk measures as well as *EOL* are compared and their implications in risk-based decision making are examined. It is shown that *EOL* can reflect more accurately the relative merit of two competing alternatives without suffering the pessimism and the counter-intuition of the other two risk measures considered herein. The minimax *EOL* rule is demonstrated through an application to a river basin management decision for improving the navigation. The results show that the correlation between outcomes of competing alternatives and decision maker's acceptable risk are important in decision making under uncertainty.

Keywords Water resources management · Decision making under uncertainty · Risk · Risk measure · Opportunity loss

1 Introduction

Decision making is an integral part of water resources engineering, analysis and management. Miser and Quade (1985) state that decision making problems have five elements including objectives, alternatives, outcomes, model and decision rules. Objectives are what the decision makers desire to achieve. Alternatives are courses of action to achieve the objectives. Outcomes, or consequences, are the results ensued from the execution of the alternatives. A state of nature is an event that may occur in the future over which the decision maker has little

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or no control. Due to unforeseeable changes of state of nature or future development, each alternative outcome (e.g., project net benefit or life-cycle cost of a system) is uncertain and can be treated as random variables with known probabilistic features (Park and Sharp-Bette 1990; Porter and Carey 1974; Tung et al. 1993). Decision rules are used to compare and rank alternatives with respect to the desirability of outcomes. The model is an abstraction of the real-world by considering the factors relevant to the problem for investigating the behaviour or response of a system. It evaluates the effect of alternatives on system performance under different scenarios. Based on the model outcomes (e.g., total flood damage or benefit), decision makers determine a preferred alternative for implementation. In terms of economic cost-benefit analysis, the preferred alternative may be the one with the largest project benefit or the least life-cycle cost of a system.

A risk-based decision making process is illustrated by Fig. 1. In reality, uncertainties may exist in all elements of a model that render uncertain outcomes. Those uncertainties can arise from inherent randomness in nature, and knowledge deficiency due to inadequate data and model, as well as scenario uncertainties. The uncertainty inherently present in the scenario outcome prediction is difficult to control and evaluate in decision analysis. The effect of a chosen alternative is rarely under one's firm grasp when the associated outcome is affected by factors with considerable uncertainties. With uncertain state of nature, the outcome of the alternative cannot be predicted with absolute certainty to allow making straightforward decision in step (4) of Fig. 1. Ignoring uncertainties in outcome prediction can misrepresent the true merit of alternative outcomes and hinder rational decision making. Tung (1987) has shown that the annual expected damage in a flood levee design can be significantly underestimated if hydrological parameter uncertainties are not accounted for, even with a 75-years long flood record.

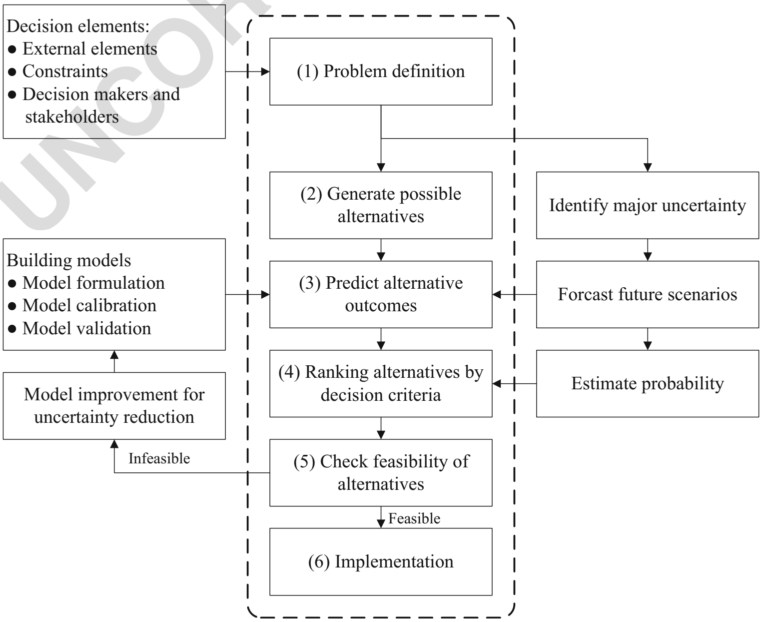

Fig. 1 Risk-based decision making procedure

1.1 Decision Rules Considering Uncertainties

In general, zero-risk for decision under uncertainty is unattainable (Kaplan and Garrick 1981). An analysis of outcome uncertainty can provide decision makers with a comprehensive basis to formulate proactive management strategies. It is desirable to have a decision procedure which can explicitly incorporate outcome uncertainties, and to effectively assess the influence of uncertainties on the merit of each alternative. Incorporating uncertainties in decision process is important but challenging. Risk-based decision-making has been advocated for water resources management and design (Duchesne et al. 2001; Jenkins and Lund 2000; Kangas et al. 2000; Melching and Yoon 1996; Tung 2005; Vreugdenhil 2006; Walker et al. 2003; Xu and Tung 2009).

Some conventional decision rules under uncertainty are briefly summarized here. The expected-value rule is widely used in engineering practice for its easy implementation without requiring detail statistical properties other than the expected outcomes. If direct use of expected monetary terms in decision analysis is not suitable, a utility function can be used to reflect the value of each wealth level to a decision maker as well as his/her risk attitude. Although the expected utility theory is often applied to problems of decision making under risk, its application usually encounters practical difficulties in decision making for public affairs including water resources management. The form of a utility function is not easy to determine, especially when the interests of multiple stakeholders involved are in conflict with one another. The mean-variance (M-V) rule, first proposed by Markowitz (1952), is frequently used in investment and project evaluation under uncertainty to narrow down to a few alternatives that are not inferior to one another. For a risk-averse decision maker, an alternative with higher expected outcome and/or lower variability is preferred. Under the notion that the variability of returns is not undesirable, the mean-semivariance rule is used to consider the mean and focus only on the variability of negative outcome (Estrada 2007). This method requires a full knowledge of the probability distribution. The two M-V rules are easy to implement but might not give a clear indication of the ranking among competing alternatives. To consider the downside risk, the probability-of-loss rule is used of which a well-known variation is the safety-first rule (Bonini 1975; Roy 1952) by which the decision maker favours the alternative with the smallest probability of loss. This rule, however, overlooks the magnitude of potential risk.

Stochastic dominance (SD) rules provide more theoretical examination in determining the preference among various competing alternatives with uncertain outcomes. The implementation of the SD rules requires the knowledge of marginal probability distribution, not just the mean and variance of alternative outcomes (Hadar and Russell 1969; Hanoch and Levy 1969; Quirk and Saposnik 1962). The first three degree SD rules are commonly used to determine the relative merit of alternatives (Castro et al. 2009; Tung and Yang 1994; Whitmore 1970). The second and third-degree stochastic dominance are applicable for risk-averse decision makers to determine the preferred alternative.

In practice, the decision problem may not be quantified because of ambiguity of sources of uncertainty, such as lack of precise understanding of the problem and subjective interpretation of the objectives. In this case, the approach on the basis of fuzzy set theory (Zadeh 1965) is another way to expand on the existing decision making procedure to account for the so called information uncertainties (Teegavarapu and Simonovic 1999). The fuzzy approach, since its introduction, has been widely applied in a variety of fields. Its applications in water resources management started about a decade ago (Simonović 2012) for solving reservoir operation problems (Teegavarapu and Simonovic 1999), for qualitative evaluation of flood control measures (Despic and Simonovic 2000), and for water resource systems planning under uncertainty (Bender and Simonovic 2000).

Generally speaking, the probabilistic approach is beneficial in quantifying objective uncertainties. On the other hand, the fuzzy approach can be used to deal with subjective uncertainties (Simonović 2012). The utilization of these two approaches depends on the available information and the precision of the model formulation. The fuzzy approach can be used when the uncertainties are not quantifiable or sufficient historical data is not available. In this study, the probabilistic approach is used in dealing with decision making under uncertainty.

1.2 Need for Risk Measures for Decision Making Under Uncertainties

When uncertainties are present, no matter which alternative is chosen over the others, the selection always has a certain probability to succeed or fail, even though the decision makers anticipate the chosen alternative would bring more desirable outcome than those unselected ones. A correct decision here is referred to as the chosen alternative turns out to yield a better outcome than the others. Apostolakis (2004) listed the benefits of the quantitative risk assessment in the process of risk-based decision making: (a) facilitate communication among analysts, decision makers, and stakeholders in different groups and disciplines; (b) quantify the uncertainties and provide valuable information toward decision; (c) identify critical scenarios and facilitate risk management; and (d) lead to a risk-informed decision making. Therefore, a quantifiable risk measure is needed to assess the relative merit of a chosen alternative with reference to the other and to quantitatively assess the potential loss.

Two other issues are relevant in risk-based decision making: decision maker’s acceptable risk and correlation among uncertain alternative outcomes. The convention methods mentioned above cannot address three important issues in decision making: (1) how much better is a preferred alternative over its competitor? (2) Is the preferred alternative feasible and implementable from the decision maker’s view point? (3) How does the outcome correlation among the alternatives influence their relative merit and subsequent decision?

From the viewpoint of prudent management, setting an acceptable tolerance for potential loss and preparing a proper contingency in advance are advisable practices for dealing with the adverse impacts of failing to achieve the anticipated outcome. This acceptable tolerance for potential loss or contingency can be interpreted as acceptable risk (Su and Tung 2013). If the potential loss associated with the decision of selecting one particular alternative is lower than the acceptable risk, this decision is implementable because the associated loss is tolerable. Otherwise, implementing the alternative may not be prudent because the associated potential loss could be beyond the decision maker’s or stakeholder’s capacity to absorb. Hence, the acceptable risk set by the decision maker should be considered and used to examine the feasibility of implementing a chosen alternative as shown in step (5) of Fig. 1. Stewart et al. (2001) applied the concept of acceptable risk in the ranking of alternatives of four different bridge designs and informed the decision maker the acceptable alternatives. Xu (2005) designed a questionnaire to obtain decision makers’ acceptable risk as a feasibility threshold for a river basin management project.

In real-life water resource management, it is not uncommon that outcomes of various competing alternatives are dependent on some common factors or attributes which renders outcomes being correlated. For example, in designing a flood control system for a river basin, the project alternatives might be different protection levels against the same random flood load. In this case, the project cost and benefit are affected by the common factors such as rainfall, flow hydrograph, channel geometry, boundary conditions, and topographical/land use features of the study area. To some degrees the outcomes of each alternative are expected to be correlated. In this situation, ignoring the dependence of alternative outcomes will not truly reflect the uncertainty features of relative merit among different alternatives and, hence, affect the validity of the decision. Practically, all conventional decision making decision rules mentioned earlier are univariate that do not have the provision to account for the effect of correlation among alternative outcomes.

In addition, from the 'damage control' viewpoint, a decision method should consider the consequence of making a wrong decision. Reducing the cost of over-design and the unexpected loss of under-design is the essence of the risk-based design (Schoustra et al. 2004; Tung 1994). Recently, the idea of considering the potential loss and gain as the consequences of disease diagnoses is applied in the retrieval stage of case-based reasoning (Castro et al. 2009). This method aims at choosing a best possible diagnose that minimizes the potential loss in case the diagnose turns out to be wrong.

Recently, the concept of opportunity cost is incorporated into the decision analysis for evaluating the expected loss of choosing a project alternative among multiple risky ones. The minimax-based expected opportunity loss (*EOL*) rule is developed for engineering decision making under uncertainty (Su and Tung 2013). Different from the conventional definition of opportunity loss, the *EOL* is obtained by integrating the opportunity loss of a chosen alternative and the associated probability density function of the outcome when the induced outcome is inferior to its competitor.

In this study, the properties of two related risk measures developed earlier: Xu's risk measure (*XRM*) (Xu and Tung 2008) and the conditional risk measure (*CRM*) (Xu et al. 2009), along with the *EOL*, are demonstrated and compared through an application to a simplified river basin management of the Elbe River. Both risk measures of *EOL* and *CRM* share the same notion that a best alternative should have a minimum loss when the decision turns out to be wrong.

2 Three Quantitative Risk Measures

Consider a decision problem of selecting between two alternatives A_i and A_j with uncertain outcomes X_i and X_j, respectively. Treating alternative outcomes X_i and X_j as random variables, the mean μ_i, μ_j and standard deviation σ_i, σ_j of outcome X_i, X_j, respectively, are assumed to be known. When $\mu_i > \mu_j$, it is logical to choose alternative A_i over A_j because of its higher long-term expected outcome. However, it is still possible that the chosen alternative A_i could turn out to be worse than the unselected A_j. There is a possibility that the resulting outcome of selected alternative is less desirable than the unselected one in that the decision maker's anticipated net gain from choosing alternative A_i over the other may not be realized. The probability that the chosen alternative A_i would be wrong can be mathematically expressed as

$$P_r\left(X_i < X_j\right) = \int_{-\infty}^{\infty}\left[\int_{-\infty}^{x_j} f_{i,j}\left(x_i, x_j\right)\, dx_i\right] dx_j \quad (1)$$

where $f_{i,j}$ (x_i, x_j) is the joint probability density function (PDF) of X_i and X_j. The *XRM* corresponding to the decision of selecting alternative A_i instead of A_j is defined as (Xu and Tung 2008)

$$XRM\left[A_i^*, A_j\right] = \left(\mu_i - \mu_j\right) \times P_r\left(X_i < X_j\right) \quad (2)$$

where $(\mu_i - \mu_j)$ is the difference of expected net gain in outcome for choosing A_i (indicated by A_i^*) over A_j. Therefore, *XRM* $[A_i^*, A_j]$ can be viewed as "the risk of obtaining an unacceptable ranking for the pair of management alternatives under consideration" (Xu and Tung 2008). Therefore, if the risk can be accepted by the decision maker, the ranking of alternatives will be acceptable.

Anticipating the outcome of unselected alternative A_j being better than the chosen alternative A_i, the potential loss that would incur can be expressed as a conditional expected loss. The *CRM* associated with a chosen alternative A_i over A_j is defined as (Xu et al. 2009)

$$CRM\left[A_i^*, A_j\right] = E_L\left[X_j - X_i \;\middle|\; X_i < X_j\right] = -\frac{\int_{-\infty}^{\infty}\left[\int_{-\infty}^{x_j}(x_i - x_j) f_{i,j}(x_i, x_j)\, dx_i\right] dx_j}{\int_{-\infty}^{\infty}\left[\int_{-\infty}^{x_j} f_{i,j}(x_i, x_j)\, dx_i\right] dx_j} \tag{3}$$

The negative sign introduced on the right-hand side is to make loss positive-valued. The *CRM* represents the expected loss anticipating that the decision turns out to be wrong. This measure is also called the expected shortfall in financial risk management (Christoffersen 2003). According to Xu et al. (2009), when *CRM* $[A_i^*, A_j] <$ *CRM* $[A_j^*, A_i]$, alternative A_i is preferred, or $A_i \succ A_j$.

The risk measure of *EOL* associated with the chosen alternative A_i is a probability-weighted opportunity loss in the domain of $x_i < x_j$, which can be defined as

$$EOL\left[A_i^*, A_j\right] = -\int_{-\infty}^{\infty}\left[\int_{-\infty}^{x_j}(x_i - x_j) f_{i,j}(x_i, x_j)\, dx_i\right] dx_j \tag{4}$$

where *EOL* $[A_i^*, A_j]$ is the expected opportunity loss associated with the chosen alternative A_i which turns out to be incorrect. The condition that *EOL* $[A_i^*, A_j] <$ *EOL* $[A_i, A_j^*]$ means that the choosing A_i has more advantage than choosing A_j. This measure is analogous to the first lower partial moment of the outcome difference (Bawa and Lindenberg 1977).

The term $(x_i$-$x_j)$ represents an opportunity loss when $(x_i$-$x_j)<0$ or an opportunity gain when $(x_i$-$x_j)>0$. In general, the loss is a function of $(x_i$-$x_j)$ and the form of loss function reflects the relative importance of the error committed from a choice under a state of nature (Parmigiani and Inoue 2009).

The compliment of the *EOL* is the expected opportunity gain (*EOG*), which can be similarly expressed as

$$EOG\left[A_i^*, A_j\right] = \int_{-\infty}^{\infty}\left[\int_{x_j}^{\infty}(x_i - x_j) f_{i,j}(x_i, x_j) dx_i\right] dx_j \tag{5}$$

Eqs. 4 and 5 represent the potential loss and gain for a chosen alternative over the other. They can be used as figures of merit, along with the decision maker's risk attitude, to evaluate the relative preference among the two competitive alternatives under consideration. Notice that in the above discussion, the utility of X_i and X_j are assumed to be monotonically increasing with the values of X_i and X_j, i.e., the alternative is more desirable with higher outcome value. On the other hand, if the outcome has a decreasing utility as its value increases, such as cost, a negative sign should be attached to the outcome. In doing so, the calculations of the *EOL* by Eqs.(4) and (5) would be also applicable and valid.

It can be easily shown that the long-term expected return associated with choosing alternative A_i, $E\,[X_i$-$X_j]$, can be partitioned into two parts as

$$E\left[X_i - X_j\right] = EOG\left[A_i^*, A_j\right] - EOL\left[A_i^*, A_j\right] \tag{6}$$

Furthermore, it can also be proved that $EOL\ [A_i^*, A_j] = EOG\ [A_i, A_j^*]$ and $EOL\ [A_i, A_j^*] = EOG\ [A_i^*, A_j]$ by changing the order and the boundary of the integration in Eqs. (4) and (5). Then, Eq. (6) can be expressed as

$$\begin{aligned} E\left[X_i - X_j\right] &= EOL\left[A_i, A_j^*\right] - EOL\left[A_i^*, A_j\right] \\ &= EOG\left[A_i^*, A_j\right] - EOG\left[A_i, A_j^*\right] \end{aligned} \quad (7)$$

The equation indicates that once the *EOL* of selecting alternative A_i over A_j is computed, the *EOL* for selecting alternative A_j over A_i can be easily obtained.

It is expected that the value of $EOL\ [A_i^*, A_j]$ would be affected by the relative magnitudes of the means and standard deviations of the two alternatives. Figure 2 shows that the *EOL* value is sensitive not only to the change in mean ratio (μ_i/μ_j), but also in standard deviation ratio (σ_i/σ_j). For a fixed mean ratio μ_i/μ_j, the value of *EOL* increases with an increase in standard ratio σ_i/σ_j in choosing alternative A_i. This behaviour agrees intuitively that choosing an alternative with relatively higher outcome variance will lead to a higher potential risk and expected loss. Figure 3 can be used to explain the behaviour of diminishing *EOL* value with increasing mean ratio R_μ. With larger expected outcomes of the chosen alternative or smaller expected outcomes of the unselected alternative, the joint PDF will move to the right and/or downward in this figure as R_μ increases. This results in a decrease in probability of $x_i<x_j$ and consequent decrease in the $EOL\ (A_i^*, A_j)$ value. The effect of correlation can be accounted for when the joint PDF is used in the evaluation of potential losses. The conventional decision rules described previously (e.g., M-V and SD) only utilize information about marginal distributions.

It can be shown that the $CRM\ [A_i^*, A_j]$ is the $EOL\ [A_i^*, A_j]$ rescaled by a factor representing the probability that the outcome of the unselected alternative A_j exceeds that of the chosen A_i^*. Hence, there is an inherent pessimism built in *CRM* because the decision maker, when making the choice, has already anticipated that the decision would go wrong.

When alternative A_i has a larger μ_i than alternative A_j and $\mu_i-\mu_j$ is large, the corresponding value of *XRM* is small due to low probability of $X_i<X_j$. In this situation, alternative A_i is a more

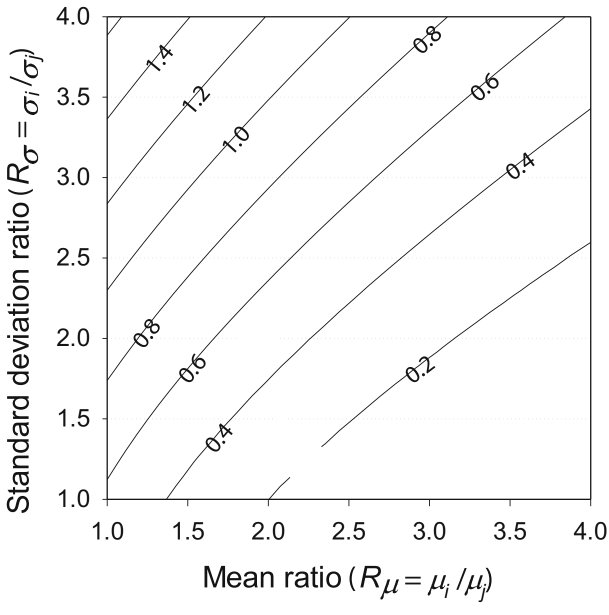

Fig. 2 Effect of R_μ and R_σ on the *EOL*

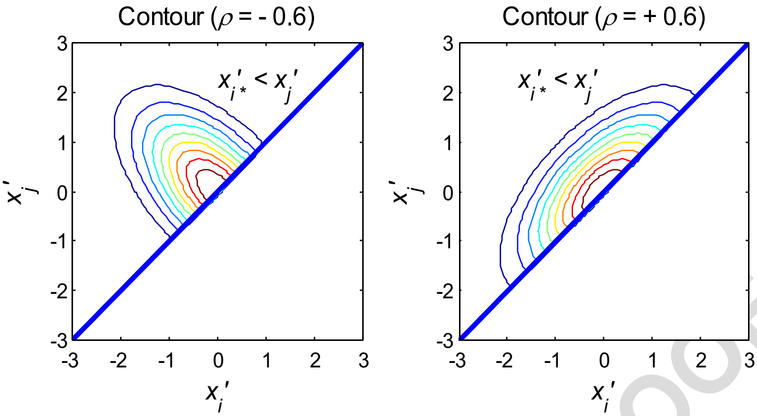

Fig. 3 Probability contour of bivariate standard normal distribution under (a) ρ= +0.6; (b) ρ= −0.6

favourable choice and the risk associated with choosing A_i would be low. Therefore, it is reasonable that the value of *XRM* increases with decreasing mean difference $\mu_i - \mu_j$, which shows the superiority of A_i is decreasing. However, the value of *XRM* decreases and approaches to zero when the mean outcome values of the two alternatives are getting closer. In this circumstance, as $\mu_i - \mu_j$ approaches to zero, the probability of making a wrong decision Pr $(X_i^* < X_j)$ for choosing alternative A_i is getting larger and reaches to its highest level (50 % under the normality assumption) when $\mu_i = \mu_j$. The *XRM* therefore has a minimum value of zero due to zero mean difference. In this sense, the influence of the probability of making a wrong decision on the potential loss is totally suppressed by the zero difference in the outcome mean values. As there is a 50-50 chance that one alternative can outperform the other when $\mu_i = \mu_j$, making a correct selection would be the most difficult, so that the value of the risk associated with making the wrong decision should intuitively be the highest rather than zero.

3 Example Applications

In this section, an example case study of a simplified river basin management study, extracted from Xu and Tung (2008), is used to demonstrated the application and compare the properties of the three risk measures: *EOL*, *XRM*, and *CRM*. Both risk measures of *EOL* and *CRM* share the same notion that a best alternative should have a minimum loss when the decision turns out to be wrong.

The study area of the river basin management problem focuses on the German part of the Elbe River, starting from the Czech Border (km 0) to Weir Geesthacht (km 568), which is the outlet to the North Sea. The major problems considered in the Elbe basin are: (1) lack of navigability along the Elbe due to low flow conditions; (2) flood risk; and (3) lack of biodiversity in the floodplains.

Three management objectives considered by the decision maker in this example are: (1) to maintain a minimum state of navigability along the Elbe main channel; (2) to reduce the flood risk along the Elbe River; and (3) to improve the ecological state of the floodplains.

In total, three management alternatives are considered. These alternatives are roughly described herein: (1) A_1: Original situation (Status-quo); (2) A_2: 50 % groyne removal in the main channel; and (3) A_3: re-naturalization in the floodplain by changing meadow grass and agriculture in the left bank to broad-leaved forest.

The water resources management problem by nature is a multiple criteria decision making considering the trade-off between three management objectives. For the purpose of demonstrating the single criterion risk-based decision rule, only the navigation aspect is considered in this example. The performance variable associated with the management objective is the annual number of shipping days for navigation in the main channel of the Elbe River. A management alternative with more shipping days in a year will be more desirable.

The annual number of shipping days can be determined by the Elbe Decision Support System (DSS) (de Kort and Booij 2007). According to Xu (2005), the DSS is constructed by two main modules: the channel module for the river and the floodplain module for small areas of interest. The channel module includes hydrological models, hydraulic models, the shipping model, and the vegetation model. The shipping model in the channel module is used to estimate the considered decision variable: the navigability of the concerned section of the Elbe River.

The main input variables in the shipping model are cross section profile, bed level measurements, discharge, ship type, and ship payload. The shipping model first calculates the critical discharge for navigation. Then calculate the annual number of shipping days for each sub-section along the river section. The calculation of the critical discharge for the navigability and the annual number of shipping days is described in more detail in Xu (2005).

The decision is to evaluate the relative merit among three management alternatives with regard to the navigability. However, the complexity of this decision making problem results from the uncertainties of model output, which is propagated from the uncertainties of model inputs consisting mainly of rating curves in the DSS model. Hence, the annual number of shipping days is random and is assumed to follow a normal distribution (Xu and Tung 2008). The uncertainties of the annual number of shipping days associated with the three management alternatives are simulated by Latin Hypercube Sampling technique coupled with the Elbe DSS. The means and standard deviations of the annual number of shipping days of different management alternatives are shown in Table 1. Among the three alternatives, alternative A_1 has the highest expected annual number of shipping days and the lowest uncertainty. Alternative A_2 has the lowest expected annual number of shipping days and the highest uncertainty, but it can enhance the performance of biodiversity.

4 Results and Discussions

The values of the three risk measures (*XRM*, *CRM*, and *EOL*) with respect to the three different chosen alternatives in the manner of pair-wise comparison are shown in Table 2. The values of *CRM* range from 23.49 to 44.35 days and that of *EOL* from 5.66 to 33.66 days. The ranking order of the three management alternatives for the navigability problem based on *XRM*, *CRM*, and *EOL* are all $A_1 \succ A_3 \succ A_2$ (A_1 is preferred to A_3 and A_3 is preferred to A_2). It indicates that for

Table 1 Management alternatives and corresponding statistics of the annual number of shipping days in the Elbe River example [Adapted from Xu and Tung (2008)]

Management alternatives	Descriptions of management alternatives	Mean (days)	Stdev (days)
A_1	Original situation (Status-quo)	307	25
A_2	50 % groyne removal	279	31
A_3	Re-naturalization, changing meadow grass and agriculture in the left bank to broad-leaved forest	306	26

Table 2 Values of three risk measures associated with pair-wise alternatives (ρ = 0.0)

Pair-wise comparison		Risk measures for navigability		
Chosen alternative	Competing alternative	*XRM* (days)	*CRM* (days)	*EOL* (days)
A_1	A_2	6.75	23.49	5.66
A_1	A_3	0.49	28.42	13.90
A_2	A_1	–	44.35	33.66
A_2	A_3	–	44.28	33.11
A_3	A_1	–	29.15	14.90
A_3	A_2	6.81	24.21	6.11

this case study, the ranking order is rather consistent among the different decision rules considered.

The basic idea for alternative selection using the *EOL* is to choose an alternative with lowest maximum *EOL* compared with all the other alternatives. In this case, the alternative A_1 of original situation is the best choice. However, the implementability of the chosen alternatives can only be determined with reference to the decision maker's acceptable risk. The best decision is the one with the lowest maximum *EOL* but also having *EOL* values less than the acceptable risk.

Since the *CRM* is computed with the anticipation that the chosen alternative would fail, the *CRM* expectedly yields larger values of the potential loss than the *EOL*. Thus, it is a more conservative risk measure and the decision maker needs to prepare more contingency and be more tolerant to offset the potential loss of anticipated failure which may not occur. As for the navigability problem, the decision maker's acceptable risk or contingency for the annual navigable days not meeting the goal should be higher.

According to *XRM*, the expected loss if the decision maker choose not to follow the ranking of $A_1 \succ A_3$ between the alternative pair (A_1, A_3) will be 0.49, which is lower than that for the alternative pair (A_1, A_2), *XRM* [A_1^*, A_2] is 6.75. In other words, the expected reduction in annual number of shipping days of not choosing A_1 over A_3 is higher than that of not choosing A_1 over A_2. Examining the situation closely, the expected annual navigable days of alternatives A_1 and A_3 are very close. This scenario presents the most difficult situation in this example to make a clear choice from one alternative to another, so that the value of a risk measure for making a wrong decision should be the highest rather than the lowest. Hence, the *EOL* is a plausible risk measure that reflects more accurately of the merit associated with the decision of choosing a particular alternative.

4.1 Effect of Acceptable Risk

A feasible alternative should have *EOL* values less than the acceptable risk when comparing with all the other alternatives. After examine the implementability of all alternatives, a set of feasible alternatives that meet the decision maker's acceptable risk can be identified. An alternative with the lowest maximum *EOL* among the feasible alternatives will be the best choice.

Based on the *EOL* values shown in Table 2, the results of the alternative selection corresponding to different levels of acceptable risk (R_A) are listed in Table 3. As can be seen, R_A has great influence on the member of feasible alternatives set. For example, if R_A = 14 days, the values of *EOL* [A_1^*, A_2] and *EOL* [A_1^*, A_3] are low enough to be acceptable so that A_1 is

Table 3 Effect of acceptable risk on the alternative selection based on *EOL* (ρ= 0.0)

Assumed R_A	Feasible alternatives	Alternatives cannot be discarded, nor implementable	Discarded alternatives
R_A = 12	–	A_1, A_3	A_2,
R_A = 14	A_1	–	A_2, A_3
R_A = 16	A_1, A_3	–	A_2
R_A = 34	A_1, A_2, A_3	–	–

considered as implementable. Consequently, the alternative A_1 could eliminate both alternatives A_2 and A_3 and choosing it would leads to a minimum and acceptable loss. In this condition, the status-quo (A_1) is the most preferable choice in terms of navigability. If the decision maker has a higher tolerance, say, R_A = 16 days. Then, both A_1 and A_3 are implementable because the values of *EOL* corresponding to their selection are smaller than the stipulated R_A of 16 days. In this case, the alternative A_2 can be discarded. With an even higher tolerance, say, R_A = 34 days, all three alternatives are acceptable and implementable with respect to the decision maker's R_A. However, if R_A = 12 days, none of the three alternatives can be considered implementable. In this case, the decision maker could take one of the following three courses of action: (1) conduct further investigations to reduce the uncertainty in different sources, such as collecting more reliable data and improving the simulation model; (2) have a new list of alternatives and examine them; and (3) increase the budgetary reserves for the contingency to have a higher R_A.

4.2 Effect of Outcome Uncertainty

When a large model uncertainty and/or low R_A hinder the decision maker from clearly identifying feasible alternatives, one might be interested in knowing how much reduction in uncertainty is needed to yield at least one feasible alternative among those under consideration. Table 4 shows the effect of uncertainty reduction on the values of *EOL*. The standard deviations of the three alternatives are reduced by 30 % individually, except the last row of Table 4 which involves simultaneous reduction of uncertainty in two alternative outcomes. The mean and baseline standard deviation values remain unchanged as in Table 1 and the alternative correlations are zero.

The percentages of reduction in the *EOL* are shown in the parentheses. It shows that if the expected outcomes of two alternatives are kept the same, the *EOL* values in comparing these two alternatives will be changed only when at least one of the uncertainty degrees is changed. When the standard deviation of A_i is reduced, both *EOL* $[A_i^*, A_j]$ and *EOL* $[A_j^*, A_i]$ decrease. When R_A = 5 days, the decision maker's tolerance to failure is too low to produce an acceptable alternative for implementation no matter how small the uncertainty is reduced to. When the R_A is increased to 10 days, A_1 can be selected as an ultimate alternative if σ_1 and σ_3 are both reduced by 30 %. However, the degree of reduction in expected loss has its limit. For example, even if the uncertainty of A_1 and A_3 are reduced by 30 %, A_2 and A_3 cannot be regarded as feasible with reference to R_A = 10 days. This indicates that there is a trade-off between the effort and effect in reducing uncertainty.

In this example, for all uncertainty levels considered, the *EOL*-based ranking of the three management alternatives are all $A_1 \succ A_3 \succ A_2$. Therefore, for the shipping model, the ranking order of the three management alternatives is not sensitive to model outcome uncertainty.

Table 4 Effect of outcome uncertainty on the *EOL* (ρ= 0.0)

			Changes in uncertainty			Values of *EOL* in pair-wise comparison					
σ_1	σ_2	σ_3	$\Delta\sigma_1$	$\Delta\sigma_2$	$\Delta\sigma_3$	(A_1^*,A_2)	(A_1^*,A_3)	(A_2^*,A_1)	(A_2^*,A_3)	(A_3^*,A_1)	(A_3^*,A_2)
25	**31**	**26**				**5.66**	**13.9**	**33.66**	**33.11**	**14.9**	**6.11**
17.5	31	26	−30 %	0 %	0 %	4.38 (−22.6 %)	12.01 (−13.6 %)	32.38 (−3.8 %)	33.11 (0.0 %)	13.01 (−12.7 %)	6.11 (0.0 %)
25	21.7	26	0 %	−30 %	0 %	3.67 (−35.2 %)	13.9 (0.0 %)	31.67 (−5.9 %)	31.09 (−6.1 %)	14.9 (0.0 %)	4.09 (−33.1 %)
25	31	18.2	0 %	0 %	−30 %	5.66 (0.0 %)	11.84 (−14.8 %)	33.66 (0.0 %)	31.71 (−4.2 %)	12.84 (−13.8 %)	4.71 (−22.9 %)
17.5	31	18.2	−30 %	0 %	−30 %	4.38 (−22.6 %)	9.58 (−31.1 %)	32.38 (−3.8 %)	31.71 (−4.2 %)	10.58 (−29.0 %)	4.71 (−22.9 %)

4.3 Effect of Outcome Correlation

Table 5 shows the effect of correlation on the *EOL* values of the three alternatives. The correlation of each pair of alternative outcomes ranges from -0.6 to +0.6 and the means and standard deviations are identical to those in Table 1. The table shows that the values of *EOL* decrease with a higher positive correlations. This can be explained from the definition in that the *EOL* represents the probability weighted difference between two random alternative outcomes in the standardized variable domain of $x_i' \le x_j'$. Figure 3 shows the contour of the bivariate standard normal distribution in two situations of $\rho = \pm 0.6$ in which the diagonal line represents $x_i' = x_j'$ with upper half of the domain for $x_i' < x_j'$. For different correlations, the volumes in the standardized domain of $x_i' \le x_j'$ under the joint PDF are identical. However, under the condition of $\rho_{i,j} = -0.6$, there are higher possibilities for larger values of $|x_i' - x_j'|$ than those under $\rho_{i,j} = +0.6$. This observation in the standardized domain is also valid in the original variable scale to explain the reason why a higher positive correlation would result in a lower value of *EOL*. It is clear that the outcome correlation have significant effect on the value of *EOL* which, in turn, would determine if a chosen alternative is feasible or not.

5 General Remarks

Example application in this paper indicated that the consideration of alternative outcomes uncertainty is important in the selection of different management alternative. The value of *EOL* of two competing alternatives under consideration is dependent on the magnitudes of their means, standard deviations, and correlation. Choice between two alternatives with smaller difference in mean outcome values, higher uncertainty, and/or large negative correlation could result in a larger value of *EOL*.

The *EOL* is capable of accounting for the decision maker's risk attitude. Once the ranking of alternatives is identified on the basis of lowest maximum *EOL*, the acceptable risk of the decision maker can be used to examine the feasibility of the alternative. When the value of maximum *EOL* of a chosen alternative is lower than the acceptable risk, it may be considered implementable by the decision maker. Otherwise the following course of actions might be considered: (1) formulating new set of alternatives that are not being currently considered; (2) conducting more research to reduce outcome uncertainties associated with currently considered alternatives; or (3) increasing the budgetary reserves for the contingency or acceptable risk of the decision maker.

Table 5 Effect of correlation on *EOL* value

Pair-wise comparison		Values of *EOL*				
Chosen alternatives	Competing alternatives	$\rho = -0.6$	$\rho = -0.3$	$\rho = 0.0$	$\rho = +0.3$	$\rho = +0.6$
A_1	A_2	9.05	7.41	5.66	3.77	1.78
A_1	A_3	17.70	15.91	13.90	11.55	8.61
A_2	A_1	37.05	35.41	33.66	31.77	29.78
A_2	A_3	36.64	34.94	33.11	31.12	28.98
A_3	A_1	18.70	16.91	14.90	12.55	9.61
A_3	A_2	9.64	7.94	6.11	4.12	1.98

6 Summary and Conclusions

When a decision maker faces with the choice among various alternatives with uncertain outcomes, it is difficult to ensure that the choice is really the best one. There is a likelihood that any chosen alternative could turn out to be wrong because of uncertain outcomes. There is a need to have quantitative indicators and decision rules that account for the full uncertainty features of alternative outcomes to assist the decision maker screening and ranking alternatives.

As stated by Castro et al. (2009), "Being wrong about alternatives with a lower expected loss is preferable to being wrong about alternatives with a higher expected loss". This paper focuses on decision rules that permit joint consideration of decision maker's acceptable risk and correlation among outcomes of different alternatives. The *EOL*-based risk measure reflects the potential loss in case the selected alternative turns out to be inferior to its competitor. Based on the *EOL*, the decision maker could select an alternative with minimal expected loss when the decision turns out to be wrong. The decision rule is consistent with the long-term expected-value rule but with added capability to explicitly consider the effect of correlation between two competing alternative outcomes and the decision maker's acceptable risk for loss. The *EOL* reflects more accurately the relative merit of two competing alternatives without suffering the pessimism of the conditional risk measure and the counter-intuition of the Xu's risk measure.

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