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Aspects of sustainable decision making for design and maintenance

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The interpretation and treatment of uncertainties and probabilities in engineering decision making is discussed from the perspective of necessity and consistency. Thereafter a summary presentation is given of the Bayesian decision theory as principally applied in the various forms of risk assessments usually conducted for the purpose of establishing engineering decision support. The aspects of risk perception are introduced and discussed with a view to rational decision making on behalf of society such as e.g. when calibrating design codes. The concept of "follow up" events is introduced as a means to underline the importance of assessing all consequences following from adverse events. Finally a new idea is introduced namely, the concept of sustainable decision making. It is suggested that sustainable decisions may be achieved by formal decision analysis where the preferences of future decision makers are taken into account with equal weight as those of the present time decision makers.

Key words: *uncertainties, probabilities, Bayesian decision analysis, risk, civil engineering, risk perception, risk averseness, design, maintenance, sustainable decisions.*

1. Introduction

Over the last decades decision analysis has increasingly gained importance as a means to establish rational decisions in engineering in general and civil engineering in particular. Optimal design and optimal inspection and maintenance planning are two examples hereof but many other applications such as concept feasibility evaluations and experiment planning could be mentioned as well. It is generally accepted and in accordance with e.g. the Joint Committee on Structural Safety (JCSS, 2001) that the established basis for engineering decision analysis is the Bayesian decision theory as described in e.g. Raiffa and Schlaifer (1961).

The present paper attempts, following closely a selection of previous work by the author and others (Faber (1997, 2002a, 2003), Faber et al. (2002) and Faber and Maes (2003)) to summarize the basic constituents of the decision theoretical framework as required for civil engineering decision making with some focus on design and inspection and maintenance planning. This includes first of all an introductory discussion on uncertainties and probabilities and not least how to account for these in decision analysis. Secondly the various types of decision analysis are introduced in the form relevant for typical risk based engineering decision making. Thereafter the problem of risk perception with a special view to risk averseness is discussed as this aspect is of crucial importance for the relevant modeling and assessment of the consequences of decisions. Decision making for the purpose of design and maintenance is addressed and the decision theoretical formulation for optimal design and maintenance is given, together with a categorization of the types of decision analysis which are relevant for a broader spectrum of decision problems in civil engineering. Finally a new idea concerning a decision theoretical formulation on how to establish sustainable decisions is introduced.

2. Uncertainties in engineering decision making

The consistent treatment of uncertainties and assessment of probabilities is a prerequisite for decision analysis. In the following a discussion on these aspects is given in close accordance with Faber (2003).

For the purpose of discussion consider the decision problem of choosing the height of a dike. The risk of dike flooding can be reduced by increasing the height of the dike; however, due to the inherent natural variability in the water level a certain probability of dike flooding in a given reference period will always remain. Risk assessment within the theoretical framework of decision analysis can help us in deciding on the optimal dike height by weighing the benefits of reduced dike flooding risks with the costs of increasing the dike height. However, a prerequisite for the risk assessment is that the means for assessing the probability of dike flooding are established, and this in turn requires that a probabilistic model for the future water level is available.

Let us initially assume that the universe is deterministic and that our knowledge about the universe is perfect. This implies that it is possible by means of e.g. a set of exact equation systems and known boundary conditions by means of analysis to achieve perfect knowledge about any state, quantity or characteristic which otherwise cannot be directly observed or has yet not taken place. In principle following this line of reasoning the future as well as the past would be known or assessable with certainty. Considering the dike flooding problem it would thus be possible to assess the exact number of floods which would occur in a given reference period (the frequency of floods) for a given dike height and an optimal decision can be achieved by cost benefit analysis.

Whether the universe is deterministic or not is a rather deep philosophical question with certain religious implications. Despite the obviously challenging aspects of this question its answer is, however, not a prerequisite for purposes of engineering decision making, the simple reason being that even though the universe would be deterministic our knowledge about it is still in part highly incomplete and/or uncertain.

In engineering decision analysis subject to uncertainties such as Quantitative Risk Analysis (QRA) and Structural Reliability Analysis (SRA) a commonly accepted view angle has developed where uncertainties are interpreted and differentiated in regard to their type and origin, see e.g. Apostolakis (1990). In this way it has become standard also in the Joint Committee on Structural Safety Probabilistic Model Code (JCSS, 2001) to differentiate between uncertainties due to inherent natural variability, model uncertainties and statistical uncertainties. Whereas the first mentioned type of uncertainty is often referred to as aleatoric (or Type 1) uncertainty, the two latter are refereed to as epistemic (or Type 2) uncertainties. Without further discussions here it is just stated that in principle all prevailing types of uncertainties should be taken into account in engineering decision analysis within the framework of Bayesian probability theory, see e.g. Paté-Cornell (1996) and Lindley (1976) where a more detailed treatment of this issue is given.

Considering again the dike example we can imagine that an engineering model might be formulated where future extreme water levels are predicted in terms of a regression of previously observed annual extremes. In this case the uncertainty due to inherent natural variability would be the uncertainty associated with the annual extreme water level, the model uncertainty would be the uncertainty introduced due to the chosen regression and the statistical uncertainty would be the uncertainty associated with the regression parameters estimated/fitted using a limited number of observations of previous annual extremes. The uncertainty associated with the future extreme water level is thus composed as illustrated in Fig. 1. Whereas the so-called inherent natural variability is often understood as the uncertainty caused by the fact that the universe is not deterministic it may also be interpreted simply as the uncertainty which cannot be reduced by means of collection of additional information, see e.g. Ditlevsen and Madsen (1996). It is seen that this definition implies that the amount of uncertainty due to inherent natural variability depends on the models applied in the formulation of the engineering problem. Presuming that a refinement of models corresponds to looking

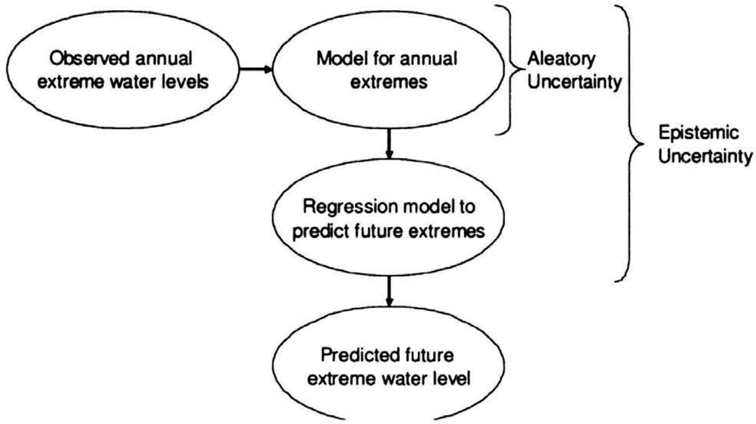

FIGURE 1. Illustration of uncertainty composition in a typical engineering problem, Faber (2003).

more detailed at the problem at hand one could say that the uncertainty structure influencing a problems is scale dependent.

Having formulated a model for the prediction of future extreme water levels and taking into account the various prevailing types of uncertainties the probability of flooding within a given reference period can be assessed and just as in the case of a deterministic and perfectly known universe we can decide on the optimum dike height based on a cost benefit assessment.

It is interesting to notice that the type of uncertainty associated state of knowledge has a time dependency. Following Fig. 2 it is possible to observe an uncertain phenomenon when it has occurred. In principle, if the observation is perfect without any errors the knowledge about the phenomenon is perfect. The prediction of the same phenomenon in the future, however, is uncertain as this involves models subject to natural variability, model uncertainty and statistical uncertainty. Often but not always the models available tend to loose their precision rather fast so that phenomena lying just a few days or weeks ahead can be predicted only with significant uncertainty. An extreme example of this concerns the prediction of the weather.

The above discussion shows another interesting effect, namely that the uncertainty associated with an uncertain phenomenon transforms from a mixture of aleatoric and epistemic uncertainty to a purely epistemic uncertainty in the same moment as it occurs. This transition of the type of uncertainty has a significant importance because it facilitates that the uncertainty is reduced by utilization of observations updating.

In summary it should be underlined that whereas the insight into the characteristics of the various types of uncertainty is not only useful but also

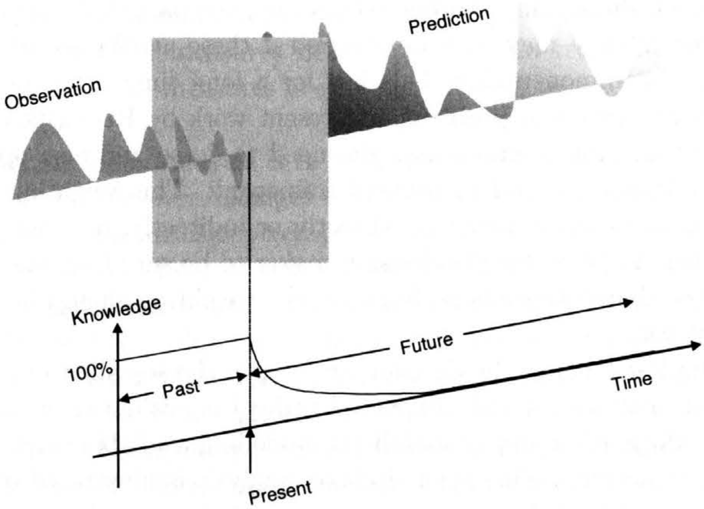

Figure 2. Illustration of the time-dependence of knowledge, Faber (2003).

a requirement for consistently treating and efficiently managing uncertainties in decision problems the decision analysis itself in no way depending on the types of uncertainties involved in a problem. Epistemic and aleatoric uncertainties should in this context be treated in the same way.

3. Framework for decision analysis

Having established a theoretical basis for the treatment of uncertainties and probabilities the next step concerns the general framework for decision making. The following introduction to this follows closely Faber (2002a) and Faber et al. (2003).

General decision problems subject to uncertainty expressed in frequentistic and/or subjective terms may be adequately treated within the framework of the Bayesian decision theory see e.g. Raiffa and Schleifer (1961) and Benjamin and Cornell (1970).

Without giving the theoretical argumentation, (see e.g. Ditlevsen and Madsen (1996)) it is simply stated here that a fundamental principle in decision theory is that optimal decisions must be identified as those resulting in the highest expected utility.

In typical engineering applications the term utility may directly be translated into consequences in terms of costs, fatalities, environmental impact etc. In these cases the optimal decisions are those resulting in the lowest expected costs, the lowest expected number of fatalities and so on. Moreover, if costs and fatalities and/or other attributes are a part of the decision problem, full consistency may only be ensured if these attributes are expressed in terms of a common utility. This has for a long time been considered to represent a controversial problem, but resent work by Rackwitz (2001) and Nathwani et al. (1997) emphasises the need to do so and also provides the required philosophical and theoretical framework. The weighting of the attributes has to be done somehow, directly or indirectly, in order to make a decision, thus, in order for the decision maker to be sure that the decision is made in accordance with his preferences, the weighting should be made in a transparent way.

The simplest form of the decision analysis is the so-called prior-analysis. In the prior-analysis the risk (expected utility) is evaluated on the basis of statistical information and probabilistic modelling available prior to any decision and/or activity. This prior decision analysis is illustrated by a simple decision tree in Fig. 3. In prior and posterior decision analysis the risk (expected utility) $R(A)$ for each possible activity/option A is evaluated in the principal form as

$$R(A) = E\left[U(A)\right] = \sum_{i=1}^{n} p(i\,|A)\; C(i) \tag{3.1}$$

where $R(A)$ is the risk, $U(A)$ the utility, $p(i\,|A)$ is the i-th branching probability and $C(i)$ the consequence (benefit as well as cost) of the event of branch i, see Fig. 3.

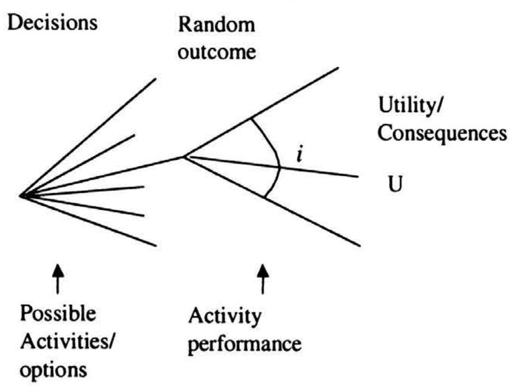

FIGURE 3. Decision tree for prior and posterior decision analysis, Faber (2001).

Prior decision analysis in fact corresponds closely to the assessment of the risk associated with an activity. Prior decision analysis thus forms the basis for the simple comparison of risks associated with different activities. The result of a prior decision analysis might be that the risks are not acceptable and the risk reducing measures needs to be considered. The efficiency of different risk reducing measures is an issue which is treated in the posterior decision analysis.

Posterior decision analysis is in principle of the same form as the prior decision analysis, however, changes in the branching probabilities and/or the consequences in the decision tree reflect that the considered problem has been changed as an effect of risk reducing measures, risk mitigating measures and/or collection of additional information. Posterior decision analysis may thus be used to evaluate the efficiency of risk reducing activities, which factually have been performed.

Pre-posterior decision analysis may be illustrated by the decision tree shown in Fig. 4. Using pre-posterior decision analysis optimal decisions in regard to activities, which may be performed in the future, e.g. the planning of risk reducing activities and/or collection of information may be identified. An important pre-requisite for pre-posterior decision analysis is that decision rules need to be formulated specifying the future actions, which will be taken on the basis of the results of the planned activities.

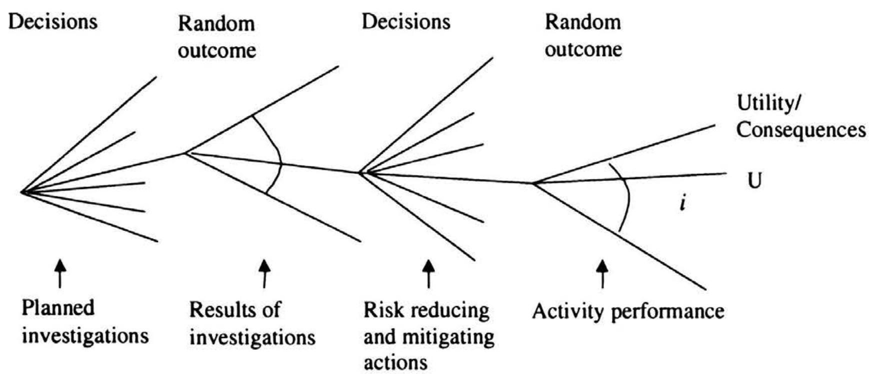

FIGURE 4. Decision tree for pre-posterior decision analysis, Faber (2001).

In pre-posterior decision analysis the risk (expected utility) for each of the possible investigations is evaluated as

$$
\begin{aligned}
R(A) = E\big[U(A)\big] &= \min_a E'_Z\Big[E''_{|Z}\big[U\big(A, a(z), z\big)\big]\Big] \\
&= \min_a E'_Z\Big[\sum_{i=1}^{n} p'\big(i\,|A, a(z), z\,\big)\,C\big(i, A, a(z)\big)\Big]
\end{aligned}
\tag{3.2}
$$

where $a(z)$ are the different possible actions that can be taken on the basis of the result of the considered investigation z, $E[\,.\,]$ is the expected value operator. ' and " refer to the probabilistic description of the events of interest based on prior and posterior information respectively see e.g. Lindley (1976).

4. Risk perception in engineering decision making

A prerequisite for decision analysis is that the preferences of the decision maker are appropriately represented in the formulation of the utility function. In the following, in close accordance with Faber and Maes (2003) this aspect is considered with special focus on risk perception and risk averseness.

In the practical application of decision theory it is often argued that risk perception needs to be taken into account in the formulation of the utility function. The reason for this being that the utility function must be able to represent the "real" behavior of the decision maker in regard to her/his preferences in a given situation. The amount of research invested into the experimental investigation and the mathematical modeling of the behavior of human decision makers is vast, see e.g. Pratt (1964), Arrow (1971) and Kahneman and Tversky (1979) and whereas this research clearly points to the basic characteristics of the perception of risks under different conditions, it also points to a whole set of problems related to the consistent formulation of utility functions as summarized in Camerer and Weber (1992) and also discussed in some detail in Maes and Faber (2003). For this reason the axioms of utility theory proposed by von Neumann and Morgenstern (1943) have been heavily disputed during the last decades and various competing formulations suggested, see e.g. Kahnemann and Tversky (1979).

However interesting the theoretical mathematical implications of the effect of risk perception may be in regard to the formulation of utility functions, it is imperative not to loose focus on the characteristics of the decision problems at hand. Here it is suggested to differentiate between two different situations, namely:

1. the situation where the purpose is to predict and represent the behavior and the attitudes of decision makers,
2. the situation where the purpose is to provide support for rational decision making.

4.1. Basic aspects of decision making

Decision making in civil engineering can be seen as being equivalent to participate in a game with nature acting as the main opponent, see also Ditlevsen and Madsen (1996). Considering Fig. 5 the illustrated constituents of the decision problem system can be considered equivalent to the constituents of a game.

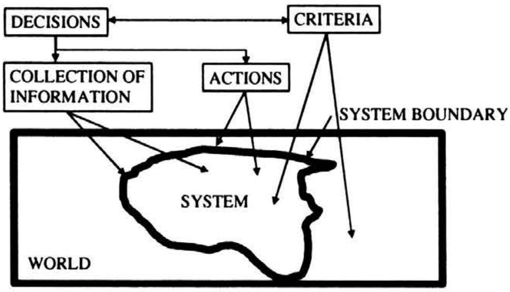

FIGURE 5. Main constituents in risk based decision analysis, Faber (2002).

Knowing the rules of the game, i.e. the (success or acceptance) criteria, the system, the boundaries of the system, the possible consequences for the system and how all these factors are influenced by the world outside the system, is essential in winning the game. For this reason a very significant part of risk based decision making in practice is concerned about system identification/definition as well as the identification of acceptance criteria, possible consequences and their probabilities of occurrence. Playing the game is done by "buying" physical changes in the system or "buying" knowledge about the system such that the outcome of the game may be optimized.

4.2. Decision making based on expected utility

As outlined in Maes and Faber (2003) it can be stated that most decision makers and risk engineers would agree to the basic principle of ranking alternatives A based on their expected utility $E\big[U(A)\big]$ (von Neumann and Morgenstern, 1943):

$$E\big[U(A)\big] = \sum_{i=1}^{n_O} p(i\,|A)\,u(A,O_i) \tag{4.1}$$

where $E\,[\,.\,]$ is the expectation operator, n_O is the number of possible outcomes associated with alternative A, $p(i\,|A)$ is the probability that each of these outcomes will take place (given A) and $u(A,O_i)$ is the utility associated with the set (A,O_i). Equation (4.1) assumes a discrete set of outcomes but can straightforwardly be generalized to continuous sample spaces.

As stated earlier the analysis of the utility function can serve two purposes; either for the prediction of the behavior of decision makers, or as basis for rational decision making. Whereas this distinction from a mathematical point of view has no implications, it provides a useful guideline for maintaining the focus on decision making in engineering.

4.3. Risk aversion in decision making

Depending on the situation at hand, decision makers reportedly (Kahneman and Tversky, 1979) feel uneasy with the direct application of Eq. (4.1), due to principally two reasons: either the decision maker is uncertain about the assessment of the utility $u(A, O_i)$ or, she/he is uncertain about the assessment of the probabilities $p(i)$. With reference to the foregoing discussion this corresponds to not really knowing the rules of the game. In principle the effect of misjudging the utility associated with a particular outcome is similar to misjudging the uncertainty associated with the probability that the outcome will occur, namely that possible outcomes associated with marginal utility are neglected. This in turn may lead to both over- and under-estimation- of the expected utility.

However, subject to the assumption that all relevant outcomes and all uncertainties (aleatoric as well as epistemic, see e.g. Faber (2003), have been included into the formulation of the utility function this behavior is fundamentally irrational and also inappropriate. Unfortunately, however, the manner in which risk based decision analysis is normally conducted, the rules of the game are often grossly violated. This in turn makes risk averse as well as risk prone behavior relevant and this becomes the source of the problem. In practical risk based decision making usually only direct consequences of the individual outcomes are taken into account. As an example consider the design of structures where it is normal practice that the acceptable (or target) level of reliability in regard to ultimate failure is assessed by considering only the loss of material in the building itself and the loss of the persons in the building itself. As experience clearly shows this is a gross simplification. In the case of the collapse of the World Trade Centre it turned out that the material losses to the surrounding buildings were four time higher than the material losses for the collapsed towers themselves. It is clear that such overly simplified modeling of the utility function gives rise to a risk perception requiring an "artificial" risk averse utility function in order to achieve rational decisions. Similarly if some uncertainties are not taken into account in the assessment of the probabilities entering the utility function, a similar effect takes place. The situation can be compared to a chess game where all moves are made by only looking one move ahead – it is rather difficult to win such games.

4.4. "Follow-up" events and generalized utility functions

In practical risk based decision making various proposals for non-linear utility functions have been suggested and applied. But the problem remains which type of non-linear utility function would be appropriate in a given situation and whether it would lead to a rational decision. To overcome this problem (following an idea in Faber (2002)) a Bayesian approach is proposed here including explicitly into the formulation of the utility function the marginal utility of all possible outcomes which may occur as a consequence of the occurrence of other outcomes. The aim being to arrive at a formulation of the utility function that is (possibly) more complete, more transparent to the decision maker and one that explicitly takes into account the effect of epistemic uncertainties.

In Eq. (4.2) an expansion or generalization of the utility function from Eq. (4.1) is given:

$$\begin{aligned} E\left[U(A)\right] &= E_{\mathbf{e}}\left[\sum_{i=1}^{n_O} p(i\,|A,\mathbf{e})u(A,O_i) + \sum_{j=1}^{m} p(\mathbf{O}_j\,|A,\mathbf{e})u_{FO}(A,\mathbf{O}_j)\right] \\ &= \sum_{i=1}^{n_O} p(A,i)u(A,O_i) + E_{\mathbf{e}}\left[\sum_{j=1}^{m} p(\mathbf{O}_j\,|A,\mathbf{e})u_{FO}(A,\mathbf{O}_j)\right]. \end{aligned} \tag{4.2}$$

In Eq. (4.2) the probabilities $p(i\,|A,\mathbf{e})$ are aleatoric probabilities, conditional on decision A and the outcome of the epistemic uncertainties $\mathbf{e}$. An additional term has been included to take into account marginal "follow-up" consequences. In this term $\dot{m}$ is the number of different combinations $\mathbf{O}_j$ of one or more of the n_O outcomes associated with the alternative$A$, $p(\mathbf{O}_j\,|A,\mathbf{e})$ is the probability that this combination occurs and $u_{FO}(A,\mathbf{O}_j)$ is the corresponding marginal utility. Notice here that the difference between the utility functions given in Eq. (4.1) and (4.2) is that m "follow-up" events are included which occur as conditional events with marginal utility $u_{FO}(A,\mathbf{O}_j)$ given the occurrence of at least one of the n_O outcomes. The probabilities $p(\mathbf{O}_j\,|A,\mathbf{e})$ may be assessed by means of probabilistic analysis conditional on the epistemic uncertainty $\mathbf{e}$ but may also be purely subjective in which case, however, the expectation operation becomes obsolete. In the latter case the subjective probabilities may be updated using a Bayesian framework at the same rate as evidence becomes available.

5. Decision Making for Design and Maintenance

5.1. The design and maintenance decision problem

The decision problem associated with design and maintenance of structures (see also Faber (1997)) may be represented in a decision event tree as shown in Fig. 6.

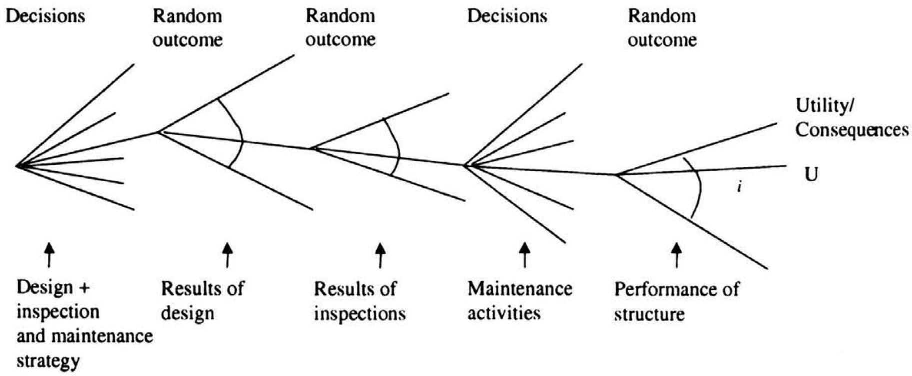

FIGURE 6. Decision/event tree for the design and inspection and maintenance decision problem.

The decision on design and future inspection and maintenance is made in principle at the same time initially when the structure is designed. The realization of the design S – as built – is in nature unknown at the point in time when the decision is made. However, when the structure has been realized it can be inspected and again the outcome of the inspections Z will be unknown at the time of the inspections. Depending on the condition of the structure as it has been realized initially and as this might have deteriorated over time decisions $a(s,z)$ may now be implemented in regard to maintenance. The efficiency of the maintenance is, however, again subject to uncertainty and the resulting condition of the structure is thus uncertain. Depending on the decisions made from the point in time of the design and through the whole life cycle of the structure as well as the uncertain performance of the structure during this period the structure will generate a benefit as expressed in Fig. 6 through the utility. The optimal decision considering both the design and the inspection and maintenance strategy may be identified by optimization of the expected value of the utility. In Eq. (5.1) the expected value (equivalent to Eq. (3.2)) of the utility is given as a function of the design and inspection and maintenance strategy:

$$\min_a E'_{S,Z}\left[E''_{|S,Z}\left[U(A,a(s,z),z,s)\right]\right] = \min_a E'_{S,Z}\left[\sum_{i=1}^{n} p''(i\,|A,a(s,z),s,z)C(i,A(s,z),s,z)\right]. \quad (5.1)$$

Based on Eq. (5.1) the optimal decisions in regard to design and inspection and maintenance may now be derived. Whereas studies of optimal design and optimal inspection and maintenance considered individually has been reported in numerous publications, so far simultaneous optimization of design and inspection and maintenance has only been performed on a very small scale. This observations unfortunately holds not only for research but even more so for practical application why much more work still needs to be devoted to these aspects.

5.2. Categorization of engineering decision analyses

Engineering decision problems may in fact all be categorized as prior, posterior or pre-posterior decision problems. In Table 1 a non-exhaustive categorization is suggested.

TABLE 1. Categorization of engineering problems as decision problems, Faber (2003).

Engineering Problem	**Decision Theoretical Problem**		
	Prior	*Posterior*	*Pre-posterior*
Risk assessment for verification Design and strengthening optimization	X		
Calibration of: • risk acceptance criteria, • code formats (γ, ψ).	X		
Reliability updating for: • service life extensions, • re-qualification.		X	
Planning of collection of information: • tests, • experiments, • proof load levels.			X
Inspection and maintenance planning			X

Whereas the prior and the posterior decision problems listed in Table 1 may be solved using standard approaches of Quantitative Risk Analysis (QRA) and Structural Reliability Analysis (SRA), the efficient solution of pre-posterior decision problems may in some cases call for the use of special tools. Such tools can either be built directly on the basis of SRA and or QRA such as iPlan – a tool for risk based inspection and maintenance planning, see e.g. Faber et al. (2002b) or more specific decision analysis tools such as Bayesian probabilistic Nets and Influence Diagrams, see e.g. Heckerman (1995).

6. Sustainable decision making in engineering

With the view-point that civil engineering decision making can be seen as playing a game against nature (see Sec. 4.1) it is obvious that the fundamental rule set is dictated by nature. However, we (men) being the conscious player in the game need to establish a set of strategies for playing the game which are in consistence with our fundamental moral and philosophical settings. These strategies might be seen as an extension of the basic rule set for the game. First when the rules of the game are well defined we can attempt to optimize our outcome.

The following first proposes two basic principles of sustainable decision making. It is then discussed how these basic principles of sustainable decision making can be applied in a context of decision making where monetary tradeoffs are made and the stake holders are individuals of society and nature. Thereafter the decision theoretical framework previously applied for the purpose of life cycle optimal decision making is reviewed and reformulated such that it becomes possible to optimize decisions in accordance with the basic principles of sustainable decision making.

6.1. The basic principles for sustainable decision making

As a prerequisite for sustainable decision making the following is concerned about the setting of some basic rules or principles for the decision making process.

The basic principle of equity of decision makers over time:

> *Decisions with potential implication for future decision makers shall be based on an equal weighing of the preferences of present and future decision makers.*

This principle, under the assumption that the future decision makers will comply with the UN Charter of Human Rights (1945), can be seen as an extension of the equality principle stated in these over future societies. The implication of this principle is that the utility function to be considered in sustainable decision making should be formed as the sum of the utility functions of present as well as future decision makers.

In addition to the basic principle of sustainable decision making another principle is introduced to ensure decisions based on the viewpoint that the life of any person is of "equal value", also lives of future generations.

The principle of life-value invariance:

Decisions by present and future decision makers shall value life-saving activities in accordance with the LQI at the time of the decision.

Here LQI denotes the Life Quality Index as introduced by Nathwani et al. (1997).

It should be noted that from a societal point of view "a tradeoff between monetary benefits and the safety of individuals" is not a meaningful sentence since economical growth of society ultimately should aim to increase life quality and thus implicitly also the safety of individuals.

In regard to decisions involving tradeoffs between monetary benefits and damages to the qualities of the environment the basic principle of sustainable decision making implies that decisions made at present involving damage to a quality of the environment can only be justified if it can be substantiated that the achieved monetary benefit, e.g. measured in increase of LQI, is transferred unreduced to the future decision makers.

It is clear that societies and the world in general change as function of time – insofar that such changes may be predicted (hypothesized) this can without problem be taken into account in the evaluation of the preferences of future decision makers. Sustainability can thus only be ensured conditionally on predicted future developments.

6.2. Theoretical framework for sustainable decision making

Decision making in the field of civil engineering often take basis in optimization problems of the form given by:

$$\max_{\mathbf{D}(0)} B\big(\mathbf{D}(0)\big) \tag{6.1}$$

where B is the total expected life cycle benefit and $\mathbf{D}(0)$ is a vector of decision alternatives where the parameter 0 indicates that the decision alternatives which indeed might involve activities in the future are decided upon at time $t = 0$, i.e. the time of the decision by the present decision maker. In this formulation of the decision problem we implicitly set utility equal to monetary benefits.

The total expected life cycle benefits for the reference period T are in accordance with existing formulations for life cycle costing assessed as

$$B\big(\mathbf{D}(0)\big) = \int_0^T b\big(t, \mathbf{D}(0)\big)\, \kappa(t)\, dt \tag{6.2}$$

where $b\big(t, \mathbf{D}(0)\big)$ is the expected benefit per time unit and $\kappa(t)$ is a function capitalizing the benefits possibly gained in the future into net present value. In the assessment of the expected benefits $b\big(t, \mathbf{D}(0)\big)$ it is assumed that future decision makers will act rationally. The decision problem as stated in Eq. (6.1) and Eq. (6.2) might be solved within the framework of the pre-posterior decision analysis as outlined in e.g. Raiffa and Schlaifer (1961). This corresponds exactly to the approach taken in previously performed decision analysis, not only in the field of engineering decision making but also in financial decision making.

If the basic principle of sustainable decision making is invoked this implies that we have to extend the benefit function given in Eq. (6.2) with the preferences i.e. the benefits of the future decision makers. The principle is illustrated in Fig. 7.

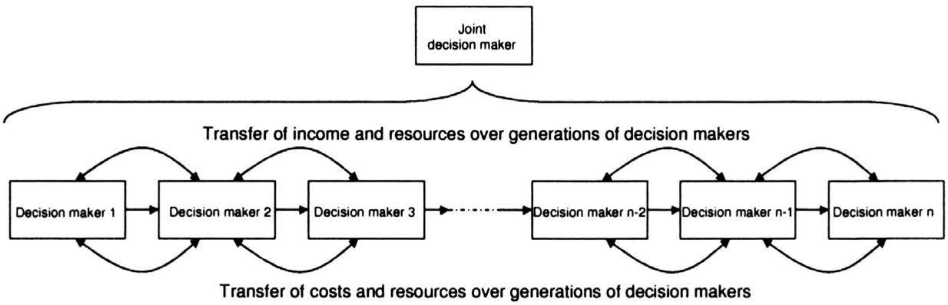

FIGURE 7. Illustration of the interaction between present and future decision makers.

In Fig. 7 it is indicated that exploitation of resources and the benefits achieved by this can be transferred between decision makers at different times. Also costs, e.g. associated with the maintenance of structures, may be transferred between decision makers at different times. In Fig. 7 the joint decision maker is assumed to make decision for the best of all considering with equal weight the preferences of the present and all future decision makers.

Following this principle we have to add the benefits of future decision makers as it is seen from their perspective (e.g. in accordance with the state of the world at their point in time and capitalized to their point in time).

The benefit function for the joint decision maker (see Fig. 7) can then be written as

$$B(\mathbf{D}(\mathbf{T})) = \sum_{i=1}^{n} \left[\int_{t_i}^{t_{i+1}} b_{G_i}\big(\tau, \mathbf{D}(t_i), t_i\big)\, \kappa(\tau - t_i)\, d\tau \right], \tag{6.3}$$

where $b_{G_i}\big(\tau, \mathbf{D}(t_i), t_i\big)$ is the benefit function and $\mathbf{D}(\mathbf{T}) = \{\mathbf{D}(t_i);\ t_i \in \{t_0, t_1, \ldots, t_n\}\}$ are the possible decision alternatives for the decision maker at time t_i.

It is noted that decisions made on the basis of Eq. (6.3) without any constraints might violate the philosophical principle of life-value invariance. The solution of Eq. (6.3) must thus be identified under the prerequisite that life saving costs at the time of any future decisions is evaluated according to the LQI as evaluated at that time.

Based on Eq. (6.3) optimization of decision may now be undertaken considering to the best of knowledge the preferences of future decision makers as well as the way resources and economical means might be transferred over time. It should be noted that the way usual decision analysis is being applied at present e.g. for the purpose of optimization of design and inspection and maintenance planning is in contradiction of the formulation given in Eq. (6.3). This is because the real mechanisms of the transfer of e.g. monetary benefits and costs are not taken properly into account in the decision analysis. The formulation in Eq. (6.3) is in this sense not only new but might provide a very illuminating insight into aspects of sustainable decision making in the future.

7. Discussion and conclusions

The basic aspects of decision making in engineering is reviewed and discussed with special focus on the modelling and representation of uncertainties and probabilities. Uncertainties are differentiated into two types, namely epistemic and aleatoric uncertainties and it is discussed how this differentiation is useful and necessary to acknowledge in the context of probabilistic modelling. However, the differentiation between the different types of uncertainties in the context of decision analysis is not relevant – in this context all uncertainties must be included, however of course in consistency with evidence and knowledge.

The representation of preferences in the formulation of utility functions for the purpose of decision making on behalf of society is discussed with special emphasis on risk aversion. The concept of follow up consequences is introduced to bring focus on all consequences which might follow from an adverse event. It is emphasized that the introduction of non-linear utility functions for the representation of risk averseness is neither necessary nor leads to rational decisions. Only when a rigorous assessment of direct and derived consequences is undertaken may a rational basis for decision making be established.

The decision theoretical framework for engineering decision making in regard to optimal design and maintenance is summarized and categorised as prior, posterior or pre-posterior decision problems. In principle the optimal design and maintenance problem can be formulated as a pre-posterior decision analysis problem. Even though such problems have actually been formulated for some time still little effort has been put into the study of simultaneous optimisation of design and maintenance.

Finally a new concept is introduced on how sustainable decision making may be addressed and formulated in decision theoretical terms. The basic principle behind the idea is to formulate a utility function which takes into account he preferences of not only the decision maker at the present time but also and with equal weight the preferences of decision makers at later times. Depending on how the flow of income, costs and resources between decision makers at different points in time is organized or pre-scribed the developed formulation will yield decisions differing from those applied so far in e.g. optimal design and maintenance of structures. More research into this subject is necessary and underway.

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