

Working Paper

Decision Analytic Modeling of Uncertainty and Subjectivity in Water Quality Management

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WP-92-054
August 1992



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Preface

The management of increasingly complex water resources problems influenced by climate change, environmental degradation and other factors, more and more requires comprehensive decision analyses. These should account for uncertainty, subjectivity and risks of various sources. The present paper discusses several approaches and concepts of decision analysis, relying upon earlier works done at IIASA. The application of two methods for which commercial computer software is available is illustrated by a number of case study examples.

Abstract

Quantification and reduction of uncertainty associated to decision making is one of the primary functions of modeling and monitoring targeted to assist decision making in reservoir, river, and lake water quality management. In many practical activities such as environmental impact assessment, the inference is bound to be based primarily on subjective, expert judgments, supported by empirical data and models. A bulk of analytical approaches is presently available for modeling purposes. The paper discusses selected decision analytic approaches to the handling of uncertainty associated to information available, uncertainty as a decision criterion, and as a component influencing the model structure. Computational solutions based on experience on six case studies are reviewed.

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DECISION ANALYTIC MODELING OF UNCERTAINTY AND SUBJECTIVITY IN WATER QUALITY MANAGEMENT

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1 INTRODUCTION

Limnology – the science of freshwater quality – has classically two major facets, theoretical and applied one. The latter one belongs obviously to applied sciences. Fundamental to them is that the information obtained should yield sooner or later, in a form or another, to decision support. This is evident generally for entire watersheds and all their components, perhaps most plainly when discussing man-made ecosystems such as reservoirs, which have been designed and constructed to meet one or more societal targets such as energy production, water supply, or recreation.

Decision making, when given a form of a decision analytic model, consists typically of following components:

- (1) Management objectives, goals, targets, criteria, and constraints.
- (2) Elements in the system that are under control, at least partially.
- (3) The information conditioning the above entities.

As elements of models, those objects are usually called objective functions (including constraints), decision variables, and chance variables, respectively. A decision analysis attempts to structure and quantify this – often subjective – information, in order to find most essential influences within the system, to detect critical components of total risk and uncertainty, to identify proper variables and policies to be controlled within the system, and to provide scenarios and sensitivity studies to support the above targets.

Modeling exercise in general is most useful and pedagogic to the agent personally interactive with the construction and analysis of the model. Accordingly, the methodological scope of the study was to find approaches that are practical, interesting, relevant, and rewarding to both scientists and decision makers, since modeling could be a real bridge between those often too distant bodies, once a methodology is used which allows both of them to construct and interact with models. Such modeling environments should be truly interactive and user friendly, and allow structuring of the model, and adjacent uncertainty, sensitivity, risk, and optimization studies.

When using computer models, it is also essential that the whole inference and decision support process is considered as a whole, and not, e.g., only as parameter or state uncertainty as is often done. Hence the role of uncertainty and subjectivity in all the three categories given in the title will be discussed. These two aspects are particularly relevant from the point of view of the needs of practical management, where in principle everything costs: delaying a project, collecting new information, or making faulty decisions based on inadequate information. Next section lists a selection of approaches to presenting and managing those types of uncertainty, and thereafter two straightforward ways to computational implementation of those approaches are presented. For more information on decision analysis, see, e.g., Raiffa (1968), Howard & Matheson (1983), Bunn (1984), and von Winterfeldt & Edwards (1986).

2 DECISION ANALYTIC MODELING OF UNCERTAINTY AND SUBJECTIVITY

2.1 Information

Pearl (1988) divides the computational approaches to propagation of uncertainty into two groups. One includes logic based approaches dealing with non-numerical techniques, such as monotonous logic. They are known as, e.g., production systems, rule-based systems, and procedure-based systems, in which uncertainty is treated as a generalized truth value attached into formulas, and, as in classical logic, the uncertainty of a formula is calculated as a function of the uncertainty of its subformulas.

The other group has its roots in calculus and in probability theory. Uncertainty is attached into 'state of affairs' or descriptions of 'possible worlds'. Representation is numeric, and in addition to classical probabilistic and Bayesian calculus, also approaches such as Dempster-Shafer calculus and fuzzy logic are used.

Each approach has its merits and deficiencies. For further details on approaches and their essentials, see Pearl (1988). In this study, probabilistic, Bayesian calculus has been chosen under focus due to its several favorable properties (Pearl 1988, Howson & Urbach 1991). Many of the following issues are, however, valid for many other approaches as well.

2.2 Objectives

Models can be classified in many ways. One very basic property dividing them into two groups is whether they include decision variable(s) or not. If yes, then there must be a component involving the criteria for decisions, i.e., the values, targets, preferences, objectives, constraints, etc. They constitute the objective function in large. If decision makers do not care about uncertainty, the problem is typically to minimize or maximize the expected value of the objective function. There are a number of ways to take uncertainty into account as one component in the objectives.

The concept of utility

Utility theory has a long history in decision sciences (von Winterfeldt & Edwards 1986). The most essential feature of the theory with respect to this study is that the utility U of a good x to be maximized or minimized is primarily subjective, and not always linear. For instance, the marginal value of money is often decreasing: the utility of additional \$1 to \$10 is typically greater than that of additional \$1 to, say, \$1 000. The same is often true even if the units are, say, kg of fish, or $\mu\text{g/l}$ of phosphorus. Such nonlinearities imply in fact that the manager has an attitude towards risk, he/she either tries to avoid risks or seek them, as is presented below.

The assessment of the form of an utility function is an important task. But no standard method is available. One must most often use soft approaches such as interviews, standard devices (based on series of comparisons such as: "Would you rather choose a lot with probability P to win an amount of x , or the given decision alternative"), or direct comparisons of numerical probabilities (Bunn 1984, von Winterfeldt & Edwards 1986). Often fixing of one single function is not rational, but a sensitivity analysis within a domain of interest can be conducted (cf. Varis et al. 1990 & 1991).

Risk attitudes

One widely used approach to present risk attitudes is to take also an uncertainty measure, such as variance, into account. Take a simple example. If two management alternatives yield in expected harvest of fish from a reservoir with volumes such as 6 ± 2 (let 2 equal the standard deviation σ), or 8 ± 5 kg/ha, respectively, the expected value, 6 or 8, may not be informative enough as a criterion. A risk averse manager would be obviously willing to choose the first option, while a risk neutral one – comparing only the expected values – and risk prone (risk seeking) one would rather go for the second option.

It is easy to conceptualize a risk averse manager. He or she is concerned about uncertainty involved in management options, and tries to limit it, keeping in mind that the expected utility does not go too far down. Typically the reduction of uncertainty leads to decreased expected utility. A risk neutral manager is perhaps more rare, but definitely there is a legion of cases where uncertainty is not a very dominant criterion, and this assumption is justified.

Risk prone attitude is evidently not so frequently encountered in environmental management. Yet examples are not very difficult to find. Assume that a group of households get a part of their income from pike-perch fisheries by a reservoir. The annual fish catch must exceed certain threshold to become profitable. In conditions where the threshold is well above the expected catch level, it is rational to aim at a strategy which increases variance of the annual catches, because then it is more probable that very high catches occur every now and then, bringing good revenues. It is assumed that the households notice in good time when there is no profit to be expected and adapt towards other activities. In this formulation, recreational fisheries are given far less value than part-time professional fisheries. This is a clearly risk prone strategy.

A more general example on risk proneness, including actually also the previous example, is to consider cases in which low yields are compensated in a way or another. In such conditions, only high catches matter. Actually, this is one of the major problems in agricultural policy making in many overproduction countries in Europe. In macroeconomic level, the target should be in stable production level (risk averse), but at microeconomic level compensations constitute an incentive to increase variability (risk prone).

Pratt (1964) and Arrow (1971) have presented the following approach to the risk attitude problem. In utility theory, the character of the utility $U(x)$ tells about decision maker's risk behavior. If the marginal utility is decreasing, as in the example within the context of the concept of utility, then its second derivative is negative. Scaling it with the first derivative, we get a metric for risk attitude $r(x)$:

$$r(x) = -U''(x)/U'(x) \quad (1)$$

This, in turn, can be used to give a measure of a premium $\pi(x)$ of taking a risk $r(x)$, once the uncertainty, i.e., here, the variance $\sigma^2(x)$ is known:

$$\pi(x) \approx 1/2 \sigma^2(x) r(x) \quad (2)$$

Decreasing marginal utility implies risk averse attitude, while increasing one tells, that only big things matter, and the attitude is risk seeking. Often this approach is called a trade-off between mean and variance. The price that has to be paid for decreased uncertainty is actually the risk premium $\pi(x)$. It is, derived from another direction, the difference of expected utility $E(U(x))$ and the so-called certainty equivalence $\pi_a(x)$:

$$\pi(x) = E(U(x)) - \pi_a(x) \quad (3)$$

Certainty equivalence is a value of utility, obtained with certainty, which is equivalent to the uncertain, real option.

If a manager considers that a catch of 6 kg/ha obtained with certainty is equivalent to a

catch of 8 ± 5 kg/ha, then the certainty equivalence is 6 kg/ha, and risk premium is 2 kg/ha. The latter is the expected price he/she is ready to pay for eliminating the uncertainty. If risk premium is positive, then the manager is risk averse, if zero, then he/she is risk neutral, and if negative, then risk prone. More extensive examples of the use of the criterion in water quality and fisheries management models are given by Varis et al. (1990 & 1991).

Clearly also other properties of probability distributions besides expected value and variance can be useful. In this respect, basic concepts concerning the type, parameters, and biases of distributions as known from statistics and probability theory cannot be forgotten.

There are a number of other approaches to measuring the uncertainty as a decision criterion. Let us mention the following three (Hashimoto et al. 1982a), which are not based on parameters of distributions, but rather on assessing the mass of the frequency distribution below or above a certain threshold value. Such practical criteria are very sensitive to – often subjective – assumptions of both the type of the distribution and its parameters, when the tails of the distributions, i.e., extremes – as often is the case – are considered.

Reliability

A threshold value is used to divide the distribution of objective function to satisfactory and unsatisfactory. Reliability α is the probability (relative frequency) with which the model gives a satisfactory outcome, getting values between 0 and 1. This can be also understood that a target for, e.g., phosphorus or BOD concentration, is defined and the probability with which this target can be obtained is assessed, with respect to competing management options. A typical criterion for cases where a norm has to be fulfilled.

Resiliency

Resiliency is a metric for how long a failure or unsatisfactory condition usually would last. Lets us define ρ as the probability that the system being in satisfactory state at time step k turns to unsatisfactory at $k+1$. Resiliency γ is then

$$\gamma = \rho / (1-\alpha) \quad (4)$$

Vulnerability

Vulnerability addresses to both probability and magnitude of system failure, how bad things may become. Let s_j be the severity of a failure, and e_j the probability that s_j is the most severe situation among the situations under concern. Then vulnerability v of the system can be expressed as:

$$v = \sum s_j e_j. \quad (5)$$

2.3 Structure

Structuring the model

An important source of information for a decision analytic model is the acquisition and merging of subjective, expert knowledge. Often several persons with varying backgrounds are to be taken into analysis, e.g. engineers, ecologists, economists, managers, and politicians.

Model structuring is an iterative procedure. It is essential throughout the analysis. A graphical, interactive presentation of the structure is very helpful in providing an unambiguous schematic interpretation of variables and their relations. It also supports expert knowledge acquisition (see Shachter & Heckerman 1987).

Causality vs. correlation

The classical problem in interpreting correlated information is that the correlation as such does not necessarily imply a causal relation between correlated variables. They may instead be outcomes of a common cause, or be just by chance correlated. As an example of the former, certain cyanobacteria genera, say, *Anabaena* and *Aphanizomenon*, are often highly correlated. This does not mean that those genera favor the appearance of one another. In contrary, they are strict competitors. The causal reason is that they favor rather similar environmental conditions.

Often also decisions have to be based on very small data sets. High correlations can be found, but the confidence is still low. Such structural uncertainty can only be judged subjectively, based on knowledge, beliefs, and assumptions of the structure of the system, given limited evidence.

Model structuring must take also these problems into consideration, and the aforementioned interaction, iteration, and clear the schematic interpretation of variables and the nature of their relation should support this procedure, and subject it to critical evaluation.

Value of information and control

There are analytical techniques to study various impacts of the model structure, two of which are referred to here. They both require that the model has an objective function and decision variable(s), and additionally they have also dimension which bring them close to both information uncertainty and uncertainty included in the objectives.

Questions like: what if we knew more, would the collection of new information be worthy, and where it should be directed, can be studied by the value of information analysis. It takes either the form of a sensitivity analysis, in which the impact of reducing or increasing the uncertainty of an element of a model is studied, or adding new information links to the

model, e.g., to express that we start to obtain information directly on a substance which in the original model is obtained indirectly. In the latter case, the analysis changes the structure of the model. The concept is closely related to decision flexibility (for details, see Merkhofer 1977). Value of perfect information equals the concept of opportunity cost. Hashimoto (1980) and Hashimoto et al. (1982b) use it as a measure for the adaptivity of the system, in terms of information-robustness.

Technically, e.g., using the approaches described in the following section, it is rather easy to redefine a decision variable to a probabilistic or deterministic variable, or vice versa, and to see how this influences the value or distribution of the objective function. Also a partial control can be studied using the value of control analysis. Questions such as what should we try to control and to what extent, could be studied. An analogical concept with information-robustness can be derived: the less components we need to control, and the less value the control shows, the more control-robust the system is.

There are several reasons to target on control- and information-robust systems including, above all, first that there are no pragmatic reasons to know too much about such systems: they run on their own, and second that the systems are adaptive, flexible, and robust. These criteria can ad-hoc be associated as prerequisites with sustainable management. In addition to these two analyses, there exists procedures for inductive identification of a model, especially the structure, from data. For those techniques, the reader is referred to Pearl (1988).

3 COMPUTATIONAL ASPECTS

There exists today many ways to use these – and many more – issues in a rather user-friendly way. Here two approaches are presented, which have been experienced in six case studies (Varis et al. 1990, 1991, Varis & Kuikka 1990, Kuikka & Varis 1991, Koivusalo et al. 1992, Taskinen et al. 1992) to be very practical and straightforward. One case analyses restoration management of a eutrophic lake, two study river water quality management, one deals with river basin management including reservoirs, and two cases with fisheries management, in a reservoir and in brackish water, respectively.

The two approaches below are principally rather analogical and the same uncertainty metrics and criteria are potentially usable, however, realization and computational implementation are different.

3.1 Influence diagrams

Decision theory knows several types of probabilistic models (von Winterfeldt & Edwards 1986, Pearl 1988) including tree- and network models, using various computational schemes (see Modeling Uncertainty). Among Bayesian, optimization models, typical representatives

include decision trees and influence diagrams, among which the latter one is considered.

An influence diagram (Shachter 1986) is a probabilistic network model focusing on influences of variables to one another. The variables (nodes) are connected with directed arcs. The whole diagram is directed, and no cycles are allowed. In case an arc is heading to a decision node, the value of the predecessor is known before the decision can be made. In all other cases an arc stands for a conditional dependence between two variables. Depending on the type of the node, it may contain arithmetic functions, IF-THEN-ELSE rules, or probability distributions.

There exists commercial computer software for the purpose (Shachter 1987, Balson et al. 1991). They allow the model structuring in an interactive way, and include some of the above presented approaches to handling uncertainty. Also additional analyses than those provided by the software can be made, but they require specific computational solutions. Partial evaluation of the model is possible. For examples of the use of influence diagrams, see Varis et al. (1990, 1991) and Varis & Kuikka (1990).

3.2 Spreadsheets

Another approach discussed here is to use one of the widely used spreadsheet programs. Most practitioners – both scientists and decision makers – are already familiar with them, they are easily programmable for arithmetic calculations and graphical interface. Additionally, models can be constructed and used in very close association with databases. Probabilistic functions are included in some programs, and to many of them, probabilistic simulation add-in packages (e.g., Anon. 1990) are available. Many spreadsheet programs provide certain optimization and statistics routines. They are also typically rather well compatible with many other software, and powerful even in negotiations and meetings. Here I refer to the experience on fish quota negotiations at International Council for Exploitation of the Sea.

Structuring of the problem is not as easy as when using influence diagrams. However, computational power, possibilities to program own criteria, and design the interface are merits of the approach. For instance, optimization can simply be made by coding a model to consist of one line (row or column). Cloning that line, and giving a decision variable a series of values allows the analyst to see from all subsequent variables very easily, graphically if wanted, what happens to them. In other words, any of them can also serve as an objective function. Also new functions are easy to code.

Enhanced facilities for doing probabilistic simulations, by using sampling such as Monte-Carlo or Latin Hypercube, are available. Also value of control and information analyses can be made easily. Examples of the use of the approach are given by Kuikka & Varis (1991), Taskinen (1992), Taskinen et al. (1992), and Koivusalo et al. (1992).

4 CONCLUSIONS

In applied sciences such as applied limnology, the impact of decisions is important, even crucial. This fact should be reflected in the approaches used to research and modeling. Decision analysis should more often be a part of applied limnological studies. The classical division of limnology to applied and theoretical, although being fuzzy in practice, is relevant as a very general concept. Both aspects are needed, and this study focuses on the former one.

Often uncertainty, and typically subjectivity, are essential features in environmental decision making, such as reservoir, lake, and river water quality management. Structuring of the model is a crucial task. Management options and water quality problems are very case specific, and often subjective expert knowledge is a major source of information. Uncertainty and subjective information should more often be handled analytically.

Those involved in research, management, and administration should find common computational tools – relevant and effective also for inter-group use – which contribute to the lowering of communication gaps between those parties. Two suggestions were made, namely the use of influence diagrams, and the use of spreadsheets. They both have been experienced in a number of case studies. It is clear that there exists a countless number of ways to perform the computational realization of approaches such as described above. Which one is preferred, depends on purpose, convention, and resources available.

To us it appears, that limnological and environmental decision situations where risk neutral behavior is a correct assumption are not very frequent. Risk averse, instead, appears rather typical, i.e., the management objectives include the reduction of uncertainty involved in the project. Also risk prone cases definitely exist. Therefore, risk attitude analysis is a very important phase in decision analytic studies. Exclusion of it leads to the assumption of risk neutral behavior.

There is no single, correct way to model water quality. Instead, multiple tools are needed (cf. Varis 1991). The selection of the approach should be a conscious choice. There are different phases in decision and systems analysis, that addressed here is one of them.

5 ACKNOWLEDGEMENTS

I greatly appreciate the support, ideas, and critical comments of many co-workers, especially those by J. Kettunen, S. Kuikka, D.P. Loucks, H. Sirviö, L. Somlyódy, A. Taskinen, and P. Vakkilainen.

6 REFERENCES

- Anon., 1990. @Risk: Risk Analysis and Simulation Add-In. Palisade Corp., Newfield, NY.
- Arrow, K.J., 1971. Essays in the Theory of Risk-Bearing. Markham, Chicago, IL.
- Balson, W.E., Gordon, M.S. & Nease, R.F., 1991. Customized Decision Models Using Embedded Influence Diagrams. Decision Focus Inc., Los Altos, CA.
- Bunn, D.W. 1984., Applied Decision Analysis. McGraw-Hill, New York.
- Hashimoto, T., 1980. Robustness criterion for planning water demand/supply decisions. *Angew. Systemanalyse*, 1: 137-144.
- Hashimoto, T., Stedinger, J.R. & Loucks, D.P., 1982a. Reliability, resiliency, and vulnerability criteria for water resources system performance evaluation. *Water Resour. Res.*, 18: 14-20.
- Hashimoto, T., Loucks, D.P. & Stedinger, J.R., 1982b. Robustness of water resources systems. *Water Resour. Res.*, 18: 21-26.
- Howard, R.A. & Matheson, J.E. (Eds.), 1983. The Principles and Applications of Decision Analysis, vols. I & II. Strategic Decision Group, Menlo Park, CA.
- Howson, C. & Urbach, P., 1991. Bayesian reasoning in science. *Nature*, 350: 371-374.
- Koivusalo, H., Varis, O. & Somlyódy, L., 1992. Probabilistic BOD balance study for the Nitra River. International Institute for Applied Systems Analysis, WP-92-xxx, Laxenburg. In Press.
- Kuikka, S. & Varis, O., 1991. Probabilistic assessment of TAC based fisheries management of Baltic Salmon. International Council for Exploitation of the Sea, C.M. M:30 (Mimeo).
- Merkhofer, M.W., 1977. The value of information given decision flexibility. *Managem. Sci.*, 23: 716-727.
- Pearl, J. 1988., Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference. Morgan-Kaufmann, San Mateo, CA.
- Pratt, J.W., 1964. Risk aversion in the small and in the large. *Econometrica*, 32: 122-136.
- Raiffa, H., 1968. Decision Analysis. Addison-Wesley, Reading, Massachusetts.
- Shachter, R.D., 1986. Evaluation of influence diagrams. *Oper. Res.*, 34: 871-882.
- Shachter, R.D., 1987. DAVID Influence Diagram Processing System for the Macintosh. Center for Academic Computing, Duke University, Durham, NC.
- Shachter, R.D. & Heckerman, D.E., 1987. Thinking backward for knowledge acquisition. *AI Magazine*, 8: 55-61.
- Taskinen, A., 1992. MSc Thesis (In Finnish, with English Abstract). Helsinki University of Technology, Laboratory of Hydrology & Water Resources Management, Espoo, Finland.
- Taskinen, A., Varis, O., Mutanen, J. & Vakkilainen, P., 1992. Probabilistic uncertainty assessment of water and nutrient balance calculations in a watershed. *Ecol. Modelling*, In Press.
- Varis, O., 1991. Computational Modeling of the Environment with Applications to Lake Eutrophication. Thesis for the Doctor of Technology, Helsinki University of Technology, Espoo.
- Varis, O., Kettunen, J. & Sirviö, H., 1990. Bayesian influence diagrams in complex envi-

- ronmental management including observational design. *Comp. Stat. Data Anal.*, 9: 77-91.
- Varis, O., B. Kløve, B. & Kettunen, J., 1991. Socioeconomic evaluation of a real-time forecasting system for river quality – a trade-off between uncertainty, costs and risk attitudes. In Press.
- Varis, O. & Kuikka, S., 1990. Analysis of sardine fisheries management on Lake Kariba, Zimbabwe and Zambia – structuring a Bayesian influence diagram model. International Institute for Applied Systems Analysis, WP-90-48, Laxenburg.
- von Winterfeldt, D. & Edwards, W., 1986. *Decision Analysis and Behavioral Research*. Cambridge University Press, Cambridge.