Incorporating Uncertainty in Watershed Management Decision-Making: A Mercury TMDL Case Study

William Labiosa[1], James Leckie[1], Ross Shachter[2], David Freyberg[1], and James Rytuba[3]

[1]Department of Civil and Environmental Engineering, Stanford University, Terman Engineering Center, 380 Panama St., MC-4020, Stanford, CA 94305-4020; email: labiosa@stanford.edu
[2]Department of Management Science and Engineering, Stanford University, Terman Engineering Center, 380 Panama St., MC-4026, Stanford, CA 94305-4026
[3]U.S. Geological Survey, 345 Middlefield Road, MS 901, Menlo Park, CA 94025

Abstract

Water quality impairment due to high mercury fish tissue concentrations and high mercury aqueous concentrations is a widespread problem in several sub-watersheds that are major sources of mercury to the San Francisco Bay. Several mercury Total Maximum Daily Load regulations are currently being developed to address this problem. Decisions about control strategies are being made despite very large uncertainties about current mercury loading behavior, relationships between total mercury loading and methyl mercury formation, and relationships between potential controls and mercury fish tissue levels. To deal with the issues of very large uncertainties, data limitations, knowledge gaps, and very limited State agency resources, this work proposes a decision analytical alternative for mercury TMDL decision support. The proposed probabilistic decision model is Bayesian in nature and is fully compatible with a "learning while doing" adaptive management approach. Strategy evaluation, sensitivity analysis, and information collection prioritization are examples of analyses that can be performed using this approach.

Introduction

This paper demonstrates a decision analytical model of mitigation/load allocation decisions for a simple mercury Total Maximum Daily Load (TMDL) setting example. Such a model can be used throughout the TMDL decision process, including initial information gathering decisions, load allocation/mitigation decisions, and post-implementation monitoring decisions. The essential insight is that information gathering/monitoring decisions, whether made before or after allocation decisions, draw their value from making better load allocation/mitigation decisions. For this reason, information gathering decision models *build on* load allocation/ mitigation decision models. Our load allocation/mitigation decision model integrates a Bayesian (probabilistic) network model of environmental system response to mitigation decisions with a valuation model, allowing insights into the credibility of compliance with multiple numerical standards, insights into sensitivity of conclusions to small changes in model parameters, and, if a value model can be defined, the determination of optimal strategies.

The approach uses a Bayesian network model of the relationships between potential mercury control efforts, total mercury loadings, methyl mercury concentrations, and mercury fish tissue levels in the Cache Creek watershed, a major source of mercury to the Bay Delta. Simulations of the probability distributions of the environmental variables of interest are made using stochastic empirical models. Model input uncertainty and model error are explicitly included and propagated through the model using Bayesian network algorithms. Various control scenarios can be explored through probabilistic modeling of the downstream effects on the environmental targets of interest.

This modeling approach allows the creation of a decision framework that integrates the various sources of uncertainty in a complex and highly uncertain TMDL decision situation. The various sources of uncertainty are integrated as decision risk, allowing decision makers to transparently consider value trade-offs between compliance costs and uncertainties in meeting the various environmental/ ecological targets. Advantages of the approach include decision basis transparency, integration of uncertainty as decision risk, and the explicit consideration of values.

A Decision Analytical Approach to TMDL Setting Decisions

At the highest level, decision analysis divides the framed decision problem into *alternatives*, *information*, and *preferences*. In the context of public environmental decision making, these could be cast as: 1) decision framing/strategy generation; 2) information modeling/synthesis/forecasting; and 3) multiattribute utility analysis, negotiation among interest groups, or other methods of eliciting and representing preferences. Each of these aspects of decision are described in detail elsewhere (e.g., Merkhofer, 1999; Labiosa et al., 2003, and references cited within). The goal of decision analysis is to create decision clarity in a complex decision problem. We present a watershed management example to demonstrate its potential.

A decision analytical approach to TMDL setting decisions allows decision makers and stakeholders to explore scenarios, conduct sensitivity analyses, and to explore the consequences of different stated preferences over outcomes. Given the decision makers' consensus on information, alternatives, and preferences, a best strategy can be determined. Decision analysis does not predict optimal decisions "objectively", since the decision makers' subjective preferences and beliefs are required by the approach. In fact, from a decision analysis perspective, all decision making is subjective and thus any decision analytical tool must be modified to reflect the beliefs and preferences of the decision makers before use. Decision analysis is a theoretically sound approach for making significant decisions under uncertainty (see, e.g., Howard, 1968; 1988; Keeney and Raiffa, 1976; Clemen, 1996; Merkhofer, 1999). There are a number of examples of the use of decision analysis for environmental decision making in the literature, often in the area of site selection or choosing between remediation, restoration, or technology alternatives (e.g., Keeney 1980; Maguire and Boiney 1994; Reckhow 1994; Merkhofer et al. 1997; Perdek 1997; Kruber and Schoene 1998; Merkhofer, 1999; Freeze and Gorelick 1999). In addition, recent work has demonstrated that water quality management effects can be effectively modeled using Bayesian (probabilistic) networks, producing results that are comparable to more complex mechanistic models (e.g., Reckhow, 1999; Borsuk et al., 2001; Borsuk et al., 2002; Stow et al., 2003).

It is emphasized that decision analysis applied to group decision situations should be thought of as a *process* by which groups may discover useful insights that highlight where consensus may be achieved and where obstacles requiring clarification, negotiation, mediation, or litigation may lay. There are many competing versions of decision analysis with variations on how alternatives are generated, uncertainty is represented, preferences are elicited, etc. In this paper we describe a decision analytic approach that is based on small group elicitation of goals, objectives, and alternatives, a probabilistic model of natural system response, and several potential methods for eliciting and representing preferences. Other related approaches may be just as appropriate, depending on circumstances.

Data and Resource Limitations

Predicting total mercury and methylmercury loadings in mine- and geothermal source-impacted watersheds is an inherently difficult problem. Since most of the total mercury mass is transported with the suspended sediment load, the many difficulties of modeling sediment transport apply. Unfortunately, even larger uncertainties are involved in modeling the relationship between stream segment methylmercury concentrations and total mercury concentrations. While several relevant and useful studies have been conducted, the available data are sparse relative to the complexity of the modeling problem and the very large uncertainties involved (Bloom, 2001; Domagalski et al., 2003; Domagalski; et al., 2004; RWQCB-CV, 2004b, 2004c; Slotton et al., 2004; Suchanek et al., 2003). In general, data collection budgets for TMDL development are very limited (Houck, 1999; Ruffolo, 1999). Other important considerations are the large costs associated with the mitigation efforts being considered and recent evidence that strongly suggests that background total mercury and methylmercury loadings may be much larger than previously thought in the Bear Creek and Sulphur Creek watersheds (James Rytuba, personal communication).

In addition to data and modeling limitations and predictive uncertainty, the California Regional Water Quality Control Boards (RWQCBs) are very limited in number of staff that can be tasked with TMDL development (Ruffolo, 1999). Since budgets are limited, the ability to contract outside expertise is also limited. Collectively, these issues point to a need for a decision framework that takes into consideration the very large uncertainties involved and the resource constraints of the State agencies tasked with TMDL development and implementation planning (Labiosa et al., 2003; NRC, 2001; Ruffolo, 1999).

Example TMDL Decision Problem: Mercury TMDL in a Mine-Impacted Watershed

This example presented here is a simplified abstraction from the Sulphur Creek mercury TMDL, a real mercury TMDL setting process in Northern, California. The 6500 acre watershed is part of the Cache Creek watershed in the California Coast Range mercury mineral belt. Sulphur Creek, Cache Creek, and other creeks within the Cache Creek watershed are on the Central Valley Regional Water Quality Control Board's (RWQCB) list of impaired water bodies due to elevated mercury levels in water (RWQCB-CV, 2004b). These watersheds are major sources of mercury to the San Francisco Bay, which is also listed as impaired due to mercury contamination (RWQCB-SFB, 2003). Elevated mercury fish tissue levels, high concentrations of mercury in the water column, and large loadings of total mercury and methylmercury have been observed in several parts of the Cache Creek watershed.

Since 2000, the Sulphur Creek TMDL workgroup has been collecting information relevant to the setting of the mercury TMDL target and for determining a proposed source allocation scheme. In addition, the CALFED Bay Delta Program, a Federal/California State partnership with the mission of developing and implementing a long-term comprehensive plan that will restore ecological health and improve water management for beneficial uses of the San Francisco Bay-Delta System, has supported several relevant research projects. The results of these studies are summarized in the November 2004 draft Sulphur Creek mercury TMDL report (RWQCB-CV, 2004b) and the various CALFED final draft reports (available on-line at http://loer.tamug.tamu.edu/calfed/ FinalReports.htm).

Before representing this small watershed mercury TMDL setting process in terms of decision analysis, we briefly define some concepts important for understanding the mathematical framework used, namely, Bayesian networks.

Significant Scientific Uncertainties as Random Variables in a Bayesian Network

Bayesian networks are probabilistic models based on a coherent set of beliefs about the relations between system variables, in contrast to deterministic approaches that model system behavior on the basis of mathematical representations of underlying mechanisms and on empirical deterministic approaches that ignore uncertainty. Bayesian network models do not ignore scientific knowledge about system mechanisms and behavior, but instead, represent this knowledge in terms of causal relations between random variables and conditional probabilities that describe these cause and effect relationships. In the Bayesian network model of the Sulphur Creek mercury TMDL setting decision situation, causal relations and conditional probabilities are based on what is currently known about the relations between HgT sources, HgT loading, MeHg production and the resulting loading, Hg fish-tissue burdens, and other natural-system variables. The model also includes a probabilistic representation of what is currently known about how mitigation efforts may impact the natural system. The composite effect of uncertainty and natural variability are represented as conditional probability in these models.

A Bayesian network consists of a graph and probabilistic data associated with the nodes in the graph. The graph consists of nodes (ovals) connected by arrows, where the ovals represent chance (uncertain) nodes, each of which is associated with a random variable. The random variables in the Bayesian network represent the attributes of interest to decision-makers. Arrows represent potential conditional-probabilistic dependence between the various random variables and can be drawn in a causal direction. Graphically, an arrow from a parent node to an uncertain variable (child) means that the probability distribution in the uncertain variable (child) is conditioned by the state of the parent node. The absence of an arrow between two variables in a network indicates that these variables are conditionally independent given their parents (Shachter, 1988).

Figure 1 shows a Bayesian network representation of the Sulphur Creek mercury TMDL decision problem. This particular network is referred to as an influence diagram, since it contains a decision node, a value node, and random variables (chance nodes). "Water year" refers to the amount of precipitation received for a particular water year, e.g., "wet" (W), "dry " (D), "above-normal" (AN), "below-normal" (BN), and "critical" (C), as defined by the California Department of Water Resources. The TMDL workgroup is considering the 2000 – 2004 water years in its TMDL development process, which included D, W, AN, and BN water years. Uncertainty in future water years could be included or ignored, depending on the perspective of the decision makers. The legacy mine waste-related annual mercury loading aggregated over all mines in the watershed is represented by the "Annual Mine Total HgT Loading" node. The associated random variable represents the uncertainty in this loading, given a particular set of water year characteristics and the uncertain effects of the TMDL strategy adopted. In general, an arrow (arc) from the TMDL Strategy Decision to a variable represents the effect of the strategy on the decision-makers' underlying uncertainty on the quantity in question. The arcs from "Annual median $[HgT]_w$" (total mercury concentration in the water column) and "Methylation Potential" (the sum total of environmental factors that promote or inhibit the formation of methylmercury) to "Annual Median $[MeHgT]_w$ (total methylmercury concentration in the water column) represent the uncertain causal relationship between the potentially manageable environmental factors (e.g., sulfate loadings from geothermal sources, the existence of water impoundments, etc.), median total mercury concentrations over the reach, and the resulting median methylmercury concentrations over the reach. While this causal relationship is "well

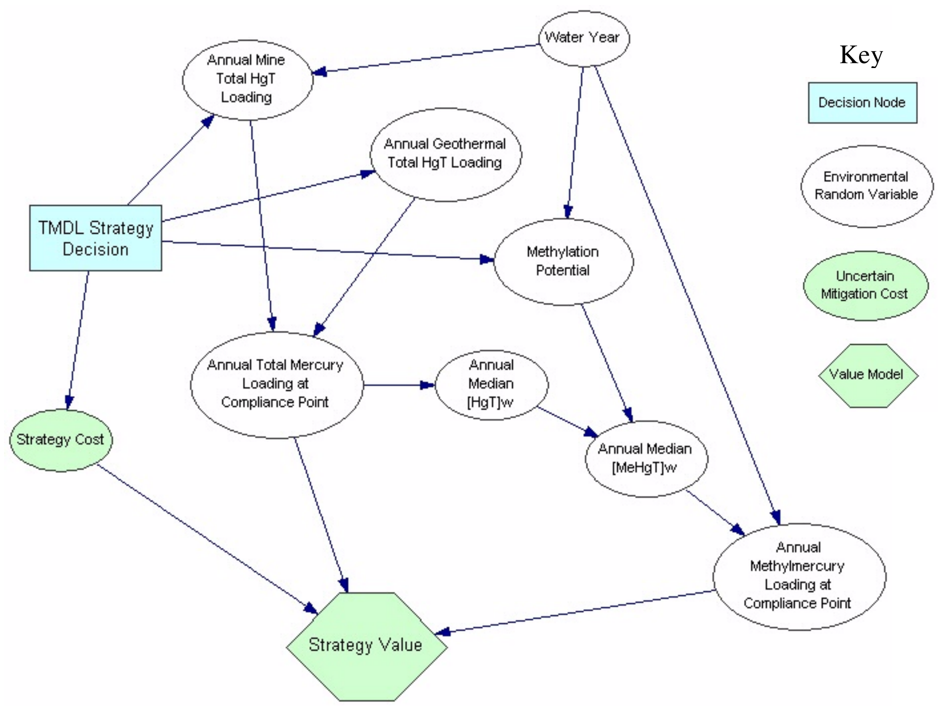

Figure 1. Bayesian network (influence diagram) for the Sulphur Creek Mercury Total Maximum Daily Load Setting Decision Situation

understood", the forecasted median methylmercury concentrations are highly uncertain.

The "Strategy Value" node represents the valuation that the decision-maker places on a particular outcome, where "outcome" refers to the costs associated with the strategy chosen and the resulting environmental consequences. Decision-maker preferences could be modeled in a number of ways, but this example uses an explicit multi-attribute utility model over strategy cost, annual total mercury loading at the compliance point, and annual methylmercury loading at the compliance point.

The variables are related in Figure 1 by cause-and-effect and they are included only if they fit one or more of several criteria. They are either: 1) potentially manageable (e.g., methylmercury potential in impounded water and total mercury loading from mines and geothermal sources); 2) predictable from available data or expert knowledge; or 3) observable at the scale of interest from the perspective of the water quality management problem. In addition to these criteria, chance variables are only included if they are: 1) of interest to the decision makers and/or stakeholders or; 2) helpful for assessing probability distributions for other variables that are of interest.

Figure 2 graphically illustrates the probability data associated with the "Annual Mine Total HgT Loading" node, assuming a three-level discrete distribution.

Any number of levels could be used, but a large number of levels has several disadvantages, including computational burden. The size of a variable's probability table grows exponentially with the number of levels per parent. If a human expert is involved in evaluating the uncertainty for each possible combination of levels for the parent variables, the number of allowable parents and levels is significantly constrained. As shown, each strategy has a different uncertain effect on the predicted annual mine HgT loading. "Mine Mitigation" refers to a strategy of requiring aggressive reductions in loadings associated with run-off from various mine wastes located throughout the watershed, while ignoring geothermal sources and methylation potential. One perceived advantage to this strategy, from the RWQCB's perspective, is that the responsibility for paying for remediation would unambiguously fall on current landowners (whether public or private). "Geothermal & Mine Mitigation" refers to a strategy in which some geothermal sources are mitigated for total mercury and a less aggressive (and less expensive) set of load reductions are assigned to the various mine wastes. Two advantages to this strategy are that the total costs are lower and more mercury is removed from the watershed. A disadvantage is that geothermal sources are perceived as "background sources" and payment for mitigation is more ambiguous. The final strategy, "Sediment trapping and methylation potential mitigation" refers to a mixed strategy of reducing the loading of mercury exported from the watershed with constructed traps, while taking care to mitigate the conditions associated with mercury methylation in the traps and elsewhere in the watershed. Since there are very few fish in Sulphur Creek, this may be an acceptable alternative that may result in lower HgT and MeHgT loads exported from the watershed than the first two. Concerns about liability for missed reduction targets, ambiguity about "who pays", etc. can be explicitly reflected in the value model.

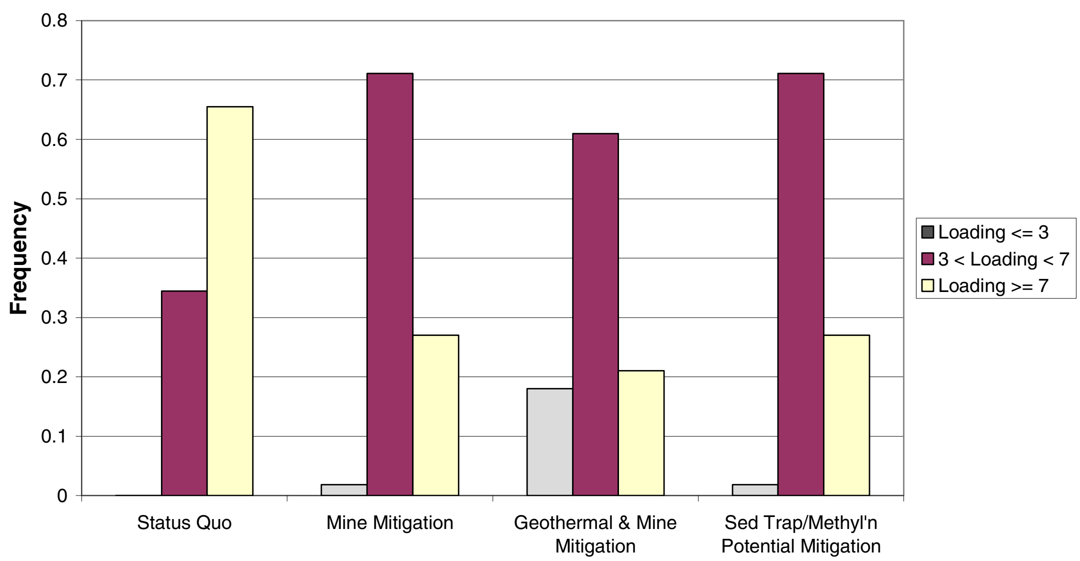

Figure 2. Uncertainty over Annual Mine HgT Loadings (kg/yr) By Strategy.

Uncertainty in Mitigation Costs and Decision-Maker Preferences

Best predictions and uncertainties in mitigation costs were estimated from an engineering evaluation and cost analysis performed by Tetra Tech, Inc. under contract with CALFED (Tetra Tech, 2003). In the value model, since strategy cost is modeled using four discrete cost levels and three discrete loading levels were modeled for each loading, there are 36 (4x3x3) combinations of mitigation cost, HgT loading, and MeHgT loading to be valued by the decision maker. For consensus-based decision-making, these values would be developed by negotiation. For a group decision-making situation without consensus, the value of loading reductions could be modeled parametrically and the decision "switch points" mapped (Labiosa, 2005).

Putting It All Together: TMDL Decision Analysis

Figure 3 shows the predicted discrete probability distribution of the typical annual methylmercury loading at the point of compliance for each mitigation strategy, given the flow conditions for the water years 2000 – 2004. Uncertainty in future flow conditions could be included to forecast future loadings, but decision makers have chosen to think in terms of predicting "what would have happened if we mitigated before 2000". The probability distributions in Figure 3 represent the uncertainty in the effects of mitigation on total mercury (HgT) loading, median $[HgT]_w$, the effects of mitigation on methylation potential, and the formation of methylmercury. Given the estimated probability distribution over mitigation costs and an elicited value model over possible environmental outcomes, a best strategy can be determined. In this example (abstracted from a real situation), the best strategy was determined to be "Sediment trapping and methylation potential mitigation". Figure 4 shows the expected strategy values (in $) for each strategy based on the current state of information. While this example is monetized, this is not necessary to fully apply decision analysis. For examples of using a decision analytical approach with an incomplete or missing value model (i.e., no consensus on values), see Labiosa et al. (2003). As can be seen from the figure, the "Mine Mitigation" strategy has lower value than "Status Quo", which means that doing nothing would be better than implementing the "Mine Mitigation" strategy, given current information and understanding. As an example of the value of collecting new information, it should be noted that collecting more information and reducing material uncertainties may result in the "Mine Mitigation" be more valuable than "Status Quo". Formal value of information analyses based on sensitivity analysis can also be performed in a decision analytical framework to prioritize information collection activities (see, e.g., (Howard et al., 1972); Labiosa et al., 2003).

While decision analysis does require active involvement of decision makers relative to many other decision making approaches, one could argue that this fact is responsible for much of the power of the decision analysis process. When decision analysis is properly performed, decision makers (or sub-groups) should *believe* the insights, given that the expertise and knowledge represented in the model should

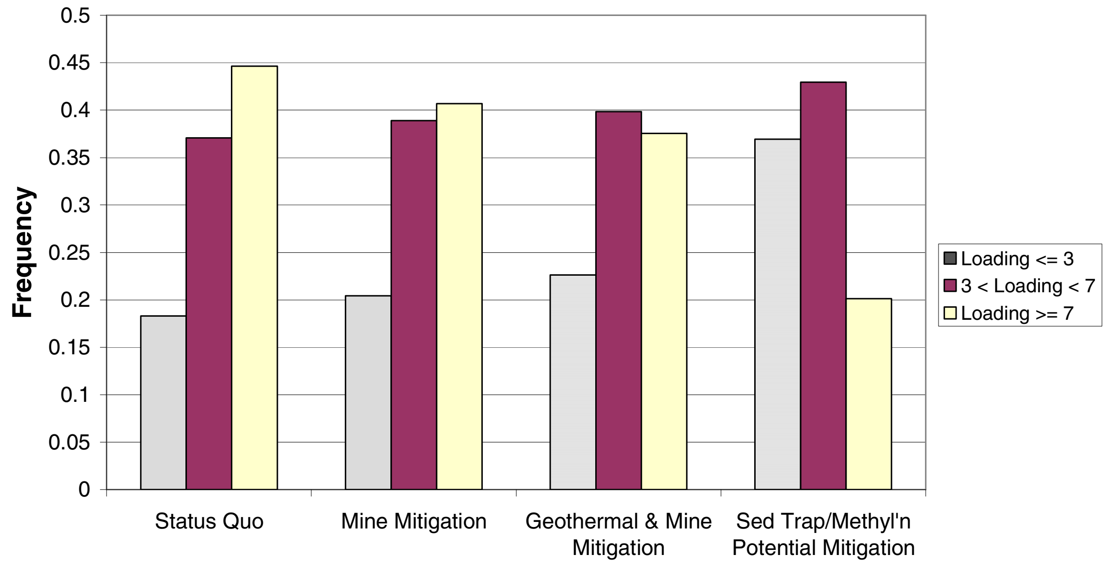

Figure 3. Discrete probability distribution over "Annual MeHgT Loadings at Compliance Point" By Strategy

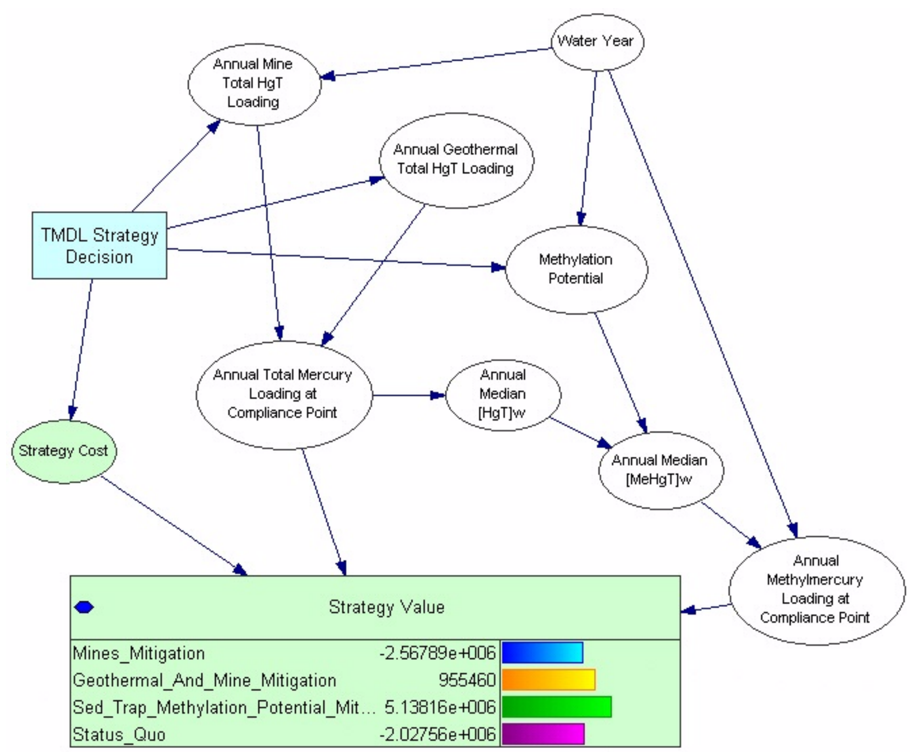

Figure 4. Strategy Values for the Example Mercury Total Maximum Daily Load Setting Decision Situation Calculated Using a Bayesian Network

reflect trusted information and that the preferences expressed should be their own. While the application of decision analysis in group decision making situations can be problematic, since individual group members may have significantly different beliefs and preferences that cannot be simultaneously modeled, decision analysis can be used to generate sub-group negotiating positions and can shed light on the sources of disagreement (Merkhofer, 1999).

The various decision analysis tools, including objectives hierarchies, strategy tables, influence diagrams, and decision trees, can be very useful aids for communicating, eliciting knowledge and preferences, organizing a complex decision situation, and generating insights that can highlight sources of disagreement and areas of agreement. When properly applied, decision analysis can help decision makers make better decisions in terms of the consideration of uncertainty and value.

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