# *A New Approach to Environmental Decision Analysis: Multi-Criteria Integrated Resource Assessment (MIRA)*

**Cynthia H. Stahl**
*U.S. Environmental Protection Agency Region III and University of Delaware*

**Alan J. Cimorelli**
**Alice H. Chow**
*U.S. Environmental Protection Agency Region III*

*A new approach to environmental policy analysis is introduced that is designed to mitigate the exacerbation of environmental problems, which can result from the application of traditional approaches in environmental decision making. These approaches are problematic because they tend to rely on technical fixes, a single-discipline focus, and optimality. When such traditional approaches are applied, complex environmental problems are simplified beyond recognition, and the solution produced no longer matches the original problem. An alternative approach has been developed at the U.S. Environmental Protection Agency (EPA) that is designed to improve the utilization of scientific research results and data (social, physical, and biological) through a more inclusive problem-solving process aimed particularly at difficult and complex environmental issues. Using a policy application pertaining to the EPA's 1995 decision to approve a fuel additive, the authors illustrate how integrated environmental policy decision analysis can be made operational using this new approach.*

***Keywords:*** *decision analysis, environmental policy management, consensus building, sustainability*

Decision analysis in many fields, including that of environmental policy and regulation, is often guided by the goal of finding a single "optimal" answer from the multitude of possibilities. This premise is a result of our training and is subsequently exhibited in our decision making (Kuhn, 1970; Vanderburg, 2000). In such a system, when there is a crisis that forces divergent views together, the debate and process are focused on selecting the single "best" answer rather than expanding overall knowledge and understanding among participants.

Frequently, environmental decisions are reduced to the search for so-called least-cost options, which necessarily require monetizing the decision criteria. As a result, for social and ecological factors to be considered, they must be filtered by an economic perspective. As such, these criteria become represented by a surrogate measure (i.e., cost) that may not fully capture their

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AUTHORS' NOTE: Correspondence concerning this article should be addressed to Cynthia H. Stahl, U.S. EPA Region III (3AP21), 1650 Arch Street, Philadelphia, PA 19103; telephone: (215) 814-2180; fax: (215) 814-2124. The views expressed in this article are those of the authors and do not necessarily reflect the views or policies of the U.S. Environmental Protection Agency (EPA). 

Mentoring and resource support by Professor John Byrne, director of the Center for Energy and Environmental Policy at the University of Delaware, is much appreciated and gratefully acknowledged. The advice, generosity, and friendship of Professor Tom Saaty, University of Pittsburgh, contributed to the expansion of our minds and helped us persevere in the early development of Multi-Criteria Integrated Resource Assessment. In addition, we appreciate the support of staff and management in the U.S. EPA Office of Air Quality Planning and Standards and the U.S. EPA Office of Research and Development, who were instrumental in providing technical assistance and advice. Although too many to name, we also appreciate the support provided by others who engaged us in interesting discussions and provided useful criticism and moral support.

Bulletin of Science, Technology & Society, Vol. 22, No. 6, December 2002, 443-459
DOI: 10.1177/0270467602238888

meaning or content. Furthermore, criteria that are difficult or impossible to monetize are often excluded from consideration. Factors such as the impact on a beautiful vista, sensitive or unique species, recreational enjoyment, and social justice may not be part of the least-cost perspective (i.e., a search for the optimal, lowest cost solution).

Optimal, least-cost decision analysis processes may offer little opportunity for meaningful stakeholder participation because stakeholders must become versed in economic optimization methods to contribute. When economic or other single-criterion perspectives serve as the basis for analysis in environmental policy decision analysis rather than integrating a diversity of perspectives, the decision analysis process is typically reduced to a power struggle, with advocates of one view pitted against advocates of another, and "resolution" is found in the declaration of a survivor or winner.

Traditional scientific approaches to decision analysis often do not alter the fundamental property of a search for single answers. Only the search domain is changed, with analytical approaches evaluating research-inspired solutions rather than, for example, economic or political power. Learning through a diversity of perspectives is seldom a key element of this process, even if a more analytical search style is embraced. Instead, the process is often governed by adversarial and exclusionary practices.

Recent discussions of environmental policy highlight the difficult conflicts that occur when environmental decisions are made (Kinsman, 2000; Masera, 2000; Sankovski, 2000). These conflicts occur because sustainable environmental solutions require compatible but difficult social, economic, and political changes (Byrne & Rich, 1992). Complex policy questions have ecological, social, economic, and political impacts, the implications of which cannot be resolved through optimality-based solutions that conventional social, physical, and biological science render. Crafting sustainable policies requires policy makers to simultaneously address the full range of complexities. Furthermore, policy makers seeking holistic strategies need to draw from multiple theories, methods, and so on. In so doing, these policy makers need to understand that this will change our comprehension of our problems and our views of what are acceptable and practical solutions. Policy makers facing these sorts of challenges need a multicriteria decision analysis framework that (a) brings together technical knowledge and social values and (b) fosters learning and seeks a consensus solution. In this article, we discuss a new framework that takes these conceptual aims and offers a concrete opportunity for policy makers and other stakeholders to explore decision options that manifest sustainable strategies.

## Current Approaches

Decision analysis approaches have been extensively employed for the past several decades to resolve public-sector planning and regulatory problems (Dyer, Fishburn, Steuer, Wallenius, & Zionts, 1992; Giupponi, Eiselt, & Ghetti, 1999; Martin, Bender, & Shields, 2000; Ridgley & Lumpkin, 2000; Saaty, 1990b; U.S. Environmental Protection Agency [EPA], Ecological Benefit Assessment Workgroup, Social Sciences Discussion Group, Science Policy Council, 2002). Most decision analysis models are built on optimization algorithms and depend on probability-based modules to rank alternative options (Chechile, 1991; Dyer et al., 1992; Saaty, 1982, 1990a, 1990b; Winkler, 1972). Any single decision may have multiple goals or objectives and will involve trade-offs among relevant objectives. In decision analysis, decision makers' opinions typically are modeled as sources of rankings or relative priorities among the impacts and objectives. Once these are entered into the model, results are determined and optimized. That is, present-day decision models are generally designed to find the single best solution from a predetermined set of options.

Other decision analysis models rely on the participation of stakeholders in finding the best decision. One type of participation decision model relies on value-tree structures and group Delphi methods to extract consensual expert judgments (Renn, Webler, Rakel, Dienel, & Johnson, 1993). These expert-stakeholder models allow for the use of technical (expert) information and social value judgments with the aim to determine an optimal consensus among expert and lay opinions.

Other public participation decision models rely on stakeholder judgment alone, without the use of independent experts. In effect, "expert" opinion is deduced from stakeholder discussions in a manner that combines expert data with social value judgments as a single exercise. All stakeholders' opinions are accepted as the basis for possible solutions (Gregory & Keeney, 1994).

## The Problem

To date, multicriteria decision tools have been applied only to find the "best solution" from a set of predefined options using technological and single-discipline approaches. Approaching decision analysis as an optimization exercise assumes that learning is a less important feature of the analytical process than determining an optimal solution. Applying this approach to the policy decision analysis process can result in misunderstanding and polarization among stakeholders and hampers the creation of options that could otherwise have developed had the process afforded participants a learning opportunity.

Expert-stakeholder models using methods such as group Delphi tend to blur the important differences between expert judgments and stakeholder values and, like the optimization approaches, do not offer a learning-based framework for consensus building. Because the ability to derive consensus from the range of expert and lay opinions is presumed, these models are less helpful when the science is controversial or when significant lifestyle issues are involved.

Stakeholder-only models are also problematic because without a structured means for discussing expert information and relevant social issues, stakeholders are not offered an opportunity to learn from a discourse shaped by expert information and other stakeholder perspectives. Although stakeholder opinions are valuable, they are not always unchangeable. Stakeholders may choose to change their opinions when informed through applicable expert data. Likewise, expert choices may change when researchers learn about social concerns not previously examined in analytical models.

Consequently, a new approach to decision analysis is needed that provides an interdisciplinary atmosphere for learning that can lead to the resolution of multifaceted issues while integrating expert judgment with stakeholder values rather than seeking an optimized solution. In the following sections, we discuss a new learning-based approach to environmental decision analysis and present both a description of its principles and a case example.

## Multi-Criteria Integrated Resource Assessment (MIRA)

MIRA is a new approach to environmental policy decision analysis. Its purpose is to facilitate decision analysis through an improved understanding and interconnection between both the scientific data and the societal values that are present in all environmental policy questions. MIRA incorporates the latest methods and concepts of, for example, ecologists, toxicologists, economists, statisticians, and sociologists in an innovative, interactive system. Through MIRA, links among previously isolated facts or models can be made and analyzed. In addition, MIRA offers the opportunity for stakeholders to shape the core elements of decision analysis—criteria, ranking, and options—according to the knowledge and perspectives relevant to their concerns.

MIRA's major components are a data automation interface (the Data Collection Manager [DCM]), an innovative indicator formulation methodology (the Geostatistical Indicators Module [GIM]), and a decision analysis module using the Analytic Hierarchy Process (AHP). The application of the AHP to air quality and other environmental decisions is not new (Kangas, 1993; Lahdelma, Salminen, & Hokkanen, 2000; Qureshi & Harrison, 2001), but the AHP approach taken in MIRA is new. Principally, MIRA uses the AHP as a learning rather than an optimization tool.

Figure 1 illustrates the structural components of MIRA. The DCM allows an analyst to store, sort, and retrieve data such as source emissions, demographics, and air quality values. Because of the traditionally discipline-bound nature of environmental analysis, separate systems of data collection and warehousing have developed among different organizations within the U.S. EPA. For example, this can be seen through the various analytical tools that the U.S. EPA uses to determine impacts from utilities, motor vehicles, and sources of toxic air pollutants (U.S. EPA, Assessment and Standards Division, Office of Transportation and Air Quality, 2002; U.S. EPA, Office of Air Quality Planning and Standards, 1994; U.S. EPA, Office of Air and Radiation, Clean Air Markets Division, 2002). Each of these analytical tools has its own data requirements and uses its own data systems as inputs (U.S. EPA, Office of Air and Radiation, Clean Air Markets Division, 2001; U.S. EPA, Technology Transfer Network, Clearinghouse for Inventories and Emission Factors, 1996, 2001). Consequently, within the U.S. EPA, there is currently no integrated system that allows for the storage and custom retrieval of data, which can also then be used directly in decision analysis.

The indicator methodology in the GIM provides a means to reduce spatial fields of pollutant concentration, usually presented as contour maps, to a single quantitative index value. These contour maps are produced from results of the Fate and Transport Module (see Figure 1), which houses fate and transport models

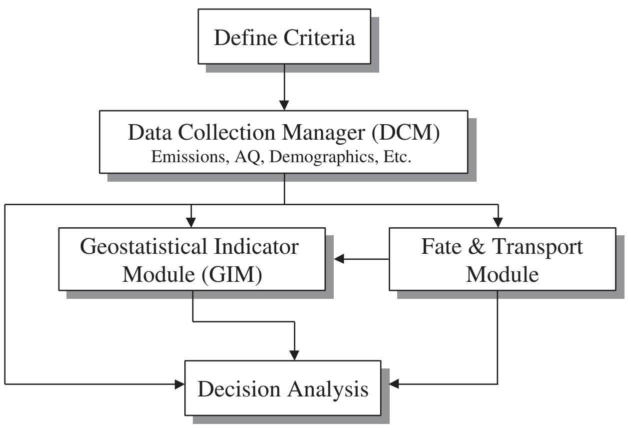


**Figure 1. Multi-Criteria Integrated Resource Assessment Structure**

such as those that determine air quality impacts. The creation of this area-weighted index allows an analyst the unique ability to compare the environmental impact among different and, if desirable, noncontiguous areas. Both the data from the DCM and the indices from the GIM can be used to populate the decision criteria in MIRA's decision analysis module. In addition, data from other expert systems, such as ecological indicators, can be incorporated into the MIRA framework and used in the decision analysis module (Lefohn & Foley, 1992; Suter, 2001; U.S. EPA, Regional Vulnerability Assessment Program, 2002). Decision maker and stakeholder preferences and judgments are obtained and used in the decision analysis spreadsheet to rank decision alternatives. The modular construction of MIRA permits an analyst the flexibility to determine which aspects of the DCM and the GIM will be used with the decision analysis module. It is the decision analysis module that is the focus of this article.

For environmental decisions to be driven by science and social values, it is necessary to introduce technical knowledge and value judgments without presuming a particular relationship between them. Instead, the architecture of a decision model must permit users to explore different ways to interconnect the two domains. A methodology is needed that integrates social value judgments with expert knowledge even while maintaining the "identities" of each of these stakeholder attributes. In MIRA, the separate identities of expert data and social value judgments are preserved, which then allows users to generate and evaluate various decision options in a learning-based rather than an optimization-based framework.

Key to MIRA's approach is the increased opportunity for meaningful participation by decision makers and other stakeholders. These participants play active roles in providing insight and judgment to the data relative to the particular decision at hand. As will be discussed below, stakeholders use MIRA to determine the quantitative importance of decision criteria, which stakeholders identify, in this decision context. Through MIRA's analytical framework, all stakeholders educate themselves about the data and their interests or values relative to the decision. One of MIRA's strengths is the ability for decision makers and other stakeholders to examine the sensitivity of a decision to both expert data and social value judgments. By avoiding optimization, MIRA leaves open the possibility of crafting a consensus decision based on mutual learning among all stakeholders.

## The General Method

Figure 2 illustrates the process flow of decision analysis using MIRA. This figure shows only a partial representation of the MIRA process because space limitations preclude showing all possible feedbacks from stakeholders and experts and their interactions with the relevant data and criteria definition. In Figure 2, stakeholder and expert input are shown as entering once at the top of the process figure, but these inputs in fact can and should occur throughout the process. The MIRA process consists of the following nine major steps: (1) Define decision criteria; (2) select the "problem set," which is the set of elements that are to be ranked using MIRA (e.g., the decision options or pollutant sources); (3) gather the data needed for each criterion; (4) index the data; (5) weight the criteria; (6) create an initial "decision set," which is a problem set whose elements are ranked on the basis of the data and criteria weighting; (7) create many different decision sets for the initial problem set and modify that problem set if appropriate as learning occurs and additional options are discovered (iteration); (8) conduct stakeholder deliberation; and (9) make the final decision. In the next sections, we conceptually describe some of MIRA's key features: indexing, criteria weighting, learning, and the increased opportunity for consensus building among stakeholders. We follow with a case study that concretely illustrates how MIRA might be applied to policy decisions.

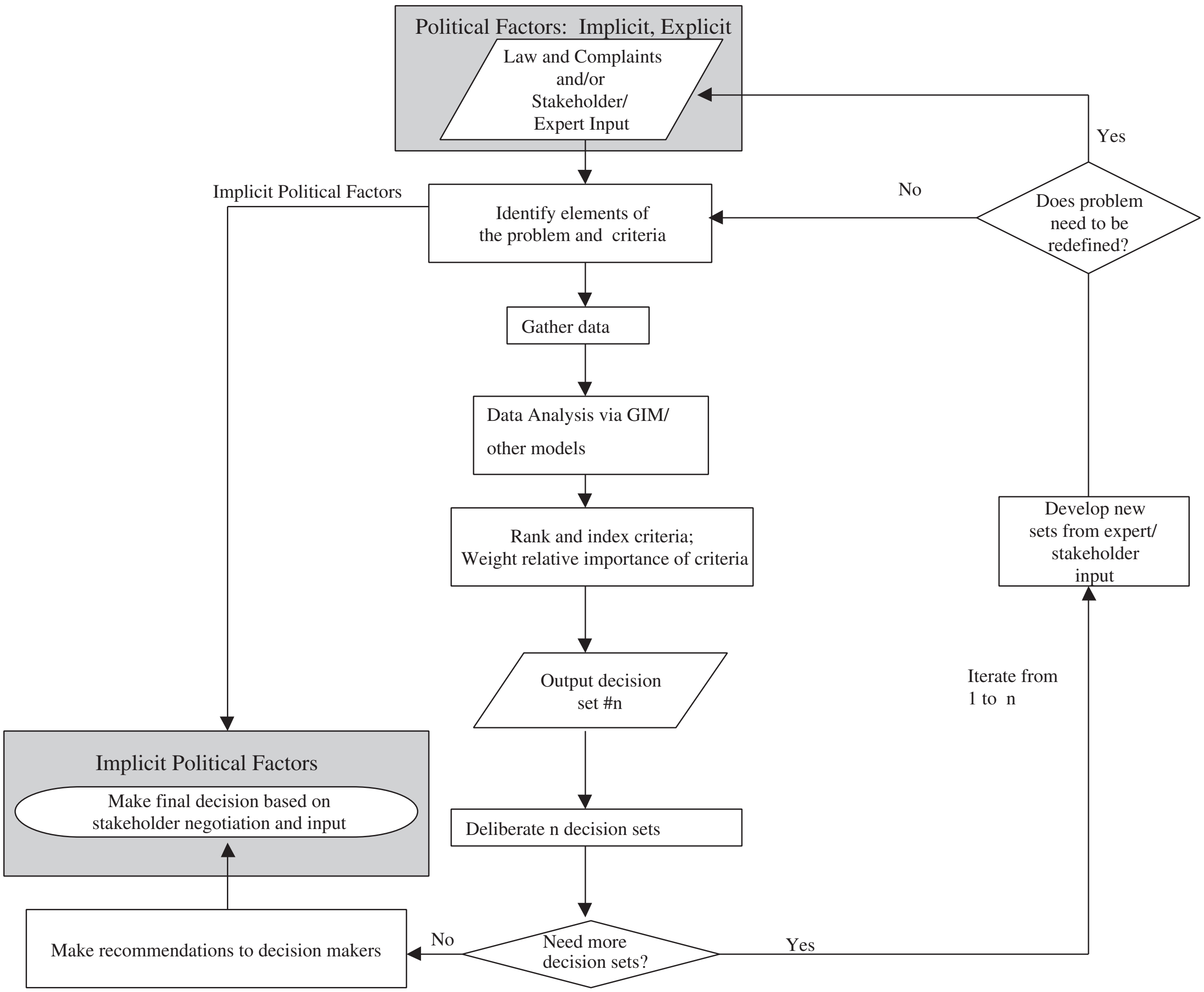


**Figure 2. Multi-Criteria Integrated Resource Assessment Process Flow**

## Indexing

In general, data alone offer limited insight until value and significance to a decision are applied by decision makers and other stakeholders. For example, cost data can be used in multiple contexts, and whereas $100 might be considered expensive for a pencil, the same $100 might be considered a bargain for a car. Furthermore, in many situations, the same data often provide different insights to different people. In MIRA, the relevant decision criteria are connected to a decision through an indexing process (Saaty, 1990b). Where the data already provide common insight to all stakeholders, MIRA is not needed. Without a framework such as MIRA, critical differences in data value and significance are often not communicated among the different parties and may underlie many disagreements, which become a barrier to arriving at consensus. Although MIRA does not presume any insight, it does require that it be expressed explicitly. This forces stakeholders to debate and discuss the given insight for the data relative to the decision at hand. In these discussions, stakeholders are free to examine a variety of insights and their effect on potential decision outcomes before coming to consensus. The indexing process is the methodology in MIRA that provides contextual meaning to the data.

A fundamental part of the indexing process is to index all criteria to a common scale. Because the various decision criteria are likely to have different units and scales, converting these units to a common decision attribute scale is needed to rank the elements of the problem set. It is through this process of deciding how each criterion is to be placed on the decision scale that insight is given to the data. Indexing is the first place in MIRA at which decision makers and stakeholders add social value judgments to a decision.

In the next section, we discuss how MIRA's decision criteria are weighted on the basis of stakeholders' opinions regarding their relative importance. The AHP is used in MIRA to explicitly incorporate these social value judgments into the decision analysis process.

## Criteria Weighting

After indexing the decision criteria, a decision maker now uses the AHP to determine the relative importance among decision criteria. Through a series of pairwise comparisons among the stakeholder-identified decision criteria, the relative importance among decision criteria can be assigned. Importantly, the assigned weights are not assumed to be optimal. In fact, weighting schemes can themselves become the focus for learning in MIRA, with changes in them used as a key means to probe for expert and stakeholder consensus and conflicts. When decision criteria are arranged hierarchically, pairwise comparisons are conducted at each level of the hierarchy until the relative criteria weights have been established for each criterion. The overall preferences among the criteria are determined by the product of indexed criteria and stakeholder judgments. In this manner, MIRA allows a decision maker to combine scientific and social value judgment elements in a consistent and systematic manner to evaluate and learn about different decision options.

We choose to use the AHP rather than multiattribute utility theory in MIRA because the AHP can be used in a manner that avoids the derivation of a single optimal answer (Chechile, 1991; Saaty, 1990b). The AHP is used to produce an array of outcomes or options, which are dependent on stakeholder-determined criteria weighting, creating a learning environment for the participants. Stakeholders' identities are preserved, because the data that represent stakeholders' interests are kept constant while allowing for changes in relative weighting among the criteria.

## Learning

The key to MIRA's learning-based decision analysis approach is its iterative feedback capability. An initial ranking of the problem set (i.e., a decision set) is produced by following the above process for indexing and criteria weighting with stakeholders' preferences. However, the stakeholders may be interested in determining what other options (or decision sets) are available if the initial ranking and decision makers' preferences are changed. Through experimentation with indexing and criteria weighting, decision makers and other stakeholders can learn about other decision options. The effect of scientific uncertainties on the decision set can be examined as well. Such experimentation, combined with stakeholder discussions, represents MIRA's decision analysis feedback loop and allows for the generation of other decision possibilities.

By altering preferences and indexing and reexamining data, decision makers and other stakeholders debate the relative importance of each of the decision criteria and the data used in an exercise to determine their effect on the problem set rankings. In this manner, the subsequent decision is informed by the relevant data as well as by stakeholder discussion and debate. Participants with preconceived ideas for the final decision may find that their ideas need to change because of the new insight learned through the data-driven MIRA approach. To this end, some intractable decision conflicts may be resolvable when decision makers and stakeholders use the MIRA framework to help inform their opinions.

In Figure 2, the feedback loop indicates a return to the beginning of the process when, in fact, stakeholders and experts can agree to revisit any of the steps from indexing to correcting or manipulating the physical or social science data to test the sensitivity of the decision sets to uncertainties. Conflicts among experts can be handled by evaluating the sources of conflicts and determining their effects on the resulting decision options. Similarly, conflicts among stakeholders and between stakeholders and experts can be examined through multiple MIRA runs, together with a discussion of the underlying interests and decision criteria. Therefore, the iterative learning process in MIRA is decision specific and includes not only the ability to test different criteria, indexing, and preference weights but also the importance of uncertainties and value conflicts and other factors that in other decision models might be dropped because of their supposed intractability.

### Stakeholder Deliberation—Facilitating Consensus

Consensus building and conflict resolution are facilitated by focusing on issues and discerning interests (Brunsson, 1985; McKearnan, Susskind, & Thomas-Larmer, 1999; Susskind, Levy, & Thomas-Larmer, 2000). By offering transparency in analysis and accessibility to information and by placing the emphasis on learning, MIRA has a greater potential to support consensus building than current analytical methods. Different stakeholders' interests and perspectives as represented by indexed and weighted decision criteria can be tested and examined as part of the policy negotiation or discussion. MIRA can facilitate conflict resolution and consensus building by helping stakeholders understand each of their underlying interests, explore salient issues, and deliberate potential options.

In contrast to the existing expert-stakeholder or stakeholder-only methodologies, MIRA maintains the separate identities and roles of experts and stakeholders while allowing for their integrated participation in the decision analysis process. Expert data are used directly, and stakeholders' judgments are applied separately but directly to those expert data. Experts and stakeholders are both part of the process but hold separate roles. MIRA supports science-intensive environmental policy decision analysis while embracing stakeholder participation and allowing all stakeholders to learn from one another and the critical data. From this process, new decision options can be explored, and consensus building can be pursued as a question of learning rather than optimality.

## MIRA Illustrated by Case Example

MIRA's utility is best illustrated through a policy example. In particular, MIRA's handling of stakeholders' identities (represented by different sets of weighted decision criteria) and the process of stakeholder feedback (including examining uncertainty) are demonstrated in the case study below. Our case study is the decision to choose among alternative fuel options for the purpose of reducing ozone air pollution, which is a subject of current debate at the U.S. EPA. In this case study, the analysis of different fuel additives is assessed with respect to their capacity to reduce air pollution, to minimize toxicological risks, and to minimize water contamination. This case is chosen to demonstrate MIRA's utility in real policy and is an illustrative example of the kind of analysis that can be done with MIRA. Readers are cautioned about making too much of the particular case study results shown here. Interested investigators are encouraged to examine the analytical framework, discuss criteria and data, and incorporate stakeholders' input where necessary before producing creditable policy options for the fuels decision.

### Alternative Fuels Case Study

In 1995, the EPA decided to approve the use of the gasoline additive methyl tertiary butyl ether (MTBE) to reduce ozone pollution and toxic air compounds (U.S. EPA, 1994a, 1994b). This decision was met with resistance and hostility by those who criticized the resulting contamination of groundwater by MTBE[1] spilled during refueling and other vehicle operations (Marcus, 1997; Moolenaar, Hefflin, Ashley, Middaugh, & Etzel, 1994; Squillace, Zogorski, Wilber, & Price, 1995; U.S. EPA, 1987; U.S. EPA, Criteria Assessment Office, 1993). The groundwater contamination made drinking water in several U.S. communities unacceptable for drinking. These communities were not reassured by the EPA's statements that drinking water was still safe to drink, even though the MTBE contamination made the drinking water odorous (U.S. EPA, Office of Water, 1997). MTBE is extremely odorous compared with other gasoline constituents. It is a compound that, when spilled, seeks water sources. The remediation of MTBE contamination in groundwater and soils is difficult (Squillace, Pankow, Korte, & Zogorski, 1996). By the use of MTBE as a fuel additive, however, gasoline refiners are able to reduce the amount of benzene added to the gasoline, which is considered a positive move in reducing the level of toxic air compounds in gasoline. The emissions of volatile organic compounds and carbon monoxide from MTBE gasoline–burning vehicles are less than those in vehicles burning regular gasoline (Committee on Toxicological and Performance Aspects of Oxygenated and Reformulated Motor Vehicle Fuels, Board on Environmental Studies and Toxicology, Commission on Life Sciences, & National Research Council, 1996; National Science and Technology Council, Committee on Environment and Natural Resources, 1996). However, although MTBE proved to be an extremely effective pollution control measure for reducing the harmful effects of gasoline to the air environment, the communities were unwilling to accept the scientific trade-off that was made to allow for any amount of groundwater contamination, even though it was determined to be within acceptable health standards. Because of the pressures from the social and political communities, in 1999, the EPA was forced to rethink its gasoline strategy (Blue Ribbon Panel on Oxygenates in Gasoline, 1999).

In this case study, some of the policy alternatives to the use of MTBE as a fuel additive are examined. These are the use of ethanol-based fuels,[2] the increased inspections and enforcement of underground storage tanks (USTs) storing fuels (including MTBE fuels), and improvements in the USTs themselves by the installation of double-walled tanks (double-walled USTs). All these alternatives are compared with the pre-1995 situation, when regular unleaded gasoline without any fuel additives was used. Each of three fuel types (gasoline, MTBE fuel, and ethanol fuel) are compared alone and with the two possible UST options, increased inspections and double-walled tanks. This results in a total of nine options being considered for this analysis (see Table 1).

### Selecting the Decision Criteria

There are 19 decision criteria used in the fuels case study example. Figure 3 shows that these criteria are arranged hierarchically and, on the primary level, include drinking water odor, air quality criteria, economics, and toxicology. The toxicology criterion, on the secondary level, includes the toxicology from the air pathway and toxicology from the water pathway. Risk factors from the inhalation of benzene, 1,3-butadiene, formaldehyde, and acetaldehyde are part of the air pathway toxicology criterion at the tertiary level of the decision criteria.

As discussed above, social value judgments enter the MIRA process at both the indexing and criteria-weighting stages. To explain the operation of MIRA, we discuss only 3 of the criteria—economics, air quality (tailpipe emissions), and air pathway toxicology. However, the results of using all 19 criteria are shown in the "Results" section to illustrate how learning occurs when all criteria are simultaneously analyzed with the MIRA approach.

### Indexing

Having selected and organized the decision criteria, the next step in the MIRA process is to index the data. Different quantitative decision criteria may have different units. In our example, costs have the units of dollars, whereas, for example, the risk from benzene is expressed as benzene emissions in grams per mile, weighted by the EPA weighting factor for benzene risk. As discussed above, direct comparison among these criteria is accomplished by converting the data to the decision units of a common decision attribute scale. Because our decision problem is to determine which fuel alternative is more preferable, all data must be expressed on a scale that represent an option's degree of preference. By convention, we establish our decision preference scale such that smaller values favor an option and higher values indicate a less favorable option.

The indexing process can be illustrated conceptually as a bin filled with marbles. Each option might be considered a bin, with each of the decision criteria (properties of that option) contributing different numbers of marbles (i.e., criteria value in decision units) to each option. The more marbles an option amasses in the analysis, the less that option is preferred. By establishing the number of index categories, a decision maker is establishing the "number of marbles" among which each of the criteria values will be distributed. In effect, deciding on the number of index categories determines the extent of the decision scale. In our case example, we use eight index categories, which establishes a maximum indexed value of 8 for any criteria data value.

The overriding consideration in selecting the length of the decision scale is to provide a degree of resolution that enables a decision maker to adequately differentiate degrees of preference for all of the criteria. Studies have indicated that seven plus or minus two index groupings are generally sufficient for discerning differences among choices (Saaty, 1990b). In our fuels analysis, we found, through the iterative learning process, that eight index categories (i.e., a decision scale ranging from 1 to 8 decision units) was adequate.

Once the decision attribute scale has been determined, the criteria are then indexed. Indexing allows decision makers to distinguish problem set elements (in our example, the nine fuel options) on the basis of the values of their various decision criteria. At this point in the process, because no judgment has been

**Table 1. Test Preferences Used to Generate Decision Sets #1 and #2 for the Fuels Case Example**

| Decision Criteria | Decision Set #1: Equal Criteria Preferences | Decision Set #2: Air Quality Is Preferred |
|---|---|---|
| Primary level | | |
| Drinking water odor | 0.25 | 0.067 |
| Economics | 0.25 | 0.271 |
| Air quality | 0.25 | 0.51 |
| Toxicology | 0.25 | 0.152 |
| Economics—secondary level | | |
| Cost at the pump | 0.25 | 0.281 |
| Cost to remediate spills | 0.25 | 0.34 |
| Cost to install double-walled USTs | 0.25 | 0.239 |
| Cost to increase inspections and enforcement of USTs | 0.25 | 0.14 |
| Air quality—secondary level | | |
| Tailpipe emissions | 0.5 | 0.4 |
| Evaporative emissions | 0.5 | 0.6 |
| Toxicology—secondary level | | |
| Air pathway | 0.5 | 0.857 |
| Drinking water pathway | 0.5 | 0.143 |
| Tailpipe emissions—tertiary level | | |
| Carbon monoxide | 0.33 | 0.163 |
| Nitrogen oxides | 0.33 | 0.297 |
| Volatile organic compounds | 0.33 | 0.540 |
| Air pathway—tertiary level | | |
| Benzene | 0.25 | 0.518 |
| 1,3-butadiene | 0.25 | 0.228 |
| Formaldehyde | 0.25 | 0.153 |
| Acetaldehyde | 0.25 | 0.101 |
| Drinking water pathway—tertiary level | | |
| Inhalation | 0.5 | 0.75 |
| Ingestion | 0.5 | 0.25 |
| Inhalation—quaternary level | | |
| Benzene | 0.33 | 0.634 |
| MTBE | 0.33 | 0.192 |
| Ethanol | 0.33 | 0.174 |
| Ingestion—quaternary level | | |
| Benzene | 0.33 | 0.342 |
| MTBE | 0.33 | 0.524 |
| Ethanol | 0.33 | 0.134 |

Note: UST = underground storage tank; MTBE = methyl tertiary butyl ether.

made regarding the relative importance among the decision criteria, all criteria (for a given hierarchy level) have equal importance. The relative importance among criteria will be established during the preferencing stage of the process. In our example, costs at the gas pump for the different fuel options' data range from \$1.33 to \$1.42 for the nine fuel alternatives being considered. We chose to group the data into eight index category ranges as follows: Index Category 1, \$1.341 and below; Index Category 2, \$1.342 to \$1.353; Index Category 3, \$1.354 to \$1.364; Index Category 4, \$1.365 to \$1.375; and so on. The criteria data can be distributed evenly or not among the index categories.

At this point, decision makers with other stakeholders should discuss the significance of a \$0.09 price spread among the fuel options. If either the data are incorrect or the stakeholders determine that the significance between \$1.33 and \$1.42 does not warrant the spread between Index Category 1 and Index Category 8, the stakeholders are free to spread the costs within a narrower index range, such as between Index Categories 2 and 4, or choose to eliminate price as a decision criterion because it does not sufficiently help distin-

| PRIMARY LEVEL | SECONDARY LEVEL | TERTIARY LEVEL | QUATERNARY LEVEL |
|---|---|---|---|
| Drinking Water Odor | | | |
| Economics | Cost at pump (CA prices) | | |
| | Cost to remediate spills ($/release) | | |
| | Cost to install double wall USTs | | |
| | Cost to increase UST inspections/ enforcement | | |
| Air Quality Criteria Pollutants | Tailpipe Emissions | CO | |
| | | NOx | |
| | | VOC | |
| | Evaporative Emissions | | |
| Toxicology | Air Pathway | Benzene | |
| | | 1,3 butadiene | |
| | | Formaldehyde | |
| | | Acetaldehyde | |
| | Drinking Water Pathway | Inhalation | Benzene |
| | | | MTBE |
| | | | Ethanol |
| | | Ingestion | Benzene |
| | | | MTBE |
| | | | Ethanol |

**Figure 3. Hierarchy of Decision Criteria for Fuels Case Example**
Note: CA = California; UST = underground storage tank; CO = carbon monoxide; NOx = nitrogen oxides; VOC = volatile organic compounds; MTBE = methyl tertiary butyl ether.

guish among the options. Because data relevance depends primarily on the decision context, MIRA is designed intentionally to provide an analyst with flexibility to determine how best to construct the decision scale. The final determination of the number of index categories, the category data ranges, and how the data should vary within categories is driven by two factors. The first is the need to appropriately differentiate the elements of the problem set. The second factor is, within the decision context, the determination of the relative significance among the decision criteria when compared to one another. Learning about the sensitivity of the problem set to the adapted indexing approach occurs through an iterative process.

### *Preserving Data Resolution*

In situations in which it is desirable to preserve data resolution, a useful indexing approach is to normalize the data within each of the index categories. For example, in our case study, the costs of installing a double-walled UST are indexed from 1 to 8, where Index Category 1 represents costs of $52,500 and less, Index Category 2 represents costs between $52,501 and $105,000, and so on up to Index Category 8, which represents costs greater than $367,500. Normalizing the costs within each index category allows us to differentiate between $26,250 at an index value of 1.0 and $48,562 at an index value of 1.85. Without such normalization, two fuel options having costs of $26,250 and $48,562 would receive the same index value of 1.0. Although the normalization within each index category allows an analyst the option of preserving the high resolution of the cost data, deciding on how the data are to be indexed depends on the decision context. Simply because the data are highly resolved does not mean that such resolution is important to the decision. Allowing stakeholders to deliberate and affirmatively determine the relevance of the data to the decision at hand is an important and unique feature of the MIRA approach to decision analysis.

In the risk factors for the fuel options, we track four fuel constituents: benzene, 1,3-butadiene, formaldehyde, and acetaldehyde. The unit risk factors for each of these fuel constituents are converted to potency-weighted toxic values to allow for a comparison among the different fuel options, each of which would result in a different exposure to the four fuel constituents. The potency-weighted toxic values are obtained by multiplying the EPA-weighted risk factor, derived from the fuel constituent's unit risk factor, by the amount of that fuel constituent in each fuel option (National Science and Technology Council, Committee on Environment and Natural Resources, 1996). Although the existing data indicate that the potency-weighted toxic values for these four compounds vary only slightly, for illustrative purposes, we treat these potency-weighted toxic values as if slight differences are important to the fuels decision. For example, the potency-weighted toxic values for benzene among the nine fuel options vary between $2.58 \times 10^{-4}$ to $2.7 \times 10^{-4}$ g/vehicle mile traveled. Similarly small differences among each of the potency-weighted toxic values for the other three fuel constituents are also found. Therefore, although in this example the differences in potency-weighted toxic values are not appreciably different and should not be treated as such, the flexibility in MIRA's analytical framework allows for data resolution when it is needed.

*Addressing Qualitative Data*

Not all data relevant to a decision are quantitative. MIRA allows for the quantifiable use of decision criteria that are not typically quantified. Although there were no qualitative criteria used in the current fuels case example, it is possible for qualitative criteria to be included in a quantitative MIRA analysis. For example, some qualitative criteria might include whether a fuel constituent is part of a carcinogenic classification or not. Unlike costs or risks, which are a continuum of numerical values, these qualitative criteria are dichotomous and categorical. These kinds of criteria can be included in the MIRA analysis by placing them into the index scheme in a manner that is equivalent in purpose to the quantitative data. For example, we determine that a constituent in a fuel option that is a carcinogen would make that fuel option less preferred than another that has a constituent that is only a possible carcinogen and therefore should receive a higher indexed value. If the indexing scheme ranges from 1 to 8, an index value of 8 may be chosen for a carcinogen, whereas those that are in a class of possible carcinogens receive index values of 2. Choosing a difference of 8 compared with 2 rather than some other combination is a stakeholder-determined choice that is made regarding the relationship between the data (carcinogenicity) and the decision (preference for a fuel option). It is important to note that the final choice regarding the indexing specifics is not reached until the participants have analyzed and learned from the data through MIRA's initialization and iterative learning process.

*Addressing Data Thresholds*

Through its indexing module, MIRA has the ability to address not only the overall magnitude of risks or health standards but also thresholds and uncertainties related to those thresholds. The current case example of fuels does not contain data with thresholds, but this is an important analytical feature of MIRA that investigators may want to use in future studies. For example, health standards may exist for one or more fuel constituents, and it is important for investigators to know not only whether a particular policy option may include a concentration of a fuel constituent beyond the standard but how far the concentration estimate is from the health standard. This feature of MIRA allows investigators to examine and address data uncertainties. Therefore, if there is a concern about whether a standard will be exceeded, a concentration estimate that is farther below the health standard indicates more certainly that the compound is safe than an estimate that is close to that standard. Consequently, a fuels analysis that considers data thresholds may be structured such that the indexing reflects data uncertainty with respect to each policy option.

## Criteria Weighting

As discussed above, determining the relative importance among expert and social values can be addressed in the MIRA decision analysis process at the preferencing step. This step can be automated with a variety of available computer software, including Expert Choice. In this step, decision makers use the AHP to make pairwise comparisons among all the criteria. However, before proceeding with AHP criteria weighting obtained from stakeholders, it can be useful to produce a benchmark decision set that represents equal preferences among all criteria. Comparing future decision sets created through stakeholder-derived criteria weights to this benchmark can help analysts and stakeholders better understand how sensitive the decision (i.e., problem set rankings) is to changes in relative criteria weights. The benchmark decision set preferences represented by equal preferences among all the criteria can be seen in Table 1.

We can use three criteria—odor, cost, and toxicology—as our set of decision criteria to illustrate the criteria-weighting process. Using the AHP, a decision maker determines the importance of odor compared with cost, cost compared with toxicology, and toxicology compared with odor. In these pairwise comparisons, a decision maker indicates not only which criteria are more important with respect to the fuels decision but also by how much (i.e., using a scale ranging from 1 to 9) (Saaty, 1990b). It is important to note

**Table 2. Effect of Stakeholders' Preferences on the Fuels Decision Sets**

| Fuel Option (ranked from most preferred to least preferred) | Decision Set #1: Equal Preference Rank (criteria sum) | Decision Set #2: Air Quality Most Preferred Rank (criteria sum) |
|---|---|---|
| Gasoline | 1 (0.6004) | 3 (0.4343) |
| Gasoline–double-walled UST | 2 (0.4715) | 7 (0.2684) |
| MTBE–double-walled UST | 3 (0.46) | 1 (0.4476) |
| Gasoline–UST inspection | 4 (0.4575) | 5 (0.30) |
| Ethanol | 5 (0.4378) | 6 (0.2784) |
| Ethanol–double-walled UST | 6 (0.4348) | 9 (0.2522) |
| Ethanol–UST inspection | 7 (0.4171) | 8 (0.2570) |
| MTBE–UST inspection | 8 (0.3322) | 4 (0.4297) |
| MTBE | 9 (0.3162) | 2 (0.4465) |

Note: UST = underground storage tank; MTBE = methyl tertiary butyl ether.

that the underlying data associated with each of these criteria remain the same even as the relative weights among the criteria are altered to explore new decision options. Once the relative importance among the criteria is determined, the MIRA framework ranks the fuel alternatives (from most preferred to least preferred) on the basis of all the indexed criteria as weighted by stakeholder preferences.

Through experimentation, many different preference schemes can be generated and tested. In Table 1, two such preference schemes are shown. The first was used to generate the benchmark preferences used to produce Decision Set #1, and the second was used to produce Decision Set #2. When the preferences used to produce each decision set are examined together with the decision sets (shown in Table 2), decision makers and other stakeholders can begin a learning process to determine the influence of preferences and criteria data on the ranking of potential decision options. Furthermore, on the basis of discussions spurred from the learning produced from early decision sets, stakeholders can discuss whether more appropriate criteria should be added (such as the carcinogenicity of fuel constituents) or whether additional options should be considered and tested. By summing the products of the indexed criteria data with stakeholders' preferences for each of the criteria identified in the analysis (criteria sum), the decision options are ranked quantitatively as shown in Table 2. In Table 2, we indicate the decision options' ranks and also, in parenthesis, the criteria sums for each of those decision options.

## Results

The learning process in MIRA occurs in two places. The first place is in the construction of the analysis and the increased understanding of the relationship of the data to the decision problem. The data used in the fuels case study came from many different sources. Not all research results are directly comparable, because study parameters are different in the various studies. In addition, some data were simply conflicting. Therefore, for the illustration of MIRA's concepts, we used average data or simply chose an extreme result to use in the initial demonstration with the intent to test the other extreme in the next iteration. MIRA's analytical framework allows investigators to test different data, including data uncertainties, by rerunning the analysis and examining the sensitivity of the decision to the data. Therefore, while constructing the fuels case example, the gaps in the toxicological research and areas of data uncertainty became clearer. The clarity offered by MIRA's analytical framework helps decision makers and other stakeholders determine their resolve for the final decision on the basis of the soundness of the available data.

The second place in which learning occurs in MIRA is in the iterative analysis, which consists of varying MIRA's input components (e.g., criteria, indexing, preferencing, etc.) and reranking the problem set to produce a variety of decision sets. Table 2 shows how different judgments can affect the decision set. Table 2 is a comparison of the nine fuel options (ranked from most preferred to least preferred) when the criteria are judged to be equally preferred (namely, the benchmark decision set) compared with a decision set that, in general, assigns the greatest importance to the air quality criterion. In the column labeled Decision Set #1 in Table 2, all 19 criteria used are judged to be equally important.

**Discussion of Results**

As a point of reference, we use MTBE fuel, which was the EPA's decision option in 1995 that produced so much controversy. With all criteria determined to be equally important, the MTBE option ranks last of all options at ninth when compared with the other eight fuel options that were evaluated. We now begin a learning process to determine how much the ranking of the MTBE option changes when we alter the judgments from equality. After altering preferences among all 19 criteria, we selected one decision set generated from iterative learning to highlight the MIRA process.

In the column labeled Decision Set #2 in Table 2, air quality is assumed to be more important than the other criteria when the overall decision is weighted 51% by air quality. The other criteria preferences for Decision Set #2 are shown in Table 1. The result is that the MTBE option is ranked second out of the list of nine fuel options. Although the rank of second in the second decision set is the result of more than just a single change in the importance of air quality relative to other criteria, the comparison underscores an important policy implication, namely, that the MTBE option is more likely to be ranked as a preferred option when air quality is determined to be more important than other criteria.

By comparing the rank of the MTBE option in Decision Set #2, in which air quality is preferred over all the other criteria, with its rank in Decision Set #1, in which all criteria are equally preferred, we can see how the U.S. EPA's decision makers could have come to their 1995 decision by considering air quality over the other criteria. Note also that the other fuel options also change their relative rankings when decision makers's preferences favor air quality over the other criteria. For example, the option of gasoline with double-walled UST moves from a rank of second in Decision Set #1 to a rank of seventh in Decision Set #2. The degree to which a particular fuel option is preferred over another option depends on both the data and the preferences for the combination of the relative expense of the UST options (double wall and inspection), the reduction in risks, the reduction in tailpipe emissions, and other criteria.

**MIRA Compared With the Current Process**

In the typical environmental policy decision analysis process, illustrated in Figure 4, the decision analysis process starts in a manner that is similar to MIRA. However, the important differences between the two processes become evident as decision criteria are determined, stakeholders participate, and decision options are generated. As the typical environmental policy decision analysis process proceeds, certain important factors that reflect stakeholders' interests can remain unexpressed even though they affect the decision outcome. Without identifying these critical factors, other stakeholders can misunderstand or misconstrue the impact of the identified criteria on the possible decision options. In contrast, through MIRA, the process of identifying problem set elements and decision criteria makes such factors and interests explicit. All criteria identified by stakeholders as having relevance to the decision are explicitly indexed and weighted. This links stakeholders' interests to the data and to the particular policy decision being discussed.

The potential involvement of stakeholders in the MIRA process is strikingly different from that offered in the typical environmental policy decision analysis process. The nontransparent nature of the typical process requires stakeholders to know how to participate, thereby limiting participation to those stakeholders with access to expert data and analyses, resources, and decision makers. Furthermore, the typical process is different from the MIRA process in that the problem is not deconstructed into explicit decision criteria and the relative importance of each decision criterion to the others. The result is that decision makers are less likely to consider all stakeholders' interests or clearly identify how such interests are considered in the decision. Such ineffective communication can result in a failure to discover innovative decision options because of unrecognized biases. In the typical decision analysis process, options tend to be predetermined because there is little opportunity to use the data to inform alternative decision options.

MIRA fosters the generation of additional decision options by allowing stakeholders greater access to expert data and analyses and by explicitly incorporating stakeholders' interests (criteria selection and preferencing) into the decision process. By using existing stakeholder participation processes to guide discussion and elicit stakeholders' interests, coupled with MIRA's structured means of utilizing these inter-

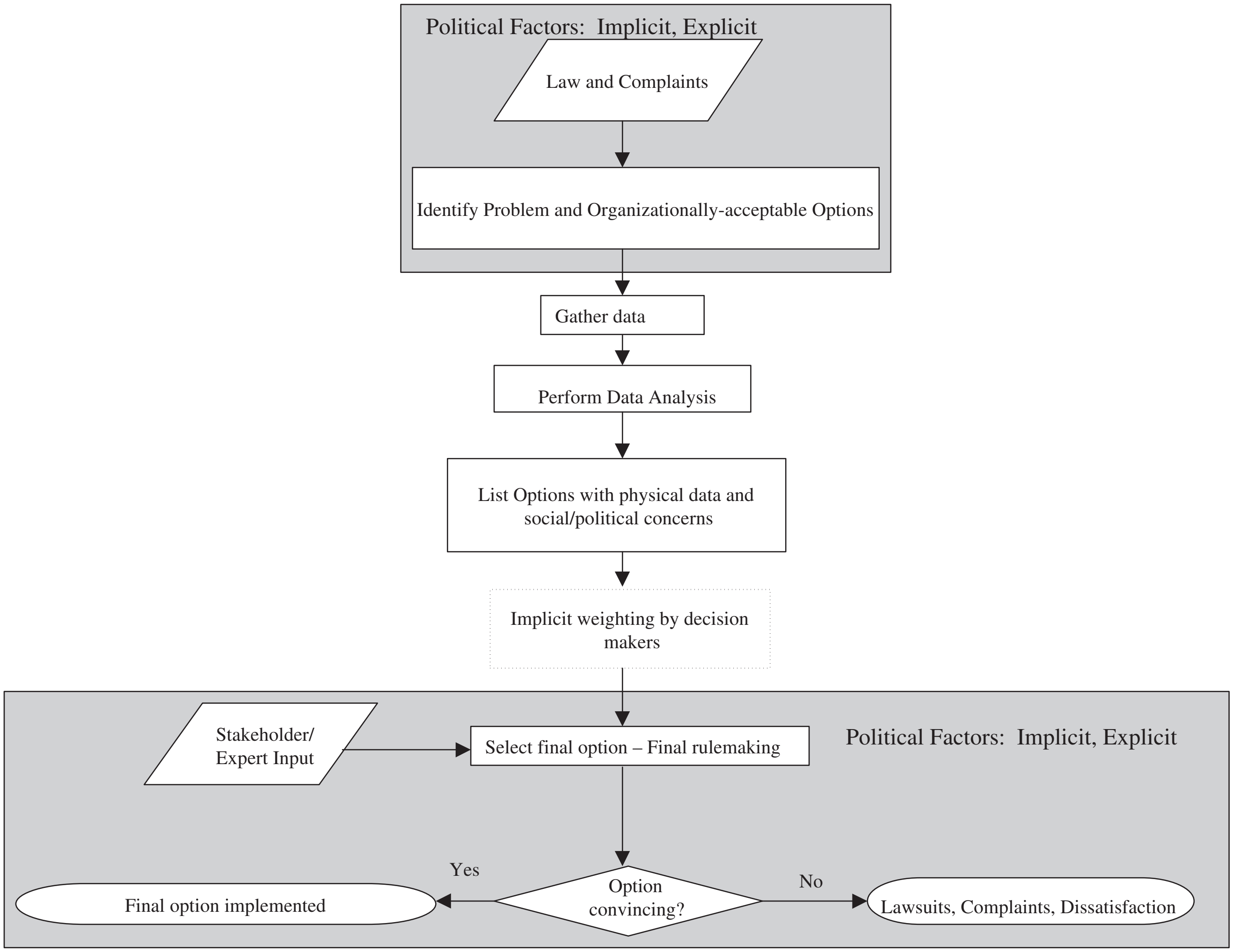


**Figure 4. Typical Environmental Decision Analysis Process Flow**

ests, the potential for building consensus is greatly enhanced. Participation is more meaningful because different interests, as represented by decision criteria and their weighting, can be included in MIRA's transparent, analytical framework. Through this increased opportunity for participation, MIRA facilitates learning among stakeholders and decision makers, which offers a potential for building consensus that is not available with existing optimization methodologies. We believe that MIRA's framework offers new opportunities for preserving diverse stakeholders' identities and for learning that have not previously been available.

As discussed above, the MIRA process provides for more effective stakeholder involvement than is present in the typical environmental policy decision analysis process. Under the typical process, we could not have produced the kinds of decision sets with regard to MTBE that so clearly show us the effect of changing preferences among the decision criteria of air quality, emissions, risks, and so on. Through MIRA, decision makers and other stakeholders are able to discern salient differences and similarities between MTBE and other fuel options when preferences are changed. By comparing these and other fuel options, decision makers and other stakeholders can better understand the criteria and data important for the consideration of different fuel options. Therefore, under the typical environmental policy decision analysis process, the options that are produced are not only based on nonexplicit decision-influencing factors but are also more limited because learning about the decision is not explicitly part of that process. The power of MIRA is that it allows stakeholders to explore the circumstances of the decision in such a way that many possible solutions can be found.

## Conclusion

With MIRA, decision analysis is informed through a process of learning by organizing the data relative to a particular decision and treating decision analysis as an exploratory, iterative effort to find alternatives. A decision-specific composite of possibilities for consensus-directed discussion among decision makers and other stakeholders is created. Single optimal answers are avoided in favor of examining the many possible solutions that are generated using diverse perspectives. MIRA improves environmental policy decision analysis by offering users the opportunity to rethink options at each stage in the decision analysis process. Through MIRA's holistic approach, a decision maker learns about possible decision options by first establishing the relevant criteria, using the latest expert data, and applying social value judgment. This approach avoids purely technical, discipline-bound, and optimality-oriented methodologies that characterize current environmental decision policy analyses. MIRA provides unprecedented flexibility for decision makers and other stakeholders to generate, test, debate, and potentially resolve difficult decision issues in a socially and ecologically sustainable manner.

MIRA's output is not an optimal decision but information that spurs discussion, debate, learning, and consensus building. With MIRA, environmental policy decision analysis is treated as an ongoing process rather than a single, discrete event. Learning and consensus building occur when decision criteria are framed within MIRA's transparent, analytical approach. The MTBE case example is typical of the kinds of multicriteria decision analyses that the U.S. EPA is tasked to do. As such, MIRA is a useful decision analytical approach that can allow the EPA to avoid the problems brought on by the application of technical fixes, discipline-bound approaches, and optimization.

## Notes

1. Methyl tertiary butyl ether (MTBE) is used as a fuel additive that is on average 11% by volume of the gasoline. Therefore, MTBE fuels are still primarily gasoline by volume.

2. On average, ethanol fuels are 5.7% by volume ethanol in gasoline.

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*Cynthia H. Stahl received her B.A. in biology from the University of Pennsylvania, her M.S. in environmental science from the University of Texas Health Science Center, School of Public Health, and is currently a doctoral candidate at the University of Delaware, Center for Energy and Environmental Policy. She is currently an environmental scientist at the U.S. Environmental Protection Agency specializing in air quality management and ozone policy development in particular. Her expertise includes knowledge of air programs pertaining to existing and new sources, volatile organic compound and nitrogen oxide control technologies, emissions trading, indicators development, and decision analysis. She is a principal developer of a new approach to environmental policy analysis, Multi-criteria Integrated*

*Resource Assessment (MIRA), which is designed to integrate environmental, social, and economic interests in a stakeholder-inclusive analytical framework.*

*Alan J. Cimorelli is the lead meteorologist for the Region III office of the U.S. Environmental Protection Agency (EPA). His responsibilities include research and development in atmospheric dispersion modeling and other related analysis techniques, the development of Agency guidance related to all aspects of air dispersion modeling, the review and conduct of regulatory air modeling studies and air risk assessments, and the development of the Multi-criteria Integrated Resource Assessment (MIRA) decision analysis framework. He also functions as the chief technical advisor to Region III state and local agencies regarding all aspects of air quality modeling. In addition to his work at EPA, he has held the position of adjunct assistant professor at Temple University and adjunct associate professor at Drexel University, where he has taught many undergraduate and graduate courses on advanced air quality modeling, environmental law, and environmental engineering. He received his B.A. in physics from Temple University in 1970 and his M.S. in environmental science from Drexel University in 1973.*

*Alice H. Chow holds a bachelor of science (1981) in environmental biology from Cornell University, at Ithaca, New York, and a master of environmental management (1984) from Duke University, at Durham, North Carolina. Her expertise has included developing national stationary source regulations, as well as directing implementation and enforcement of national air programs at the regional level.*