APPENDIX A
QUALITATIVE FACTORS ASSESSMENT TOOLS

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ABBREVIATIONS AND ACRONYMS

ADAMS	Agencywide Documents Access and Management System
AHP	analytic hierarchy process
h	hour
MAUT	multiattribute utility theory
NUREG	NRC technical report designation
NRC	U.S. Nuclear Regulatory Commission
OMB	Office of Management and Budget
SMART	simple multiattribute rating technique
SRM	staff requirements memorandum
WTP	willingness to pay

QUALITATIVE FACTORS ASSESSMENT TOOLS

A.1 PURPOSE

The purpose of this appendix is to provide guidance and best practices for use in considering qualitative factors (i.e., intangible costs and benefits) to improve the clarity, transparency, and consistency of the U.S. Nuclear Regulatory Commission's (NRC's) regulatory, backfit, forward fit, issue finality and environmental review analyses. In the staff requirements memorandum (SRM) to SECY-14-0087, "Qualitative Consideration of Factors in the Development of Regulatory Analyses and Backfit Analyses," dated March 4, 2015, the Commission directed the NRC staff "to encourage quantifying costs to the extent possible and use qualitative factors to inform decision making, in limited cases, when quantitative analyses are not possible or practical (i.e., due to lack of methodologies or data)."

Consistent with this direction, the analyst should make every effort to use quantitative attributes relevant to the cost-benefit analysis. The quantification should use monetary terms whenever possible. Dollar benefits should be defined in real or constant dollars (i.e., dollars of constant purchasing power). If monetary terms are inappropriate, the analyst should try to use other quantifiable benefits.

However, there may be attributes that cannot be readily quantified. These attributes are termed "qualitative," and this appendix captures best practices for the consideration of such qualitative factors by providing methods that can be used to support the NRC's evidence-based, analytical approach to decisionmaking. This guidance provides a toolkit to enable analysts to clearly present analyses of qualitative results in a transparent way for decisionmakers, stakeholders, and the general public. The methods described in this appendix should be used when quantification is not practical or possible.

A.2 TYPES OF COSTS AND BENEFITS

A.2.1 Tangible Costs and Benefits

Quantifiable costs and benefits have numeric values such as dollars, physical counts of tangible items, or percentage changes of a quantifiable factor. Monetized benefits are always quantifiable and measured in dollars or are tangible items with known conversion factors to monetize the variable (e.g., the person-rem conversion factor described in NUREG-1530, Revision 1, "Reassessment of NRC's Dollar per Person-Rem Conversion Factor Policy").

Examples of nonmonetized, quantifiable costs and benefits include the following:

- number of commodities or items produced for each alternative
- maintainability or supportability measures (i.e., mean-time-to-repair or average downtime)
- accuracy, timeliness, and completeness of data produced by systemic performance and operational effectiveness

A.2.2 Intangible Costs and Benefits

Intangible costs and benefits do not easily lend themselves to direct, quantitative modeling or measurement. In other words, these types of attributes (1) do not have readily available standard measurement scales and (2) tend to be subject to greater variability in modeling and results. Qualitative measures can be used to account for such benefits and make a positive contribution to the cost-benefit analysis. The analyst should use the best analytical practices (e.g., surveys and interviews) to include difficult-to-quantify costs and benefits. Examples of nonmonetized, nonquantifiable costs and benefits[1] that lend themselves to qualitative measures include the following:

- defense in depth
- perception/image
- aesthetics
- morale
- terrestrial or aquatic habitat
- quality of material or service
- safeguards and security
- operational readiness

[1] This list of nonquantifiable costs and benefits is based in part on that in SECY-14-0087, "Qualitative Consideration of Factors in the Development of Regulatory Analyses and Backfit Analyses," Attachment 1, dated August 14, 2014.

- regulatory efficiency
- improvements in knowledge
- incorporation of advances in science and technology
- greater flexibility in practice or less prescriptive requirements
- greater specificity in existing generally stated requirements
- correction of significant flaws in current requirements

While quantifying costs and benefits helps decisionmakers understand the magnitude of the effects of alternative regulatory actions, some benefits may be difficult to quantify in monetary terms. However, they can also be too important to ignore. In these situations, the analysts should use accurate information to develop realistic estimates to quantify parameters and then use the methods in this appendix to inform decisionmaking when quantitative analyses are difficult or would provide an incomplete analysis if presented alone.

A.3 METHODS

To facilitate the selection of consistent methods, this section provides analysts with several methods for modeling qualitative attributes and explains the circumstances best suited for each method. The use of consistent methods enables analysts to present qualitative results in a transparent way for decisionmakers, stakeholders, and the general public.

Several tools are available for attributes that do not lend themselves to quantification. When possible, considerations associated with these attributes should be quantified using market data, shadow pricing, or willingness-to-pay (WTP) techniques. The WTP principle captures the notion of opportunity cost by measuring what individuals are willing to forgo or pay to enjoy a particular benefit.

Examples of potential data sources for quantifying cost estimates include the following:

- budget submissions
- historical cost data reports
- manpower use records and reports
- construction materials cost database

Because data collection can be time consuming, a formal data collection plan may be useful. Such a plan would include tasks to identify the types of data available; to acquire the data with supporting documentation; to determine which estimating methods and models will be used with which dataset; and to verify, validate, and normalize the data.

If an attribute does not lend itself to monetized costs and benefits, then the analyst should describe it in sufficient detail so that the decisionmaker can determine whether the benefits for the alternative outweigh the costs. This section briefly describes some methods and references for qualitative analyses. The selection of an appropriate method depends on the issues being considered and the desired objectives. By carefully considering the descriptions and applicability of the qualitative tools in this appendix, the analyst can ensure consistency with prior regulatory analyses performed by the staff. The sophistication of the method selected should be commensurate with the complexity of the issue and will depend on the nature and importance of the qualitative factor, as described below for each method.

Analysts should remember that, because these alternatives do not estimate the net benefits of a policy or regulation, they are not the same as cost-benefit analyses in their ability to identify an economically efficient policy. The analyst should discuss such shortcomings when presenting the results.

A.3.1 <u>Narrative</u>

When there are potentially important effects that cannot be quantified, the analysts should include a discussion of the resulting benefits as well as the strengths and limitations of the information. This discussion should also include the key reason(s) that the effects are difficult to quantify. In one instance, the analysts may know with certainty the magnitude of a risk to which a substantial, but unknown, number of individuals are exposed. In another instance, based on unverified assumptions, a postulated consequence may result in an uncertain magnitude of risk.

For cases in which these costs or benefits affect a recommendation, the analysts should clearly explain the rationale behind the choice. Such an explanation could include detailed information on the nature, timing, likelihood, location, and distribution of the costs and benefits. Also, the analyses should include a summary table that lists all the quantified and unquantified costs and benefits. After careful consideration of these factors using techniques described in this appendix, the analyst should document and highlight (e.g., with categories or rank ordering) those factors that are most important for decisionmaking. Examples identified in Office of Management and Budget (OMB) Circular A-4, "Regulatory Analysis," dated September 17, 2003, in the section "Time Preference for Non-Monetized Benefits and Costs," under "Benefits and Costs that Are Difficult to Quantify," are "the degree of certainty, expected magnitude, and reversibility of effects."

While the analysis often focuses on difficult-to-quantify benefits of regulatory actions, some costs are difficult to quantify as well. For example, in its document "Informing Regulatory Decisions: 2003 Report to Congress on the Costs and Benefits of Federal Regulations and Unfunded Mandates on State, Local, and Tribal Entities," issued September 2003, the OMB stated that certain permitting requirements (e.g., the U.S. Environmental Protection Agency's New Source Review program and Clean Power Plan) have the following effects:

> [They] restrict the decisions of production facilities to shift to new products and adopt innovative methods of production. While these programs may impose substantial costs on the economy, it is very difficult to quantify and monetize these effects. Similarly, regulations that establish emission standards for recreational vehicles, like motorcycles, may adversely affect the performance of the vehicles in terms of drivability and zero to 60 miles per hour acceleration.

The cost associated with the loss of these attributes may be difficult to quantify and monetize, so the attributes should be analyzed qualitatively.

A.3.2 <u>Cost-Effectiveness Analysis</u>

Cost-effectiveness analysis can identify options that most effectively use the resources available without requiring the monetization of all relevant benefits or costs. Generally, a cost-effectiveness analysis is designed to compare a set of regulatory actions with the same primary outcome (e.g., an increase in the acres of wetlands protected) or multiple outcomes that can be integrated into a single numerical index (e.g., units of health improvement). This type of analysis is commonly used to compare alternatives when the value of costs or benefits cannot be adequately monetized. If it can be assumed that the benefits are the same for all alternatives being considered, then the task is to minimize the cost of obtaining them through a cost-effectiveness analysis. This method may be used in cases with substantial uncertainties or with important values that are difficult to quantify. In such instances, alternatives that yield equivalent benefits may be evaluated based on their cost-effectiveness. A regulatory analysis incorporating this method may also be used, if there are multiple ways to achieve compliance or reach a level of adequate protection and the Commission finds it necessary or appropriate to specify the way to achieve that level of protection. A cost-effectiveness analysis of the various alternatives under consideration improves technical efficiency in achieving a desired outcome that may be valuable to a decisionmaker.

The cost-effectiveness of an alternative is calculated by dividing the present value of total costs of the option by the nonmonetary quantitative measure of the benefits it generates. The ratio is

an estimate of the costs incurred to achieve a unit of the outcome from a particular policy option. For example, in a security scenario, the analyst should determine the costs expressed in dollars incurred to save a person's life or mitigate a security event. Presumably, there are alternative ways to achieve these objectives and determine their costs. The analysis does not evaluate benefits in monetized terms but attempts to find the least-cost option to achieve a desired quantitative outcome.

One technique for comparing and prioritizing a list of alternatives is the decision matrix. This flexible technique may be used to evaluate most quantitative and nonquantitative costs and benefits.

In this example, some decision elements are monetized, but others are evaluated qualitatively because they are not readily quantifiable. While both types of decision elements could be evaluated directly using a decision matrix, the NRC recommends evaluating only nonmonetized data using this technique. The optimum approach is to use a decision matrix to evaluate the nonmonetized criteria, evaluate the monetized data separately, and then consider both monetized and nonmonetized data to develop a recommendation. Tables A-1 and A-2 provide an example of this technique in which weighting factors are assigned based on the importance of the attribute in meeting the regulatory objective, and the rating factor is a measure assigned to determine the overall performance with respect to the decision element.

Table A-1 Example of a Decision Matrix—Quantification of Intangible Benefits

Decision Element	Normalized Weighting Factor	Alternative 1			Alternative 2			Alternative 3		
		Data	Rating	Score	Data	Rating	Score	Data	Rating	Score
Maintenance Downtime	.40	7 h	9	3.6	10 h	7	2.8	14 h	4	1.6
Reduced Error Rate	.25	5 per 100	5	1.25	2.5 per 100	7	1.75	8 per 100	2	.50
Suitability	.20	Very Good	4	.80	Good	2	.40	Excellent	6	1.20
Improved Productivity	.15	240 per cycle	8	1.20	230 per cycle	7	1.05	200 per cycle	6	.90
Total Weight	1.00	Total Score		6.85	Total Score		6	Total Score		4.2

For each criterion, the score is determined by multiplying the weighting factor for the criterion by the rating for the alternative (the weighting factor and rating being subjective numbers). The cost of the alternatives would be divided by the total scores in the bottom row to produce a cost-benefit index to arrive at a recommendation. To achieve this cost, multiply the benefit score by the cost-benefit index. Table A-2 shows an example.

Table A-2 Example of a Cost-Benefit Index

Cost-Benefit Index	Alternative 1	Alternative 2	Alternative 3
Cost	24	20	19
Benefit Score	6.85	6	4.2
Cost-Benefit Index	3.50	3.33	4.52

Cost-effectiveness results based on averages should be considered carefully. They are limited by the same drawbacks as cost-benefit ratios. The alternative that exhibits the smallest cost-effectiveness ratio, or the alternative with the highest cost-benefit ratio, may not be the preferred alternative that maximizes net benefits. Incremental cost-effectiveness analysis can help avoid mistakes that can occur when proposed regulatory actions are based on average cost-effectiveness. The incremental cost-effectiveness ratio determines the marginal or incremental cost for an additional unit of benefit when choosing between mutually exclusive alternatives.

A cost-effectiveness analysis can also be misleading when the "effectiveness" measure does not appropriately weigh the consequences of the alternatives. For example, when effectiveness is measured in a quantity of reduced emissions, cost-effectiveness estimates may be misleading, unless the reduced emission outcomes result in the same health and environmental benefits.

Likewise, if the range of alternatives considered results in different levels of stringency, the analysts should determine the cost-effectiveness of each option compared with the baseline, as well as its incremental cost-effectiveness compared with successively more stringent requirements. The analysts should prepare an array of cost-effectiveness estimates that would allow a comparison across different alternatives. However, if analyzing all possible combinations is not practical (because there are many alternatives or possible interaction effects), then the analysts should use professional judgment to choose reasonable alternatives for consideration.

Some caveats exist for the measurement of the associated costs using the cost-effectiveness technique:

- The marginal cost-effectiveness should be calculated. It is the marginal or incremental cost-effectiveness of the alternative that should be compared with the baseline cost-effectiveness alternative (i.e., the status quo). The policy that has the lowest marginal cost per unit of effectiveness will be the most efficient way to use resources.

- The costs include all compliance costs incurred by both the private and public sectors. Such costs should be based on resource or opportunity costs, not merely the monetized costs of goods and services.

- The costs should be properly defined and measured in the calculation of cost-effectiveness.

- The costs incurred may be private (i.e., capital or operating expenditures) or societal costs that are spread over several years. To compare alternative options, both the costs and benefits should be discounted to a common time period.

Shortcomings are inherent in the cost-effectiveness approach. It is a poor measure of the consumers' WTP principle, because no monetary value is placed on the benefits. WTP is defined as the amount of money that, if taken away from income, would make an individual exactly indifferent to experiencing the specified outcome or not experiencing either the improvement or any change in income.

Moreover, in the calculation of cost-effectiveness, the cost numerator does account for the scale of alternative options. Nevertheless, the cost-effectiveness ratio is a useful criterion for selecting alternative regulatory options when the benefits cannot be monetized.

The OMB does not require agencies to use any specific measure of effectiveness. In fact, the OMB encourages agencies to report results with multiple measures of effectiveness that offer different insights and perspectives. According to OMB Circular A-4, the regulatory analysis should explain which measures were selected and why and how they were implemented.

A.3.3 Threshold Analysis

A break-even analysis is one alternative that can be used when either risk data or valuation data are lacking. Analysts who have per-unit estimates of economic value but lack risk estimates cannot quantify net benefits. They can, however, estimate the number of cases (each valued at the per-unit value estimate) at which overall net benefits become positive, or where the regulatory action will break even. In its discussion of sensitivity analysis, OMB Circular A-4 refers to these values as a "switch point."

Consider a proposed regulatory action that is expected to reduce the number of cases resulting in outcome X with an associated cost estimate of $1 million. Further, suppose that the analysts estimate that the WTP to avoid a case resulting in outcome X is $200, but because of limitations in data, it is difficult to estimate the reduction in the number of cases of this outcome that would result from this regulatory action. In this case, the proposed regulatory action must reduce the number of cases by 5,000 to "break even." This estimate then can be assessed for plausibility quantitatively. Decisionmakers should determine if the break-even value is acceptable or plausible.

Similar analyses are possible when analysts lack valuation estimates that produce a break-even value requiring assessment for credibility and plausibility. Continuing with the example above, suppose the analyst estimates that the proposed policy would reduce the number of cases of endpoint X by 5,000 but does not have an estimate of WTP to avoid a case of this outcome. In this case, the policy can be considered to break even if WTP is at least $200.

One way to assess the credibility of economic break-even values is to compare them to effects that are more or less severe than the outcome being evaluated. For the break-even value to be plausible, it should fall between the estimates for these more and less severe effects. For the example above, if the estimate of WTP to avoid a case of a more serious effect were only $100, the above break-even point may not be considered plausible.

A break-even analysis is most effective when there is only one missing value (i.e., unknown) in the analysis. For example, analysts missing estimates for two different unknowns (but having valuation estimates for both) should consider a "break-even frontier" that allows the values of both unknowns to vary. This approach makes it possible to construct such a frontier, although it is difficult to determine which points on the frontier are relevant for regulatory analysis.

In 1992, the NRC used a regulatory break-even analysis to evaluate the adoption of a proposed rule regarding air gaps to avert radiation exposure resulting from NRC-licensed users of industrial gauges (57 FR 56287). The NRC found insufficient data to determine the averted radiation exposure. To estimate the reduction in radiation exposure, the NRC performed a break-even analysis. The analysis assumed a source strength of 1 curie for a device with a large air gap, which produces 1.3 rem per hour at 50.8 cm (20 inches) from a cesium-137 source. Assuming half this dose rate would be produced, on average, in the air gap, and that a worker is within the air gap for 4 hours annually, the NRC estimated the worker would receive a radiation dose of 2.6 rem per year. The agency estimated that adopting the proposed air-gap rule would be cost-effective if it saved 347 person-rem per year. At an averted occupational radiation dose of 2.6 person-rem per year for each gauge licensee, incidents involving at least 133 gauges would have to be eliminated. Given the roughly 3,000 gauges currently used by these licensees, the proposed rule would have to reduce the incident rate only by roughly 4 percent, a value the NRC believed to be easily achievable. As a result, the staff recommended adoption of the air-gap rule.

A.3.4 <u>Bounding Analysis</u>

A bounding analysis is designed to limit or provide a specified range of potential impacts or risks in order to calculate best-case and worst-case results. Such an approach might be used in a cost-benefit analysis as a screening tool to simplify assumptions and modeling, to address uncertainty, or to address unavailable or unknown data. These bounding analyses (or enveloping scenarios) should be chosen so that they present the greatest possible extremes and are limiting values for the inputs to the analysis. For the best-case scenario, the analyst would use assumptions and inputs that maximize the benefits and minimize the costs. For the worst-case scenario, the analysts would use assumptions and inputs that minimize the benefits and maximize the costs. The results of such bounding analyses can be used to inform the decisionmakers of the extent or of the severity of the results. If the sign of the net benefit estimate is positive across this range, there is confidence that the proposed regulatory action is beneficial. Analysts should carefully identify judgments or assumptions made in selecting appropriate bounding input values to describe whether they used absolute limits or reasonable maximum limits. In explaining the results, the analyst should communicate to the decisionmakers that the use of bounding analysis results may be unnecessarily conservative.

A.3.5 <u>Rank Order/Weight-Based Analysis</u>

This analysis allows for selection based on quantifiable and nonquantifiable costs and benefits and allows the Commission to adjust criteria based on perceived importance. A drawback to this method is that there is no objective basis for the ranking, which may draw criticism as it is difficult to make quantitative statements about the actual difference between alternatives.

A.3.6 <u>Maximin and Maximax Analysis</u>

The maximin and maximax analyses are two criteria of decision theory where multiple alternatives can be compared against one another under conditions of uncertainty. In the maximin analysis, the analyst looks at the worst that could happen in each alternative for a given outcome and then chooses the least worst alternative (i.e., the alternative where the loss is the better loss of all other alternatives, given the circumstances). This decisionmaking is based on pessimistic loss, in which the analyst assumes that the worst that can happen will happen and then chooses the alternative with the best worst-case scenario. In the maximax

analysis, the analyst looks at the best that can happen in each alternative for a given outcome and then chooses the alternative that is the best of the best (i.e., the alternative where the gain is the best of the best of all other alternatives, given the circumstances). This decisionmaking is based on optimistic gain, in which the analyst assumes that the best that can happen will happen and then chooses the alternative with the best-case scenario.

An example of a maximin and maximax analysis is its application to the modification of drug testing for fitness for duty. This hypothetical regulatory action has three alternatives for drug testing, with the first alternative representing the status quo. These alternatives involve modifying the procedures and cutoff levels for drug testing to reduce false positives. The exception is the first alternative (the status quo), which represents the current procedures for conducting drug testing. The following are the three possible alternative frequencies for drug testing:

(1) Test 10 times a year.
(2) Test 15 times a year.
(3) Test 20 times a year.

For each alternative, Table A-3 gives the expected number of false positives for each outcome of drug testing as determined by a panel of medical experts.

Table A-3 Expected Number of False Positives for Each Outcome of Drug Testing

Alternatives	**Frequency of Drug Tests Per Year**		
	10	**15**	**20**
Alternative 1	3	4	5
Alternative 2	1	2	5
Alternative 3	2	3	4

In the maximin analysis, the analyst looks at the highest number of false positives (worst gain) for each alternative over all possible outcomes and chooses the alternative with the lowest number of false positives (best of the worst) for some outcome. Examination of the results of each alternative shows the following:

(1) For alternative 1, the highest number of false positives is five for testing 20 times a year.
(2) For alternative 2, the highest number of false positives is five for testing 20 times a year.
(3) For alternative 3, the highest number of false positives is four for testing 20 times a year.

According to the maximin analysis, the analyst would choose alternative 3 for testing 20 times a year, because this alternative has the lowest number of false positives (i.e., four is less than five).

In the maximax analysis, the analyst looks at the lowest number of false positives (best gain) for each alternative over all possible outcomes and chooses the alternative with the lowest number of false positives for some outcome. Examination of the results of each alternative shows the following:

(1) For alternative 1, the lowest number of false positives is three for testing 10 times a year.
(2) For alternative 2, the lowest number of false positives is one for testing 10 times a year.
(3) For alternative 3, the lowest number of false positives is two for testing 10 times a year.

According to the maximax analysis, the analyst would choose alternative 2 for testing 10 times a year, because it has the lowest number of false positives.

The choice (maximin or maximax) depends on the preference of the decisionmaker. The maximin criterion involves selecting the alternative that maximizes the minimum payoff achievable, and so a decisionmaker who prefers a guaranteed minimum at the risk of losing the opportunity to make big gains would opt for the maximin result. The maximax criterion involves selecting the alternative that maximizes the greatest payoff available, so this approach would be more suitable for a “risk-seeking” investor, who wants to achieve the best results if the best happens.

A.3.7 Conjunctive and Disjunctive Analysis

The conjunctive and disjunctive analysis method requires a satisfactory performance, rather than the best, in each decision criterion. The conjunctive step requires an alternative to meet a minimal performance threshold for all criteria. The disjunctive step requires the alternative to exceed the given threshold for at least one criterion. Any alternative that does not meet the conjunctive or disjunctive rule is not considered further. These screening rules can be used to select a subset of alternatives for analysis by other, more complex methods.

A.3.8 Lexicographic Analysis

This analysis involves lexicographic ordering, which ranks alternatives one at a time, starting with the most important and heavily weighted criterion. If two or more alternatives are preferentially tied for the most important criterion, then they are compared on the second most important criterion. The surviving alternatives are then compared on the third most important criterion, and so on, until the tie is broken, resulting in the chosen alternative. This method is appealing because of its simplicity; however, it will require subjective agreement by participants on the ordering of criteria and the assumption of independent assessments when considering two or more criteria simultaneously.

One example of lexicographic ordering would be the evaluation of alternatives where attributes of each alternative are considered. For example, such an evaluation could consider six attributes over three alternatives, represented by a 6 x 3 matrix of potential evaluative information. An example of a set of attributes could consist of the following:

(1) averted occupational exposure
(2) reduction in core damage frequency
(3) training and certifications
(4) required operator actions outside the control room
(5) nuclear consequence management
(6) standard operating procedures

Based on this information, questionnaires can be prepared that will collect and present evaluative information in a format similar to that found in product ratings summaries. The questionnaires can then be distributed to a populace, in which respondents can be asked to

evaluate the information provided by the questionnaire and rank order the attributes in terms of decreasing preference. In addition to the ranking task, the respondents can be asked to assign importance weights to various characteristics of each attribute, rate each alternative's characteristics on a desirability scale, and identify a minimum acceptability limit on each attribute's characteristic contained in the questionnaire.

A.3.9 Decision Matrix

The decision matrix is a popular method for comparing and prioritizing a list of alternatives. This highly flexible tool effectively evaluates nonmonetized and difficult to quantify costs and benefits.

Monetized decision criteria are quantifiable; nonmonetized criteria are not directly quantifiable. While a cost-benefit analysis considers both types of criteria, the monetized criteria demand a more rigorous analysis, specifically because they are objective and quantifiable and less influenced by subjective assessment. If the monetized criteria and nonmonetized criteria are used in a single decision matrix, then the analysts would need to apply qualitative evaluation to the monetized data. Therefore, quantified costs and benefits should be kept separate from nonmonetized costs and benefits and not combined in a single decision matrix. The best approach is to use a decision matrix to evaluate the qualitative criteria, evaluate the quantified monetized data separately, and then consider both monetized and nonmonetized data to develop a staff recommendation.

When considering a regulatory issue in generalized form with *m* qualitative criteria and *n* alternatives, let $C_1,\ldots,C_m$ and $A_1,\ldots,A_n$ denote the difficulty in quantifying criteria and alternatives, respectively. As shown in Figure A-1, each row belongs to a criterion, and each column describes the performance of an alternative. The score a_{ij} describes the performance of alternative A_j against criterion C_i. For simplicity, the specified convention is that a higher score value means a better performance, since any goal of minimization can be easily transformed into a goal of maximization.

		x_1	.	.	x_n
		A_1	.	.	A_n
w_1	C_1	a_{11}	.	.	a_{m1}
.	.	.	.	.	.
.	.	.	.	.	.
w_m	C_m	a_{m1}	.	.	a_{mn}

Figure A-1 The Decision Matrix

As shown in Figure A-1, weights $w_1,\ldots,w_m$ are assigned to the criteria. Weight w_i reflects the relative importance of criterion C_i to the decision and, by convention, is assumed to be positive. The weights of the criteria are usually determined subjectively and represent the opinion of the analysts or the synthesized opinions of a group of experts using a group decision technique.

The values $x_1,\ldots,x_n$ associated with the alternatives in the decision table are the final ranking values of the alternatives. By convention, a higher ranking value means a better performance of the alternative, so the alternative with the highest ranking value is the best of the alternatives.

This technique can partially or completely rank the alternatives: a single most preferred alternative can be identified or a short list of a limited number of alternatives can be selected for subsequent detailed appraisal using other methods.

The multiattribute utility theory (MAUT), described next, and outranking methods, described in Section A.3.10, are two main techniques for assigning weights in decision matrices.

A.3.9.1 Multiattribute Utility Theory Technique

The family of MAUT methods consists of aggregating the different criteria into a function, which is maximized. Thereby, the mathematical conditions of aggregations are examined. As described in NUREG-1530, Revision 1, this theory allows for the complete compensation between criteria (i.e., the gain on one criterion can compensate for the loss on another).

In most of the approaches based on the MAUT, the weights associated with the criteria can properly reflect the relative importance of the criteria only if the scores a_{ij} are from a common, dimensionless scale. The basis of MAUT is the use of utility functions. Utility functions can be applied to transform the raw performance values of the alternatives against diverse criteria, both factual (objective, quantitative) and judgmental (subjective, qualitative), to a common, dimensionless scale. In practice, the intervals [0,1] or [0,100] are used for this purpose. Utility functions play another important role: they convert the raw performance values so that a preferred performance obtains a higher utility value. A good example is a criterion reflecting the goal of cost minimization. The associated utility function should result in higher utility values for lower cost values.

It is common for some normalization to be performed on a nonnegative row in the matrix of the a_{ij} entries. The entries in a row can be divided by the sum of the entries in the row, by the maximum element in the row, or by a desired value greater than any entry in the row. These normalizations can also be formalized as applying utility functions.

A.3.9.2 Simple Multiattribute Rating Technique

The simple multiattribute rating technique (SMART) is the simplest form of the MAUT methods. The ranking value x_i of alternative A_j is obtained simply as the weighted algebraic mean of the utility values associated with it, as shown in the equation below:

$$x_j = \frac{\sum_{i=1}^{m} w_i a_{ij}}{\sum_{i=1}^{m} w_i}, j = 1, \ldots, n.$$

where:
a = alternative
m = number of criteria (i.e., 1 to m)
n = number of alternatives (i.e., 1 to n)
w = weights (i.e., w_1 reflects the relative importance of criteria $\mathbf{a}_1$ to the decision)
x_j = ranking value of alternative A_j

In addition to the above additive model, another method is to assess weights for each of the criteria to reflect their relative importance to the decision. First, the criteria are ranked in order of importance, and 10 points are assigned to the least important criterion. Then, the next-least-important criterion is chosen, more points are assigned to it, and so on, to reflect their relative importance. The final weights are obtained by normalizing the sum of the points to 1.

However, comparing the importance of the decision criteria is meaningless if it does not also reflect the range of the utility values of the alternatives.

A.3.9.3 Generalized Means Technique

In a decision problem, the vector x = ($x_{1,\dots,}x_n$) plays a role of aggregation, accounting for the performance scores for every criterion with the given weight. This means that the vector **x** should fit into the rows of the decision matrix as well as possible. Mészáros and Rapcsák (1996) showed that the optimal solution is a positive multiple of the vector of the weighted geometric means of the columns; consequently:

$$w = \sum_{i=1}^{m} w_i$$

with the values

$$x_j = \prod_{i=1}^{m} a_{ij}^{w_i/w}\ , i = 1, \dots, n$$

where:
a_{ij} = the alternative listed in the i^{th} row and j^{th} column
w = total of all weighting factors, w_i
x_i = ranking value of alternative a_i

A.3.9.4 Analytic Hierarchy Process

The basic idea of the analytic hierarchy process (AHP) is to convert subjective assessments of relative importance to a set of overall scores or weights. The AHP is one of the more widely applied multiattribute decisionmaking methods.

The AHP methodology is based on pairwise comparisons of the following type: "How important is criterion C_i relative to criterion C_j?" Questions of this type are used to establish the weights for criteria, and similar questions are answered to assess the performance scores for alternatives on the subjective (judgmental) criteria.

To derive the weights of each criteria, the analyst should respond to a pairwise comparison question asking the relative importance of the two criteria. The analyst's responses use the following nine-point scale to express the intensity of the preference for one criterion versus another:

1 = equal importance or preference
3 = moderate importance or preference of one over another
5 = strong or essential importance or preference
7 = very strong or demonstrated importance or preference
9 = extreme importance or preference

If the analyst judges that criterion C_j is more important than criterion C_i, then the reciprocal of the relevant index value is assigned.

Let c_{ij} denote the value obtained by comparing criterion C_i to criterion C_j. Because the analyst is assumed to be consistent in making judgments about any one pair of criteria and since all criteria will always rank equally when compared to themselves, then:

$$c_{ji} = \frac{1}{c_{ij}} \; and \; c_{ii} = 1$$

This means that it is only necessary to make ½ m (m-1) comparisons to establish the full set of pairwise judgments for *m* criteria. The entries c_{ij}, *i,j* = 1,…,*m* can be arranged in a pairwise comparison matrix *C* of size *m* x *m*. Therefore, the analyst should make 15 pairwise judgments to establish the full set of pairwise judgments for six criteria.

The next step is to estimate the set of weights that are most consistent with the relativities expressed in the comparison matrix. Note that, while there is complete consistency in the (reciprocal) judgments made about any one pair, consistency of judgments between pairs (i.e., $c_{ij}c_{kj} = c_{ik}$) for all *i,j,k*, is not guaranteed. Thus, the task is to search for an *m*-vector of the weights such that the *m* x *m* matrix *W* of entries w_i/w_j will provide the best fit to the judgments recorded in the pairwise comparison matrix *C*. The weighting method is one of the simplest multiobjective optimizations that has been widely applied to find the noninferior optimum solution.

This method may not be capable of generating the efficient solutions of the efficient frontier. Also, the optimal solution of a weighting problem should not be used as the best compromise solution, if the weights do not reflect the Commission's preferences or if the Commission does not accept the assumption of a linear utility function.

As in calculating the weights for the criteria, AHP uses the same technique based on pairwise comparisons to determine the relative performance scores of the decision table for each of the alternatives on each subjective (judgmental) criterion. Now, the pairwise questions to be answered ask about the relative importance of the performances of pairs of alternatives relating to the considered criterion. Responses use the same set of nine index assessments as before, and the same techniques can be used as when computing the weights of criteria.

With the weights and performance scores determined by the pairwise comparison technique above, and after further possible normalization, analysts can evaluate alternatives using any of the decision table aggregation techniques of the MAUT methods. The so-called additive AHP uses the same weighted algebraic means as SMART, and the multiplicative AHP is essentially based on the computation of the weighted geometric means.

A.3.10 Outranking Methods Technique

The outranking method is based on evaluating each pair of alternatives by considering two conditions as follows. Alternative A_i outranks A_j if, generally, the criterion A_i performs at least as well as A_j (concordance condition), while worse performance is still acceptable on the other criterion (nondiscordance condition). After having determined for each pair of alternatives whether one alternative outranks another, these pairwise outranking assessments are combined into a partial or complete ranking. Contrary to the MAUT methods, where the alternative with the best value of the aggregated function can be obtained and considered as the best one, a partial ranking of an outranking method may not directly render the best alternative. A subset of alternatives can be determined such that any alternative not in the subset is outranked by at

least one member of the subset. The aim is to make this subset as small as possible. This subset of alternatives can be used to screen a long list of alternatives into a short list, within which the use of other methods could find a good compromise alternative.

The principal outranking methods assume data availability broadly similar to that required for the MAUT methods. This method requires that alternatives and criteria be specified and uses the same data as the decision table (i.e., the values represented by a_{ij} and w_i).

The ELECTRE I Method

The ELECTRE I methodology is based on the concordance and discordance indices defined as follows. The analyst starts with the decision matrix data and normalizes the weighting so that the sum of the weights of all criteria equals 1. For an ordered pair of alternatives (A_j, A_k), the concordance index c_{jk} is the sum of all the weights for those criteria where the performance score of A_j is at least as high as that of A_k. This is shown mathematically as follows:

$$c_{jk} = \sum_{i:\, a_{ij} \geq a_{ik}} w_i, \;\; j,k = 1,\dots,n \; where \; j \neq k$$

where the concordance index lies between 0 and 1.

The computation of the discordance index d_{jk} is a bit more complicated. The discordance index is zero if A_j performs better than A_k on all criteria. Otherwise, for each criterion where A_k outperforms A_j, the ratio is calculated between the difference in performance level between A_k and A_j and the maximum difference in score on the criterion concerned between any pair of alternatives. This is shown mathematically as follows:

$$d_{jk} = 0 \; if \; a_{ij} \; > \; a_{ik}\,, \;\; i = 1,\dots,m$$

or

$$d_{jk} = \max_{i=1,\dots,m} \frac{a_{ik} - a_{ij}}{\max\limits_{j=1,\dots,n} a_{ij} - \min\limits_{j=1,\dots,n} a_{ij}}\,, \qquad j,k = 1,\dots,n, \;\; j \neq k$$

The maximum of these ratios is the discordance index, which has a value between 0 and 1.

A concordance threshold c^* and discordance threshold d^* are defined such that $0<d^*<c^*<1$. Then, A_j outranks A_k if the $c_{ij} > c^*$ and $d_{ik} < d^*$ (i.e., the concordance index is above its threshold and the discordance index is below its threshold, respectively).

This outranking defines a partial ranking on the set of alternatives by identifying the set of alternatives that outrank at least one other alternative and are themselves not outranked. By using this method, the analyst identifies the most promising alternatives. By interactively changing the level thresholds, the analyst can also change the size of this set.

As shown, the ELECTRE I method may be used to construct a partial ranking and choose a set of promising alternatives. (Figueira et al. (2004) gives more details about the ELECTRE methods.)

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