Stakeholder-driven multi-attribute analysis for energy project selection under uncertainty

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Abstract

In practice, selecting an energy project for development requires balancing criteria and competing stakeholder priorities to identify the best alternative. Energy source selection can be modeled as multi-criteria decision-maker problems to provide quantitative support to reconcile technical, economic, environmental, social, and political factors with respect to the stakeholders' interests. Decision making among these complex interactions should also account for the uncertainty present in the input data. In response, this work develops a stochastic decision analysis framework to evaluate alternatives by involving stakeholders to identify both quantitative and qualitative selection criteria and performance metrics which carry uncertainties. The developed framework is illustrated using a case study from Fairbanks, Alaska, where decision makers and residents must decide on a new source of energy for heating and electricity. We approach this problem in a five step methodology: (1) engaging experts (role players) to develop criteria of project performance; (2) collecting a range of quantitative and qualitative input information to determine the performance of each proposed solution according to the selected criteria; (3) performing a Monte-Carlo analysis to capture uncertainties given in the inputs; (4) applying multi-criteria decision-making, social choice (voting), and fallback bargaining methods to account for three different levels of cooperation among the stakeholders; and (5) computing an aggregate performance index (API) score for each alternative based on its performance across criteria and cooperation levels. API scores communicate relative performance between alternatives. In this way, our methodology maps uncertainty from the input data to reflect risk in the decision and incorporates varying degrees of cooperation into the analysis to identify an optimal and practical alternative.

1. Introduction

Energy resource management often requires decision maker consensus regarding the trade-offs between a project's economic, social, technical, and environmental costs and benefits. Energy supply source selection is a common problem facing energy planners. Growing feasibility for alternative energy supply technologies and more environmentally conscious communities have made this selection process more complex, expanding the decision criteria beyond economic cost. As such, selecting an energy source for a community among a suite of alternatives can be characterized as a multi-criteria decision-maker (MCDM) problem.

In general, MCDM problems employ a set of criteria and performance measures to evaluate alternatives where data are available in qualitative and/or quantitative forms, uncertainty is high, and decision makers have different priorities. A range of disciplines use multi-criteria decision analysis (MCDA) methods to solve MCDM problems because: MCDA is well suited to incorporate conflicting criteria, it leads to explainable and tractable decisions, and it acts as a tool for discussion and participation among decision makers (Belton & Stewart, 2002). These features make MCDA methods particularly attractive for addressing natural resource management problems with incomplete datasets that require combining expert knowledge and stakeholder opinions with limited quantitative data (Mendoza & Martins, 2006). Most approaches to MCDA consider deterministic input values and rank them accordingly to one of several families of methods – elementary, unique synthesizing criteria, and outranking (Wang et al. 2009). Traditional MCDA methods have been criticized for practicality based on their assumption that a single aggregate or average value can sufficiently represent the range of possible values for a given criterion (see Madani & Lund, 2011 for a review). The methods presented in this work preserve uncertainties from the input data and therefore avoid the assumption that a single value for a given criterion is representative of the potential range.

A number of studies have used MCDA methods to analyze energy planning problems, but most limit their performance evaluation of alternatives to quantitative-based criteria, incorporating decision-maker preferences only through standard weighting rather than through engaging with partners. Earlier examples of MCDA in ranking energy supply projects applied the relatively simple Analytical Hierarchal Process (AHP) method (Akash et al. 1998); the field has expanded since then to include more complex applications that use MCDM methods (See Yazdani-Chamzini et al. (2013) for a brief review). Some applications of MCDA in the energy sector developed hybrid methodologies that combine AHP with different types of MCDM methods. For example, Kaya & Kahraman (2010) integrate AHP with the multi-attribute technique "VIKOR" to assess options in Istanbul; San Cristobal (2011) followed a similar approach to find the best alternative for developing energy sources compliant with Spain's renewable energy plan. Yazdani-Chamzini et al. (2013) present a new method merging AHP with the Complex Proportional Assessment and compare the results across five common MCDM methods to suggest a final ranking of alternatives. These hybrid methodologies respond to the growth in complexity of energy supply planning problems, as social, environmental, and political factors are treated as equally important as economic criteria in some cases. Wang et al. (2009) provide a comprehensive review of MCDA applications specific to sustainable energy supply selection that lists the most common methods for selecting criteria, weighting criteria, ranking alternatives, and aggregating ranks. Banos et al. (2011) reviewed optimization techniques for solving energy resource problems and contrasted those that employ heuristic and artificial neural network approaches with multi-objective (Pareto-based and aggregate weighting) methods.

Uncertainties can exist from several sources in MCDM problems: from quantitative uncertainty in measuring performance values (e.g. the amount of particulate emissions produced) and from qualitative responses that experts' provide regarding the performance of political and social criteria. These uncertainties should be accounted for when modeling the potential risks and trade-offs in selecting between alternatives (Hadian and Madani, 2015). Uncertainty in MCDM energy management problems has mainly been handled through sensitivity analysis (Guldmann & Wang 1999; Banos et al. 2011; Maimoun et al., 2016), where criteria weights are varied within a model to determine the decision points of the final ranking. However, this weighting approach can introduce a bias (Kangas & Kangas, 2003; Prato, 2000) that may produce unrealistic or favored results. Another common approach to deal with uncertainty in MCDM problems uses fuzzy MCDA methods. Kahraman and Kaya (2009) apply fuzzy decision-making methodologies to determine which renewable energy alternatives have minimum cost and maximum reliability. In later work, Kaya & Kahraman (2011) apply a modified fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method to an MCDM energy planning problem to evaluate seven types of energy sources by economic, social, technical, and environmental criteria to determine the optimal alternative for a theoretical case. Generally, both classes of uncertainty analysis methods (i.e. sensitivity analysis and fuzzy MCDA) provide deterministic outputs that might obscure useful information from decision makers (Madani & Lund, 2011). Therefore, MCDA methods that map uncertainty from input to output in order to communicate risk have gained popularity in recent years (Mattson & Messac, 2005; Madani & Lund, 2011; Rastgoftar et al., 2012; Mokhtari, 2013; Hadian et al., 2012 and 2014). Following these studies, we develop a stochastic group decision-making analysis framework that can incorporate uncertain input information, map it to the final decision outputs, and provide decision makers with the ability to evaluate trade-offs between alternatives while considering risk.

Group decision-making MCDM analysis often overlooks the willingness of stakeholders to cooperate (Madani, 2010; Mirchi et al., 2010). Most MCDA methods assume a perfect cooperation among the decision makers (Madani & Lund, 2011) even though perfect cooperation among the decision makers is very rare in the real world. Read et al., (2014) demonstrates that this assumption can lead to unfeasible results. Thus, alternatives' performances should be evaluated under different levels of cooperation among decision makers (Read et al., 2013a). Methods capturing the effects of willingness to cooperate on the outcomes of group decision-making problems include social choice (voting) (Sheikhmohammady & Madani, 2008; Shalikarian et al., 2011), fallback bargaining (Brams & Kilgour, 2001), and non-cooperative game theory (Madani & Hipel, 2011; Madani, 2013) for group decision-making problems with medium, low, and no cooperation among the decision making agents (Madani et al., 2014a).

Madani and Lund (2011) categorize MCDM problems into multi-criteria single-decision-maker (MCSDM) problems and multi-criteria multi-decision-maker (MCMDM) problems. They suggest that the commonly used MCDM methods are only applicable to the first category, social planner decision making problems (Madani et al., 2014b), in which a central, powerful decision-maker holds deterministic power. This category of problems thus assumes full cooperation, as there is only a single decision-maker represented in the model. Group decision-making problems with imperfect cooperation fall into the MCMDM category, which can be solved by social choice methods, fallback bargaining and non-cooperative game theoretic methods. Madani & Lund (2011), Mokhtari et al. (2012), and Madani et al. (2011 and 2014a) show the impact of cooperation levels on selecting a policy by applying various Monte-Carlo decision analysis methods to a benchmark group decision-making problem in which stakeholders need to select the best policy for exporting water from the California's Sacramento-San Joaquin Delta under uncertain information. To capture these impacts in a comprehensive approach, the current study develops a stochastic decision-making analysis framework to evaluate the effects of decision maker willingness to cooperate on the final group decision-making outcome.

The paper is structured as follows. The next section proposes a framework for evaluating the alternative scenario performances under different levels of cooperation in MCMDM problems. The following section applies the proposed framework to an energy supply selection problem in Fairbanks, Alaska. We then present the analysis results, and close with a discussion of the policy implications and conclusions.

2. Methods

MCMDM problems in energy management are complex and difficult to model for two primary reasons: (1) the subjectivity of social, environmental, and economic dynamics of the problem itself, and (2) the variable willingness to cooperate among decision makers for reasons often external to the problem at hand, such as political positioning, previous history with others, and/or personality conflicts (De Bruyne & Fischhendler, 2013). Integrating MCDA with cross-disciplinary expertise can effectively capture both technical and social elements to fully define constraints of a particular case (Belton & Stewart, 2002). Thus, a solution framework that includes participatory modeling and engagement from the start can support decision makers to collectively define performance criteria, data sources, and acknowledge uncertainties as a group. This important step establishes a common baseline for decision makers, who often differ in level of expertise and discipline, to collaborate and reach a decision. Potentially, the alternative selected by the group will in fact not be the optimal selection for all parties, but rather will represent the most stable solution, achievable unanimously given the priorities of all decision makers (Read et al., 2014). This paper illustrates such a framework (summarized in Figure 1) that uses a set of criteria developed through consensus to evaluate a pre-defined set of alternatives in order to determine the most desirable group decision. This process is described in detail in this section.

2.1 Detailed description of steps in framework

1. Participatory performance criteria selection: In this step, all stakeholders suggest performance criteria to consider for evaluating the alternatives. To facilitate the process, the person asks stakeholders to only offer criteria that reflect their own interests.

2. Criteria grouping, elimination and leveling: This interactive step is perhaps the most socially complex step of the process. It develops a consensus for a final set of criteria to evaluate for performance. First, the participants categorize the suggested criteria (e.g. economic, environmental, social and political). Through consensus, the participants merge redundant criteria and eliminate less important criteria to form the final set of performance metrics. Balancing these criteria is necessary to prevent biasing the MCDA results toward any criteria category. For example, if the environmental category includes

8 criteria and the economic category includes three criteria, in absence of balancing, the final results would be biased toward the environmental criteria. This balancing is normally done through weighting the criteria and/or developing a hierarchy among the criteria (e.g. as done in the AHP method; Saaty (1980)), which can be based on the opinions and priorities of the experts/stakeholders but in some cases is arbitrary. Note that weighting can generate controversy in cases where stakeholders are unsatisfied with the experts' opinions and/or try to manipulate the weighting process.

To avoid such complications, the proposed method here instead relies on criteria leveling. Leveling seeks to create an appropriate hierarchy between criteria by assuming that all sub-criteria of a given criterion at each level have the same importance. Figure 2 illustrates a generic criteria tree where criteria represent the main interests of the stakeholders (e.g. economic, environmental, social and political) and are treated with equal importance. In the criteria tree these are denoted by a letter (A, B, etc.), and sub-criteria are "levels" underneath represented by subscripts (i =1, 2, 3, etc., and at the next lowest level: i, j = 1, 2, 3, etc., and the pattern may continue for: i, j, k = 1, 2, 3, etc.). For example, category B has two sub-criteria at level "i" (B_1 and B_2); B_1 has two sub-criteria at level "j" ($B_{11,}$ B_{12}), and B_2 has one sub-criteria at level "j" (B_{21}). As discussed above, all main criteria groups are equally weighted such that A is not penalized for having fewer sub-criteria than B; and similarly, B_1 and B_2 are given equal weight under B even though B_1 has two sub-criteria at level j and B_2 has only one. Interests groups then independently create the appropriate hierarchy under the first level criterion that represents their interests. Each interest group performs criteria leveling to minimize the bias toward specific criteria included in the corresponding category.

The developed hierarchy relates sub-criteria in the form of a decision tree. The performance of each criterion (e.g. A) depends on the performance at the lower levels (e.g. A_1 and A_{12}, and so on). In this way, hybrid criteria are created during the leveling process to appropriately transfer performance information between levels in the criteria tree. For example, as shown later in Figure 3, “air quality” was created by the environmental interest group as a hybrid criterion, reflecting the aggregate performance of its two sub-criteria, i.e. “particulate matter” and “water vapor.”

3. Performance value determination: In this step all interest groups are asked to participate in determining the performance values of the criteria. If not based on common knowledge and agreement, performance values need to be justified through shared references of scientific literature/studies. In absence of such information, expert surveys can suffice if all stakeholders agree to the process. Two major points on the performance data collection methodology are noteworthy. First, multiple performance values or performance ranges may be proposed and justified for a given alternative under a given criterion. In this case, the inherent uncertainty in performance information makes the decision-making problem stochastic. Second, performances are difficult to quantify under certain criteria (e.g. “political support from the government”). Here qualitative (ordinal) information through expert surveys or from local literature can serve as a reasonable estimate of values and may be less controversial and easier to collect. From these points,

the group decision analysis methods used under the proposed framework are well-suited to handle both cardinal and ordinal information.

4. Hierarchical Monte-Carlo multi-criteria assessment: Once the performance values of the criteria set are finalized, decision analysis methods can be applied in a multi-stepwise approach (similar to decision making using decision trees). Given the uncertainties in the input information, following Madani and Lund (2011), Monte-Carlo sampling converts the stochastic decision analysis problem to numerous deterministic problems and solves these according to the selected decision analysis method. The step-wise process described here is general for a single decision analysis method and can be repeated for as many MCDA methods as desired. Starting with the lowest level of the criteria tree of a given branch, the winning probabilities and corresponding distribution of alternative rankings (Madani et al., 2014a) are calculated. Consider this step like a competition between alternatives, where the result yields the percentage of time the alternative is selected at a given rank. This analysis is completed independently in each branch of the criteria tree.

For example, consider a simple two-criteria two-alternative decision problem evaluated using a single decision analysis method where in the lowest level alternatives A and B have winning probabilities of 40% and 60%, respectively, based on two criteria of a single branch (e.g. water vapor and particulate matter). These probabilities are used as the performances of A and B at level two, e.g. air quality. Mathematically, we use a random rank generator which places A ahead of B in 40% of the Monte-Carlo analysis runs at the higher level two (i.e. air quality). Now alternatives in level two compete (e.g. in air quality and net carbon footprint, etc.) whereby winning probabilities are computed and then transferred in the same process to the higher level until the winning probabilities are determined at each level, ending with the highest (aggregate performance level). As discussed earlier, mapping the uncertainty from the input information to the analysis output informs decision makers about the risk associated with selection of each alternative. This combined hierarchal Monte-Carlo and criteria tree methodology is an innovative approach for transferring uncertainty between levels to ensure that input uncertainties are reflected in the output, while also simplifying the output significantly to support stakeholders in making informed decisions.

When the decision problem involves more than two criteria, the process of calculating winning probabilities and fully ranking the alternatives becomes more complex. In such cases, ranking distribution probabilities (Madani et al., 2014a) should be calculated instead, a process described for the problem with only two alternatives. The rankings of the alternatives in different rounds of Monte-Carlo sampling determine the ranking distributions. Each Monte-Carlo selection round first determines the winning alternative and then removes it from the alternatives set. The analysis is then repeated with the same performance values for the remaining alternatives to determine the next winner (second place), which will be ranked as the second most preferable alternative. The procedure continues until all alternatives are ranked in this single round of Monte-Carlo selection. Then Monte-Carlo selection rounds (for *m* experiments) proceed until each alternative has winning probabilities at each rank (producing a ranking distribution) (for more details regarding this process refer to Madani et al. 2014a).

As an example, consider adding alternative C to the previous case and respectively assigning winning probabilities for alternatives A, B and C as 30%, 40% and 30% at the first rank, 50%, 30% and 30% at the second rank, and 20%, 30% and 40% at the third rank. In other words, the ranking distributions are: alternative A is 30% (1^{st} level), 50% (2^{nd} level) and 20% (3^{rd} level); then alternative B is 40% (1^{st} level), 30% (2^{nd} level) and 30% (3^{rd} level); and alternative C is 30% (1^{st} level), 30% (2^{nd} level) and 40% (3^{rd} level). Once the ranking distributions are determined, a random performance generator is set such that the same ranking distribution structure is preserved in the hierarchal Monte-Carlo process at the next (higher) level. This multi-level Monte-Carlo analysis reaches the highest level to determine the "winner" alternative; this process is repeated after the first place winner is removed to identify second place, then repeated again until all alternatives are ranked at all levels.

Recall that the steps above describe one decision analysis method; however, each of these decision analysis methods carries different assumptions regarding the cooperativeness of the decision makers. Since we often do not know the true cooperation level of the stakeholders and but seek to understand impacts of cooperation ability, this study applies three categories of group decision analysis methods, i.e. MCDA, social choice (voting), and fallback bargaining (game theory) methods to account for the effects of high, medium, and low levels of cooperation on the outcomes (Madani et al., 2014a). Multiple methods are used in each category (as illustrated in Table 1) to increase the robustness of the results and minimize possible biases toward the specific notions of Pareto-optimality (in case of MCDA), social fairness (in case of social choice making) and stability (in case of bargaining).

5. Aggregate performance calculation: By this point, the alternatives have been ranked under different decision analysis methods in independent processes. However, reporting multiple ranking information from each method to the decision makers would be confusing and would hide the uncertainty information. Therefore, overall performance values can be calculated for the alternatives based on an Aggregate Performance Index (API), proposed by Hadian and Madani (2015):

$$API_i = 100 * \left(\frac{C * N - B_i}{N(C-1)} \right) \quad (1)$$

where N is the number of decision analysis methods applied (e.g. 9 if all the decision analysis methods shown in Table 1 are used), C is the number of alternatives, and B_i is the Borda score (De Borda, 1781) for each alternative i.

The API is a simple and insightful index that provides valuable information to the decision maker in the following ways: (1) an API value is the relative quantitative performance of the alternatives (2) the API uses the familiar 100-point scale to communicate the risk associated with selecting each alternative. That is, a project that scores 100% is expected to be the absolute winner based on all decision analysis methods, and a project that scores 0% is expected to be the absolute loser based on all decision analysis methods. For all API values in between, decision makers learn about the effects of input uncertainties on the output information and the sensitivity of the results to the Pareto-optimality, social fairness, and stability notions as well as cooperation levels. This learning occurs when decision makers compare API scores between two alternatives that are ranked sequentially, indicating the relative risk of selecting one over another. API scores are calculated for all the decision analysis methods used in a study (illustrated in Table 1) or any given group of these methods. For example, API scores can be computed for each of the three groups of methods in Table 1 to demonstrate to decision makers how their willingness to cooperate effects analysis outcomes.

3. Case study: Energy supply selection for Fairbanks, Alaska

The methodology was developed specifically to address the MCMDM problem described here, of selecting a new energy source to provide both electricity and space heating for residents and industry in Interior Alaska. The current sources of heat are electric (provided by coal-fired power plants with fuel oil backup) and fuel oil (the primary source for residential heating). The volatility of oil prices during the past decade has driven energy costs to unaffordable levels for many in the Fairbanks region. In recent decades, state and private entities have proposed numerous alternatives to mitigate this impact; however, none of the proposed projects have reached fruition largely due to changes in the size and scope of proposed projects, economic constraints, and a divided public opinion. Of the major energy alternatives proposed by both private and public entities during 2011 and 2012 (Table 2), each one varies in social and political support, economic valuation, and environmental impacts.

In fall 2012, investigators at the University of Alaska Fairbanks and Alaska Center for Energy and Power engaged in a three-month stakeholder-driven process to examine each alternative's performance under specified criteria and performance measures. Academics acted as decision makers, role playing a number of stakeholders to represent each interest group during the decision-making process.

This section integrates parts from the Methods section to explicitly discuss the stakeholder process that emerged as a response to the needs and objectives of the Interior Alaska energy project. Recall that step one engages stakeholders to select performance criteria where each role player (group of academic experts) identifies all potential criteria relating to their field of interest. This step was implemented over multiple hour-long weekly meetings and email correspondence. Following this, an open facilitated discussion identified the main categories for evaluating the alternatives' performance and a list of concrete criteria to use.

The next step required the role players to coordinate and compromise to finalize a set of criteria for project evaluation. They began by grouping criteria into a tree, e.g. distinguishing a criterion as "social" versus "political." They then assigned relative importance to each criterion, e.g. should "job creation" be placed at the same level with "political support by state legislator." Finally, the role players determined which criteria could be merged and/or completely eliminated from the set due to redundancy or similarity. After several iterations of moderated discussion, the group reached a consensus on the final criteria tree, as illustrated in Figure 3.

As discussed, the need to evaluate criteria at different levels and the type of data collected, both qualitative and quantitative, drove the development of the hierarchical Monte-Carlo multi-criteria method presented in this work. The use of a criteria tree for this type of problem has three main advantages: 1) Organizes criteria to provide a systematic MCDA at each level; 2)

Transfers/maps uncertainty from lower level to higher level; and 3) Equally weights criteria groups to prevent bias in the results for cases where criteria have a different number of sub-criteria in a particular level.

Once the criteria set was established, the role playing experts were asked to provide metrics for performance evaluation, i.e. measureable outcomes for each criterion, as well as performance values for each alternative under the lowest level criteria in all branches. To do so, these experts formed small-focus groups according to their interest (social, political, economic, and environment) to gather data from literature, surveys, and local knowledge.

The final criteria tree (Figure 3) has three main branches (categories) – environment, economics, and socio-political – with smaller branches (sub-categories) for each criterion. The environment criteria address aerial particulate matter reduction, and consider energy sustainability (footprint) of each alternative. The economic criteria included capital and O&M project costs as well as market commodity prices for each type of energy, estimated by experts from Alaska Energy and Power. The socio-political criteria combined opinions from local politicians and surveys from Fairbanks residents to reflect the impact and preference for each alternative. Table 3 provides a detailed description of the criteria.

Actual data values for environmental criteria were estimated from formal reports issued by impacts assessments and companies involved in preliminary design and construction (Hatch Ltd, 2008; TransCanada Alaska Company, 2011) and experts' calculations. Net carbon footprints for pipeline projects were computed from the pipeline volumetric flow rate over the project life.

Carbon footprints for the LNG projects were calculated from the projected BTU productivity for gas delivery to Fairbanks over the lifetime. Carbon footprints for the HVDC and Susitna Dam electric line were based on the expected KWh delivery. Ecological footprints were calculated for each pipeline project by multiplying the length of the pipe by an assumed 30 meter right of way. Water footprints for pipeline projects were calculated based on usage data from State of Alaska natural resource reports, and account for the risk of contamination of supply in the case of failed safety measures. Criteria values for air quality (particulate matter and water vapor) were computed using the emission rates projected for each project.

To provide an example of data processing for each branch of the criteria tree, Table 4 presents three economic sub-criteria and corresponding data values collected from experts on the projects. Note that one sub-criterion, "estimated project levelized costs" is quantitative and within a range of possible values, while "commodity prices" and "capital costs" values are given as ranks. The methods described in section two provide a framework that requires conserving the uncertainties in the alternatives' performance, combining quantitative and qualitative data, and aggregating sub-criteria ranks from one level to the next higher level.

4. Results

In this section we present final rankings and APIs for the energy supply alternatives as presented to decision makers. We also describe a rationale for the alternatives as ranked through the modeling process. Figure 4 summarizes the overall performance of the alternatives according to the criteria tree in Figure 3 and using the nine different analysis methods from Table 1. An API close to zero indicates that this alternative consistently had low winning probabilities across the nine MCDA methods at each level. The small diameter pipelines to Fairbanks has the highest score, with a three-way tie for second between the LNG trucking project, the Big Lake pipeline, and the HVDC current line. These close API scores indicate that selecting one of these four projects over another has a low relative risk compared with selecting say, the coal-to-liquids plant which performs significantly worse than the other alternatives. The API reflects expectations of poor performance of the coal-to-liquids plant in the categories of economics and environment, since it carries a high footprint in these areas. Also note that no alternative receives a perfect API of 100, an indication that none of the proposed energy source projects performs best under all decision analysis methods.

Figure 5 shows the API distribution according to the three categories of decision analysis methods –MCDA, social choice, and fallback bargaining. Since the type of decision method is a proxy for cooperation level, Figure 5 illustrates how alternatives' overall performance is impacted by cooperation level. The first four alternatives (A1-A4 from left in Figure 5) display minimal performance variation across all method categories, suggesting that cooperation does not impact API (i.e. the decision). APIs of alternatives A5-A9 were more heterogeneous. Under MCDM, Big Lake pipeline to Fairbanks would be the best choice, but under fallback bargaining, it would be the fourth best choice.

Figure 5 shows the importance of analyzing performance across a variety of decision analysis categories (i.e. for a range of cooperation levels) since the degree of cooperation has demonstrable impact. This added information enables decision makers to select a more practical alternative considering the expected level of cooperation among the stakeholders in that group. This is an improvement from social planner models which conventionally select the unstable, non-achievable Pareto-optimal solution (Madani and Hooshyar, 2014).

Sensitivity Analysis

We performed a sensitivity analysis to understand the impact that each major criteria group has on the final API scores. To identify which criteria unduly influenced the APIs, we ran the model eliminating one of the major criterions. Results are illustrated in Figure 6; each shaded bar represents a model run without one major criterion.

When economic criteria are eliminated from consideration in the criteria tree (blue bars in Figure 6), the LNG export to Valdez (A2) has the highest API. The improved performance of A2 when economic criteria are not considered owes to the project's relatively high levelized and capital costs which lower the expected economic performance.

Eliminating one criterion also places greater emphasis on the other three criteria. This can contribute to raising or lowering an alternative's API. For example, when all criteria are included, Susitna (A8) scored relatively well in environmental but lower in economic while the coal-to-liquids plant (A8) scored lower environmental but better in economic. For this reason, Figure 6 shows that eliminating economic criteria, increases the API of A8 and decreases the API of A9. In this way, the sensitivity analysis provides a rationale for the rankings that experts can confirm or contest using the constituent data.

When socio-political criteria are eliminated, the small diameter pipeline (A4) scores the highest API, likely due to omitting its low performance in the job creation category. Omitting socio-political criteria from the analysis improves the APIs of the Big Lake (A6) and HVDC line (A7) as both have low scores in sponsor credibility and use of local resources. Finally, eliminating the environmental criteria (green bars) selects the LNG trucking project (A5) as the best alternative since its poor performance in air quality and carbon footprint categories are removed from this analysis.

Overall, the sensitivity analysis illustrated in Figure 6 indicates that the small diameter pipeline (A4) has a high API in each elimination round and the LNG trucking project (A5) only scores higher when environmental criteria are eliminated. Conversely, the LNG export to Valdez (A2) has a competitive API only when economics is eliminated whereas Susitna dam (A8) consistently has among the lowest API. The sensitivity analysis adds transparency to the decision making process by enabling decision makers and experts to rationalize the model's findings.

The sensitivity analysis also examines the impact assigning weights to the criteria. In practice, the economic performance may carry more importance than environmental performance, so testing the rankings according to different weighting (priority) schemes shows decision makers' the impact of their priorities. This can facilitate a learning process among stakeholder groups, especially when priorities are not well established and open to negotiation.

In order to test the weighting of major criteria, we performed a second analysis. The "four-branch case," disaggregates the socio-political criteria into two categories: "social" and "political," thus reorganizing the criteria tree into four equal branches as shown in Figure 7.

Results shown in Figure 8 indicate that API scores are sensitive to changes in the structure of the criteria tree, since APIs shows some differences between the baseline and the four-branch case, a validation for the methodology. For example, the HVDC line (A7) demonstrates a lower API in the four-branch case because it has poorer performance in both the social and political criteria which now carry higher weights than when they were lumped in the baseline analysis. This has implications for understanding how weighting criteria and decision maker preferences influence rankings. Since the alternatives' APIs between the baseline and the four-branch case are relatively similar (both in sensitivity analysis and final rankings), we are confident that combining the social and political into one major criteria is a reasonable assumption especially given that socio-political criteria were perceived to be related by the experts.

5. Discussion

The Fairbanks, Alaska energy supply problem presented here demonstrates a case where decision makers seek to select an alternative that can satisfy the plethora of performance criteria. We present this relatively complex case to demonstrate our methodology for factoring both qualitative and quantitative information into a multi-dimensional multi-decision-maker problem. Our methodology provides a simplified yet representative score to help decision makers evaluated their project choice.

Results indicate that two alternatives (the small diameter pipeline - A4 and the LNG trucking project - A5) perform well overall with reliably high API scores across all the nine types of decision analysis methods tested. On the other hand, the coal-to-liquids power plant (A8) and Susitna dam (A9) projects consistently show low scores across all methods, suggesting that these two projects may be too risky for investment according to the performance metrics and data provided by the expert role players.

A sensitivity analysis of the baseline case indicates that scores and rankings change when one major criterion is eliminated. This sensitivity analysis offers a rationale for the final rankings, and suggests that if decision makers can further influence the scores/rankings with the weights they apply to criteria. In evaluating the baseline (with three major criteria), and the four-branch case which separates the social and political criteria, the overall sensitivity of the criteria tree structure was tested and shown to impact the resulting APIs. This confirmed the extensive impacts of the methodology's first steps that collaboratively brainstorm and establish criteria and their leveling and grouping.

Participants of the Fairbanks, Alaska case study commented on the ability of this exercise to increase knowledge on technical and social aspects of the decision process. This case study was an initial first-cut analysis that relied on a small group of experts for qualitative data inputs. Since the completion of this study in 2013, independent of its results, decision makers began implementing LNG trucking project (A5) to providing energy to the interior Fairbanks region. This acts as an informal validation of our findings, since A5 scored consistently high according to the aggregate API and across social-choice and fallback bargaining analysis methods. In 2016, fluctuating oil prices drove up costs and since stalled progress of any project; we anticipate that politics will ultimately dictate motivation for continuing a project.

6. Conclusions

This paper presented a stochastic group decision analysis framework that combines Monte-Carlo selection with different decision analysis methods to identify the best alternative for a problem with competing criteria and multiple decision makers. Our method began with a collaborative process to identify criteria for assessing the problem. Experts acting as stakeholders collaboratively eliminated, grouped, and leveled a criteria tree to organize the performance data. The experts then collected data and sources to determine the performance values for the alternatives to populate the criteria tree. We conducted a hierarchical Monte-Carlo multi-criteria assessment at each level of the criteria tree across all alternatives using different decision analysis methods to calculate winning probabilities and map these probabilities between levels. A final score was computed for each alternative according to each decision analysis method and then combined into an aggregate performance index (API) to reflect performance and the relative risk in choosing between alternatives.

The decision analysis methodologies applied in this analysis – MCDA, social choice, and fallback bargaining – approach the problem with different assumptions regarding the degree of cooperation between the decision makers. Since in practice the level of cooperation in a negotiation is unknown, we include these methods to account for a feasible range of possible low, medium, and high levels of cooperation. For example, in cases where the parties are not cooperative but willing to bargain, the game theory (fallback bargaining) methods are more suited to solve the problem. On the other hand, if decision makers are only concerned with the optimal solution and benefit from a high level of cooperation, then MCDA methods can inform this decision. Thus, our methodology adds robustness to ranking solutions, even in challenging cases such as a regional energy supply problem, by including a range of decision analysis methods and accounting for uncertainty.

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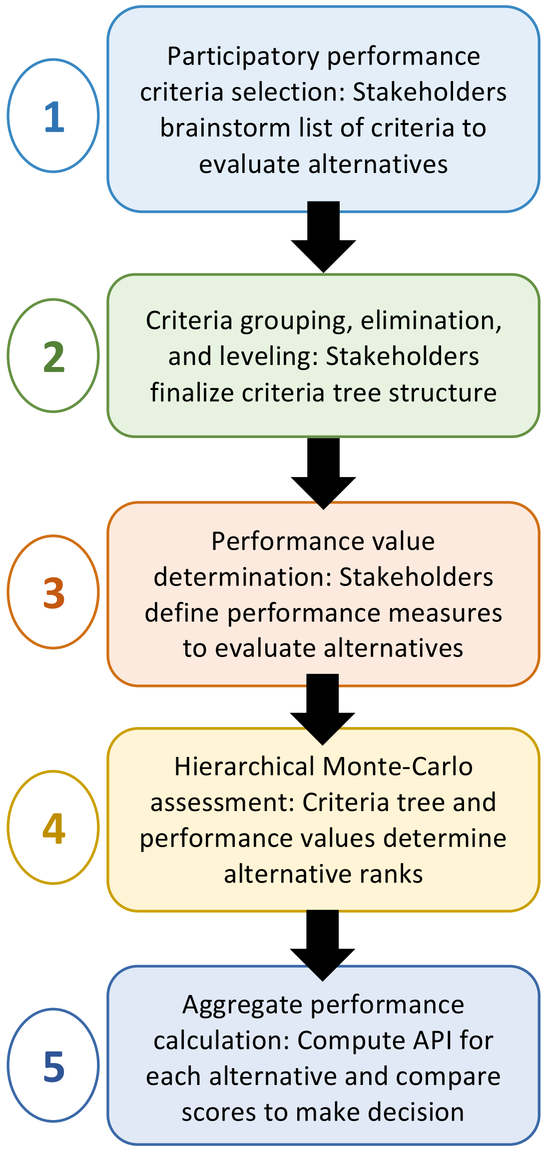

Figure 1. Overview of proposed methodology for comparing performance between alternatives

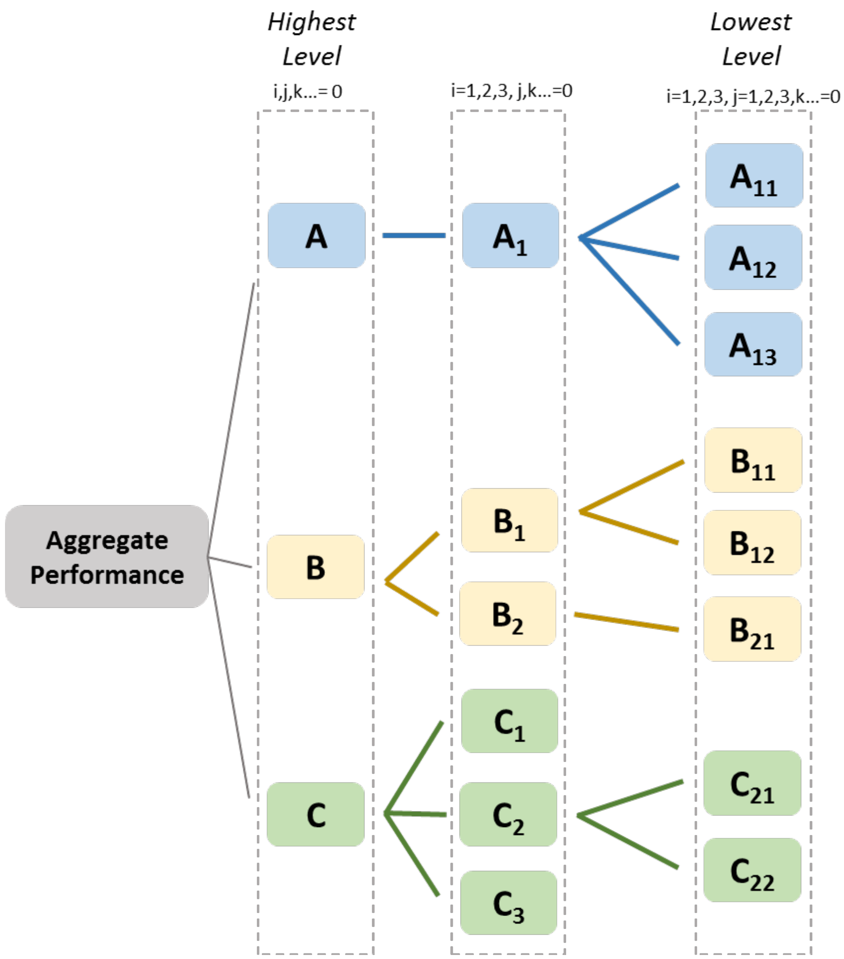

Figure 2. Example of a criteria tree illustrating leveling of sub-criteria

Table 1. Decision analysis methods used in this study

Category	**Method**	**Description**	Stakeholders' Willingness to Cooperate
MCDA	Dominance (Fishburn, 1964)	Makes pair-wise comparisons across all combinations of criteria; the best alternative is the one that has the highest score most often	High
	Maximin (Wald, 1945)	Ranks alternatives by maximizing the worst performance; represents a pessimistic or "best of the worst" case perspective	High
Social Choice Rules	Borda Count (De Borda, 1781)	Scores alternatives according to highest score for each criterion, with the top choice receiving N points, second receiving N-1, etc.; sums these values to select the best alternative as the one with the highest overall score	Medium

	Plurality	Identifies the alternative with the highest score for each criterion; winning alternative is the one which has the majority of "votes;" ties are allowed here	Medium
	Median Voter Rule (Black, 1948)	Selects an alternative that receives the majority of votes for the greatest number of criteria (from the majority of decision makers); if no alternative wins outright, each decision maker (criterion) votes for the second most preferred alternative. The procedure continues until a unique alternative receives the majority votes.	Medium
	Condorcet Practical Method (Nanson 1882)	Ranks alternatives according to majority support; works by the same logic as dominance	Medium
	Majoritarian Compromise (Sertel & Yilmaz, 1999)	Acts similar to Median Voter Rule except that when ties exist in the rankings the winning alternative is one with the greatest number of votes (supporters)	Medium
Fallback Bargaining	Unanimity (Brams and Kilgour, 2001)	Selects the alternative that receives all stakeholder support as bargainers fallback (retreat) to agree on an outcome; this solution is always Pareto optimal because each decision-maker receives at least their middle preference	Low
	q-Approval (Brams and Kilgour, 2001)	Selects the alternative that is preferred by "*q*" parties, where *q* (minimum threshold of persons required for consensus) can be set by the stakeholders	Low

Table 2. Proposed energy supply alternatives for the Fairbanks region (Read et al., 2013b)

Alternative	Description
A1	Large diameter pipeline Edmonton, Canada to Chicago, Illinois
A2	Liquid natural gas export (LNG) from North Slope to Valdez
A3	Bullet line to Anchorage, spur to Fairbanks
A4	Small diameter pipeline: North Slope to Fairbanks
A5	Liquid natural gas (LNG) trucking project
A6	Big Lake gas pipeline: Beluga to Fairbanks
A7	High voltage direct current line from North Slope
A8	Coal-to-liquids power plant in Fairbanks
A9	Susitna Hydro-electric dam

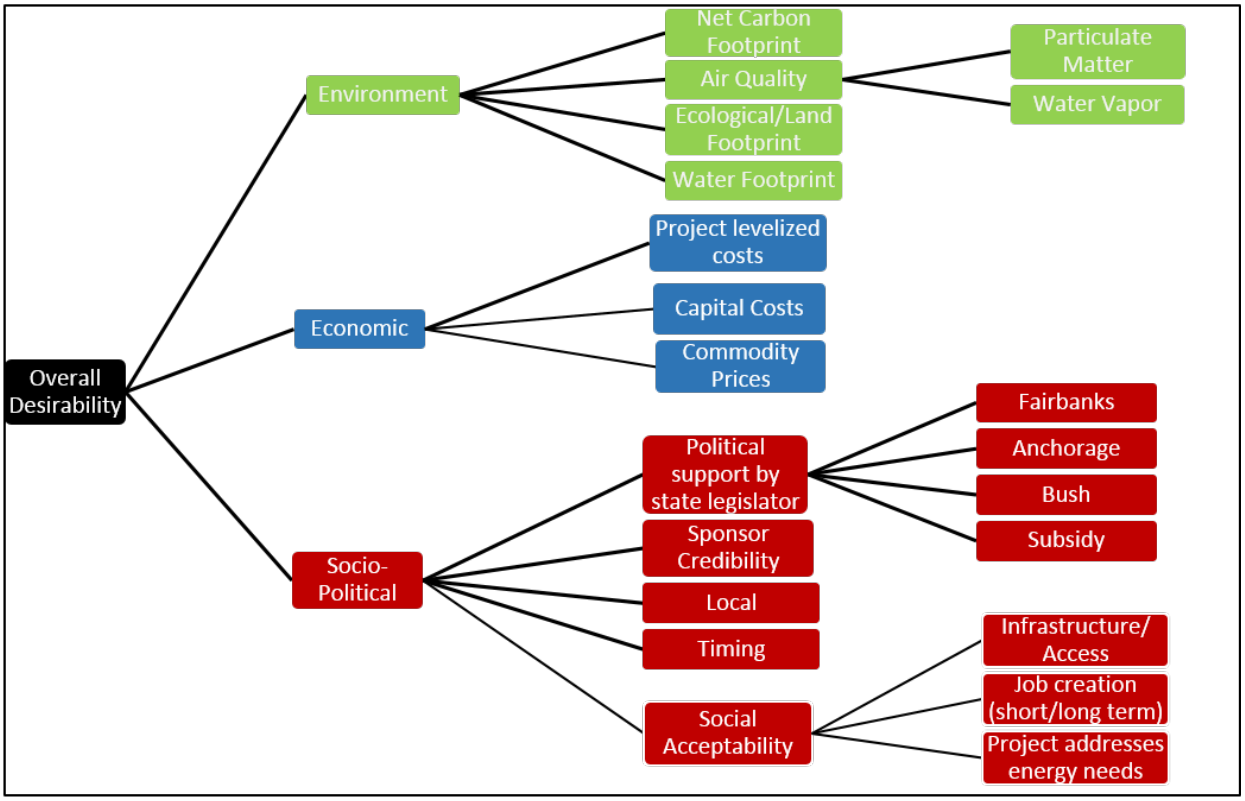

Figure 3. Criteria tree for Fairbanks, Alaska energy supply alternative assessment; levels increase from right (lowest) to left (highest)

Table 3. Descriptions of the criteria used in the energy supply alternative assessment (Read et al., 2013b)

Major Category	**Criteria**	**Description**
Environment	Net Carbon Footprint	The carbon footprint of each project including construction and operation
	Air Quality: *Particulate Matter*	The level of PM 10 and PM 2.5 emitted by each project
	Air Quality: *Water Vapor*	The amount of water vapor released for each project
	Ecological/Land footprint	The land area affected by the construction and operation of each project
	Water footprint	The amount of water used to construct and operate each project
Economics	Project levelized cost	The levelized cost of each project including development, capital, and operations and maintenance costs
	Capital cost	Immediate cost burden
	Commodity price reliance	Price volatility; the degree to which the price of the sale is expected to change with the given markets
Socio-Political	Social acceptability: *Infrastructure/access*	How the projects' scheduled impacts on land use and accessibility affect the personal view of the resident

	Social acceptability: *Job creation*	The likelihood of a project to create local jobs and whether the resident sees this as a positive addition (long-term jobs) or potentially negative (transient, short-term jobs)
	Social acceptability: *Address energy needs*	Projects receive higher rankings according to whether the respondent believes the project will address their personal energy concerns
	Political support by legislator: *By region and subsidy*	Viewpoints of politicians divided by location, since a Fairbanks politician has a different agenda than one from Anchorage or the Bush communities. For this sub-category, each project is ranked based on how it meets the needs of the local political constituent from that region; the subsidy sub-category refers to whether the project will rely heavily on a government subsidy (lower rank) versus externally funded (higher rank)
	Sponsor credibility	Projects are ranked according to the credibility (and existence) of a sponsor – taking into consideration both funding and status
	Local materials and labor	Ranks projects on their reliance on local resources versus bringing in external resources, crediting projects that rely more on local supplies
	Timing	Projects receive higher rankings if they are expected to be operational earlier

Table 4. Sample of input data for economic criteria per project

	Economic Criteria - Sample		
Alternatives	Estimated Project Levelized Costs ($/mm btu)	Commodity Prices (rank)	Capital Costs (rank)
A1: Large Diameter Pipeline	7.00	7	9
A2: LNG export from North Slope to Valdez	13.03-16.38	8-9	8
A3: Bullet line to Anchorage, spur to Fairbanks	10.61-14.45	8-9	6
A4: Small Diameter Pipeline, North Slope to Fairbanks	13.74-19.16	3-6	2
A5: LNG Trucking	12.53-19.41	3-6	1
A6: Big Lake Gas pipeline	18.31-26.87	3-6	4
A7: High Voltage direct current line	0.05-0.12 $/kwh	3-6	3
A8: Coal-to-Liquids Power Plant (Fairbanks)	16.77-26.76	1-2	7
A9: Susitna Hydro-Electric Dam	0.26-.028 $/kwh	1-2	5

Note: rank 1 is highest, 9 is lowest

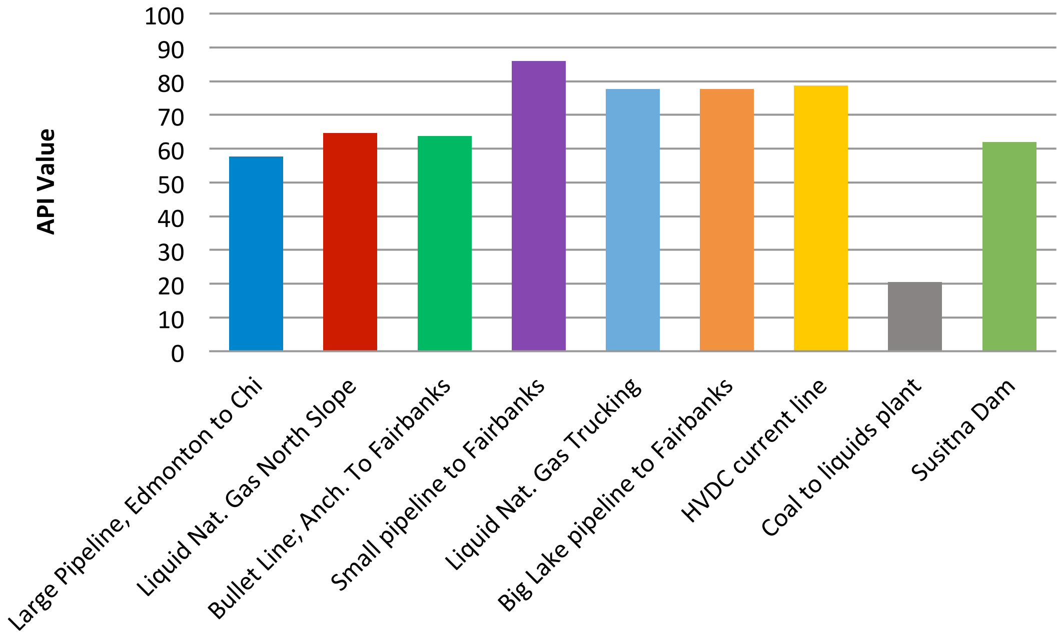

Figure 4. Overall API scores of all alternatives based on the stakeholder-defined criteria tree across all decision analysis methods

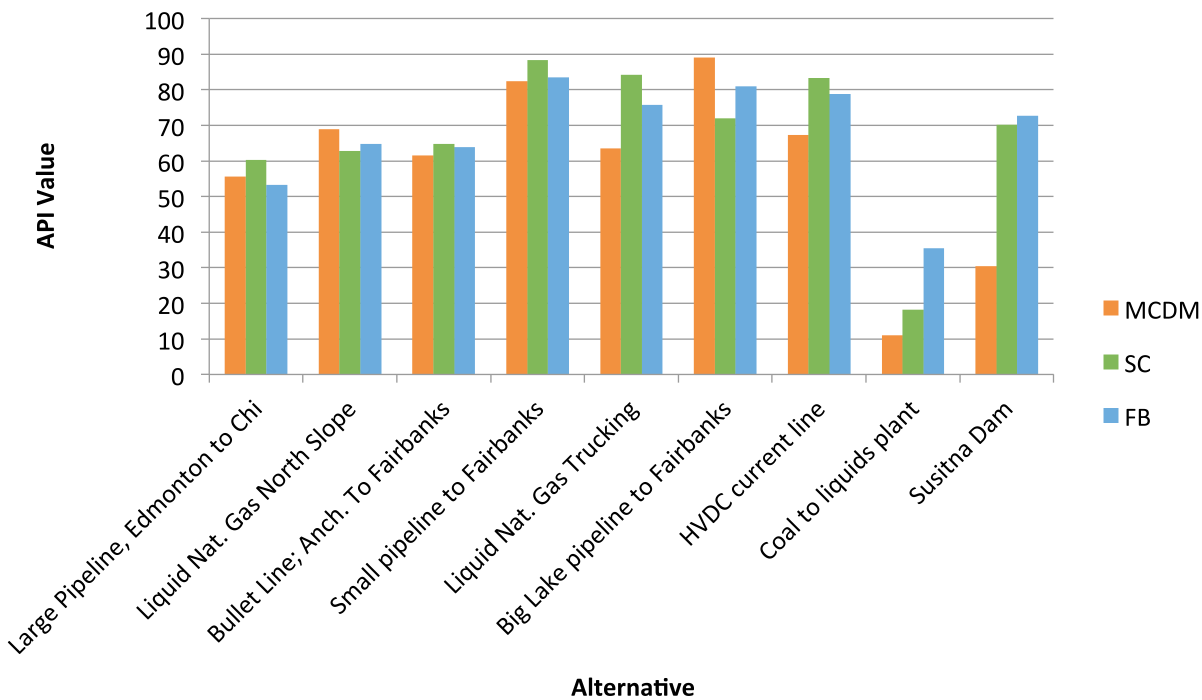

Figure 5. API values according to the three types of decision methods applied (MCDA = multi-criteria decision analysis; SC = social choice; FB = fallback bargaining)

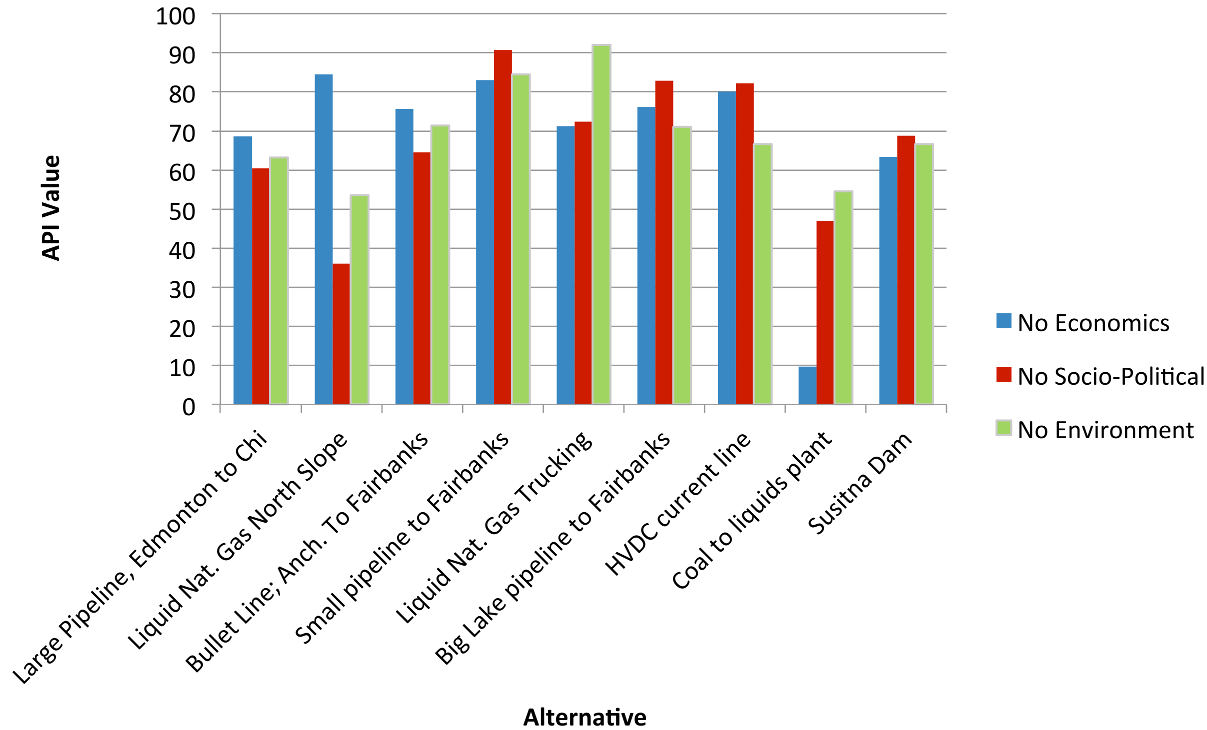

Figure 6. Sensitivity analysis results from eliminating one major criterion from the analysis: no economics (*blue*); no socio-political (*purple*); no environmental (*green*)

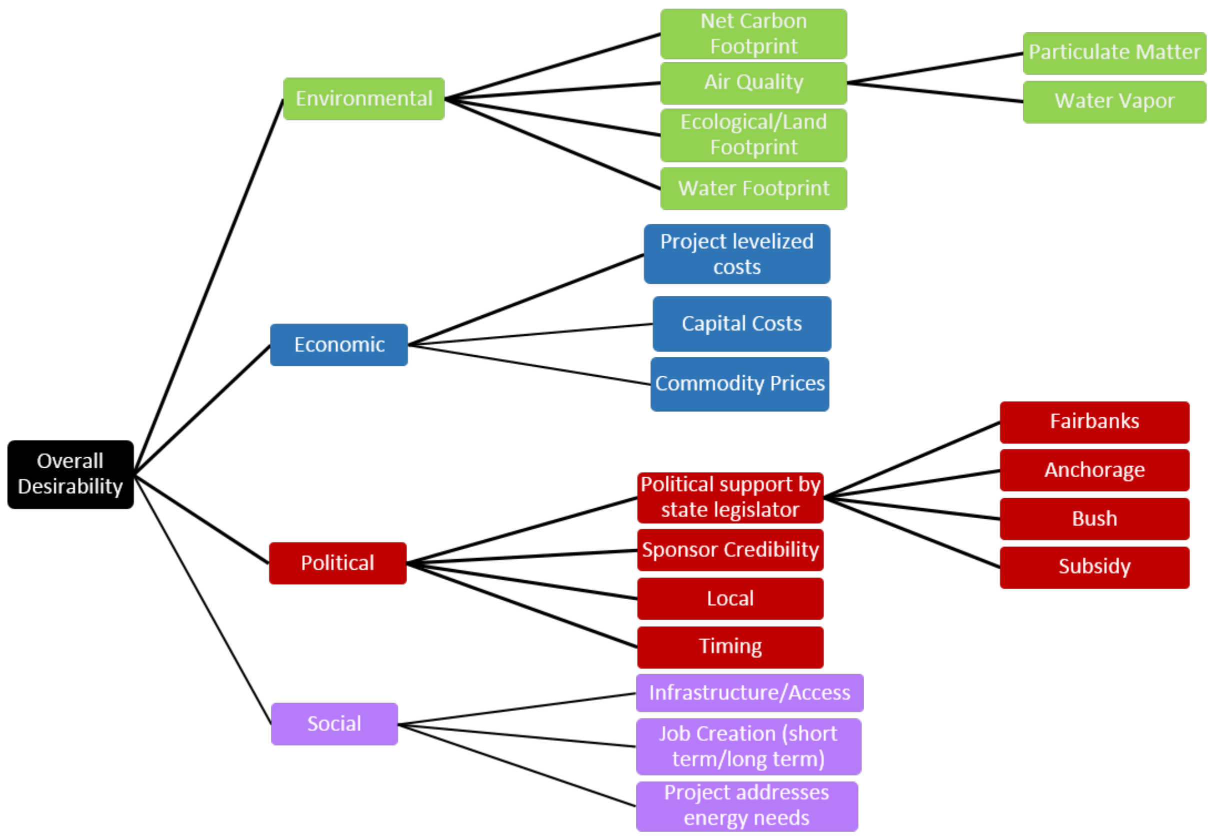

Figure 7. Criteria tree for the four-branch case, where social and political are disaggregated into four equally important criteria

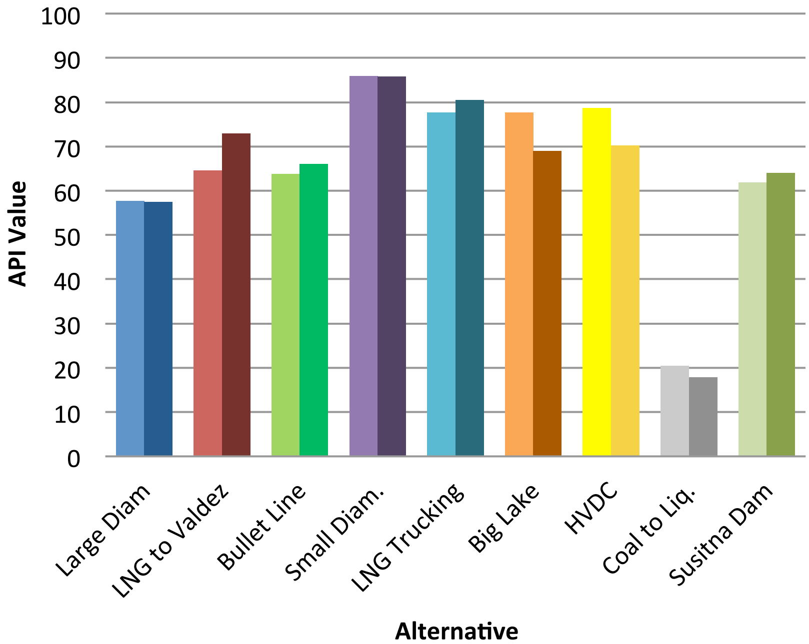

Figure 8. Comparison of scores between baseline (with three major criteria) on the left bars in light colors to the four-branch case on the right side bars in dark colors