Socio-technical multi-criteria evaluation of nuclear waste management strategies: Introducing the method

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Abstract

In the absence of a federal geologic repository or consolidated, interim storage in the United States, commercial spent fuel will remain stranded at some 75 sites across the country. Currently, these include 18 "orphaned sites" where spent fuel has been left at decommissioned reactor sites. In this context, local communities living close to decommissioned nuclear power plants are increasingly concerned about this legacy of nuclear power production and are seeking alternative options to move the spent fuel away from those sites. In this paper, we present a framework and method for the socio-technical multi-criteria evaluation (STMCE) of spent fuel management strategies. The STMCE approach consists of (i) a multi-criteria evaluation that provides an ordinal ranking of alternatives based on a list of criterion measurements; and (ii) a social impact analysis that provides an outranking of options based on the assessment of their impact on concerned

socio-technical actors. STMCE can handle quantitative, qualitative or both types of information. It can also integrate stochastic uncertainty on criteria measurements and fuzzy uncertainty on assessments of social impacts. We provide a numerical example to illustrate the outputs generated by the STMCE method using published data. The STMCE method provides a new way to compare nuclear waste management strategies and support the search for compromise solutions.
Keywords: radioactive waste; multi-criteria analysis; conflict analysis; impact assessment, geological disposal; interim storage

1. Introduction

In the absence of a geologic repository or interim storage in the United States, commercial spent fuel is stranded at some 75 “orphaned sites” where nuclear reactors continue to operate or, in a growing number of instances, have been decommissioned. As of June 2020, there were 18 of such orphaned sites across the U.S.—a number expected to increase to twenty by 2025 (Reset Steering Committee, 2018). In this context, local communities living close to decommissioned nuclear power plants are increasingly concerned about the legacy of nuclear power production and are seeking alternative options to move the spent fuel away from those sites (Reset Steering Committee, 2018). The management of spent nuclear fuel is thus increasingly seen not only as a technical challenge, but also as a societal issue affected by social, environmental, political and legal constraints (Ramana, 2018). This situation means that spent fuel management is no longer limited to a discussion among experts and scientists who advise the federal government on the “best” technical and policy choices to be approved by Congress and regulators. Rather, the scope of the discussion and decision-making must be broadened to consider both technical and societal dimensions (Bonano et al., 2011; Ramana, 2019; US NWTRB, 2015). In addition, there has been an expansion in the number and diversity of socio-technical actors, at the level of local communities, Native American tribes and states, willing to participate in the debates over the future of spent fuel stranded at or near reactor sites across the country (US DOE, 2016a). The complex nature of the socio-technical problem of nuclear waste management in the U.S. thus poses methodological challenges about how to make decisions that account for the diversity of perspectives from the various interested socio-technical actors.

This paper presents a socio-technical multi-criteria evaluation (STMCE) framework and method that supports the search for *compromise solutions* for nuclear waste management. Section **2** discusses the main issues affecting the U.S. nuclear waste management program. Section **3** presents the objectives of the STMCE approach that seek to respond to the needs of the U.S. program. Sections **4** and **5** present the framework and method of the STMCE approach, respectively. Section **6** provides a numerical example of the STMCE method based on the case of a decommissioned nuclear power plant in San Onofre, California. Section **7** discusses the advantages and limitations of the STMCE approach for nuclear waste management. Finally, Section **8** concludes the paper.

2. The issues of nuclear waste management in the U.S.

For decades, the U.S. nuclear waste management program has suffered from many factors that made it progressively ineffective, imbalanced and even contested. These factors include major changes to the original law, a succession of amendments to the Nuclear Waste Policy Act of 1982, a changing regulatory framework, an unpredictable funding, significant policy changes with changing administrations, conflicts between Congressional and Executive policies, as well as an inadequate public engagement in decisions about nuclear waste storage and disposal strategies (Reset Steering Committee, 2018). These factors profoundly affected the U.S. program which became (Reset Steering Committee, 2018, p. 1): “an ever-tightening Gordian Knot—the strands of which are technical, scientific, logistical, regulatory, legal, financial, social and political—all subject to a web of agreements with states and communities, regulations, court rulings and the Congressional budgetary process. There is no single group, institution or governmental organization that is incentivized to find a solution, nor is any single institution entirely responsible for the failure of the U.S. program.”

In this section, we discuss three issues affecting the U.S. nuclear waste management program that provide the context within which the method presented in this paper was developped.

2.1. Ineffective management program

Under the Nuclear Waste Policy Act, the federal government, through the U.S. Department of Energy (DOE), is the sole responsible for the disposal of the nation’s commercial spent nuclear fuel (US GAO, 2014). Yet, the failure of the federal government to take ownership on the spent fuel since 1998 has led to court-ordered compensation payments to the utilities charged with the safe temporary storage at or near reactor sites until a geologic repository becomes available for disposal (Reset Steering Committee, 2018). The reasons for the government’s failure to have a federal repository for commercial nuclear waste constructed and operating are multiple and complex. However, there is a broad consensus among experts that the U.S. nuclear waste management program has become a partisan issue in national politics drawing on diverging public opinions (Blue Ribbon Commission, 2012; Reset Steering Committee, 2018; US NWTRB, 2015).

The political maneuvering affecting the nuclear waste management program has been evident as regard its financing. In the U.S., nuclear waste disposal is already financed since the 1982 NWPA by the ratepayers through the collection of a fixed fee of one-tenth of one cent per each kilowatt-hour of nuclear-generated electricity (revised annually, though never changed) following the principle of the "polluters pays" (Blue Ribbon Commission, 2012). The revenues from the collected fee are then contributing to the government's Nuclear Waste Fund. The Fund was established for covering exclusively the cost of the disposal of commercial nuclear waste so it would be free from the Federal budget constraints. In that sense, it was often referred to in Washington D.C. as a "trust fund" giving the impression of being immune from political intervention (Saraç-Lesavre, 2018). However, the spending mechanism of the Fund depends on the annual budgeting process that is subject to the approval by Congress through appropriations. Thus, the disposal program has to compete every year for federal funding that makes it subject to the budget constraints and uncertainties that the Fund was especially created to avoid. Over time, this dependence of the Nuclear Waste Fund on the annual federal budgeting process has hampered the long-term planning that the U.S. nuclear waste management program requires by making the Fund vulnerable to immediate budgetary politics (Saraç-Lesavre, 2018). But because the U.S. was not making progress in developing a geologic repository, a Federal court ruled in 2014 to suspend the collection of the fee (Reset Steering Committee, 2018). By 2015, the Fund total had accumulated over $40 billion and it continues to grow significantly thanks to interest. Besides, due to successful law suites against the Federal government for not taking ownership of the fuel at sites across the country, the utilities now receive approximately $650 million per year in compensation from the Judgement Fund (not related to the Nuclear Waste Fund). By 2018, the Judgment Fund, paid for by taxpayers, had paid out $5.3 billion and payments are projected to reach $23.7, even if the federal government begins to accept spent fuel before 2030 (Reset Steering Committee, 2018).

To protect the long-term budgeting of the nuclear waste management program from political influences, some experts have recommended passing new legislation that provides access to the Nuclear Waste Fund and fees independent of the annual Congressional appropriations process while still being subject to rigorous independent financial and managerial oversight (Reset Steering Committee, 2018). In addition, other independent expert panels have called for the creation of a new federal agency that would take over the responsibility of managing commercial radioactive waste in the U.S.; thus, independently from the changing political context (Blue Ribbon Commission, 2012; Davis et al., 2012). Such a reform of the U.S. program by the creation of a new national radioactive waste management organization with a new funding mechanism, however, is likely to become itself a political battle. Congress has been shown in multiple occasions unwilling to cede significant power to the states and tribal nations (US NWTRB, 2015). For instance, the 1997 Nuclear Waste Policy Amendments Act included the creation of the Office of the Nuclear Waste Negotiator in charge of identifying a volunteer site for either a centralized interim storage facility or, less likely, a geologic repository. But, just as the Negotiator was starting negotiations with the Mescalaro Apache nation, Congress disbanded the office. Therefore, even if successful, reforming the U.S. program would still take many years, especially if a new management organization is to be authorized by Congress, funded, staffed and fully launched.

2.2. Imbalanced power distribution

Under the current U.S. policy, local communities and tribal nations have virtually no power on the decision-making process other than, indirectly, through elections at state level. So far in the U.S., localities and tribes have had no real negotiating power with the federal government or regulatory agencies about which sites are selected and how the safety of a repository project is assessed. Moreover, the implementer of the nuclear waste management program, the U.S. DOE, is not required to respond to comments and recommendations from independent scientific commissions and boards, such as the National Academies or the Nuclear Waste Technical Review Board, despite having expressed diverging views on multiple occasions as regard those of the Administration (Alley and Alley, 2012; Diaz-Maurin and Ewing, 2018). This power imbalance is reinforced by the existence of strong socio-economic drivers of public acceptance. That is, local communities are more likely to accept hosting a federal repository or interim storage facility that will bring jobs and tax income if they are economically impoverished (Ramana, 2013). In particular, because of the severe and long-lasting socio-economic impacts from nuclear power plant closure and decommissioning (NDC, 2020), local communities would be even more likely to vonlunteer to become host communities for potential disposal and storage sites if they live close to an operating or decommissionned plant (Greenberg, 2009). Yet, support from local communities is not sufficient to achieve public acceptance as nuclear waste management straegies necessarily involve larger regions, namely the state (Ramana, 2018). In fact, because of a specific political structure, in the U.S., local autonomy often conflicts with state control over reporitory siting and selection of transport routes (Bonano et al., 2011). In fact, state-level actors often exhibit diverging perceptions and preferences over proposed solutions as compared with local communities and federal agencies (Diaz-Maurin and Ewing, 2020a).

In the U.S., states are widely viewed among experts as one main obstacle to nuclear waste management by preventing local communities from negotiating solutions directly with the federal government and unduly using of their veto power. For instance, in the late 1990s, when local communities expressed interest in hosting a repository, their states vetoed the agreements with the Nuclear Waste Negotiator. Later, in 2002, the state of Nevada vetoed the President's decision to host a repository at Yucca Mountain despite strong local support by the potential host county, Nye County (Bonano et al., 2011). Yet, past decisions by Congress and the Administration help explain the skepticism of states over proposed solutions. In the 1980s, when the Administration's strategy was toward having multiple regional repositories, states had no voice in selecting sites that were instead selected by Congress based on a list made by the Administration (Carter, 1987; US NWTRB, 2015). Later, after the strategy had changed to only building one repository and the state of Nevada vetoed the Yucca Mountain project, the Administration revised its siting rule and had Congress pass a resolution, by simple-majority vote under the current Law, overriding Nevada's veto power and approving the Yucca Mountain site (US NWTRB, 2015; Vandenbosch and Vandenbosch, 2007). Because states are not involved in the negotiations over nuclear waste management strategies in the U.S., they are more likely to use of their legal powers through vetoing or challenging in courts any decision being proposed.

2.3. Competing risk rationalities

Nuclear energy facilities are different from other energy technologies and public policy issues in that their risks are strictly regulated. In the U.S., federal regulatory agencies, such as the U.S. Nuclear Regulatory Commission (NRC) and the U.S. Environmental Protection Agency (EPA), and federal management organizations, such as the U.S. DOE, are expected to account for both technical and social dimensions in their responsibilities. Yet, the legal and regulatory frameworks demand a very rigorous and objective form of knowledge so that courts and regulatory agencies can make technological decisions (Jasanoff, 1990). This has led to the creation of specific methods of risk analysis that rely on the unbounded quantification of risk levels as calculated by mathematical models (Porter, 1995). However, this "rationalization" of risk is said to be made at the expense of the plurality of legitimate perspectives about the very nature of the risk (Funtowicz and Ravetz, 1993a). Seeking objectivity in the regulatory process, and consequently, in the decision process, has resulted in a standard of rationality that has become the preferred strategy to mitigate the overwhelming public distrust by regulatory agencies unable to negotiate solutions. In fact, U.S. regulatory agencies have long been unable to negotiate solutions with communities over environmental conflicts (Jasanoff, 1990; Robinson et al., 2017). A prime example of this problem can be found in the regulation of chronic long-term risk from low-level radiation exposure affecting communities in Missouri's North St. Louis County (Diaz-Maurin, 2018). This conflict has highlighted the cultural gap that exists between the federal bureaucracy and lay people's lives over the perception of what risk is—a widespread and long-observed phenomenon (Wynne, 1992). Such gap sustains public distrust in the institutions in charge of regulating risk and implementing risk mitigation plans. More generally, the existence of incommensurable perceptions between "insiders", mostly focusing on the technical impacts and financial costs, and "outsiders", mostly focusing on the social, economic and environmental impact, is at the origin of the controversy of nuclear energy technologies (Diaz-Maurin, 2014; Diaz-Maurin and Kovacic, 2015).

Although there is no legal link between the operation of nuclear power reactors and the disposal of radioactive waste materials, these two technologies are undeniably connected in the public perceptions (Greenberg, 2012). The link between nuclear power and radioactive waste management is reinforced with U.S. regulatory agencies using for geologic repositories the same probabilistic risk analysis methods that were first developped for nuclear reactors (Diaz-Maurin and Ewing, 2019a). However, since its inception in the late 1970s, this "rationalization" approach to risk and regulation has been challenged by earth scientists, geotechnical engineers and social scientists who expressed concern over the use of mathematical models for assessing the risks of geological disposal (Bredehoeft et al., 1978; Ewing, 2006; Ewing et al., 1999; Metlay, 2000; Oreskes et al., 1994; Shrader-Frechette, 1993). In contrast, proponents of the rationalization of risk, mainly nuclear engineers and mathematicians, have consistently dismissed public concerns over this approach as being irrational (e.g., Peterson, 2017) and rooted in ignorance (Bergmans et al., 2015; Flynn et al., 1992; Greenberg, 2012; Leiss, 1995; Rossignol et al., 2017; Slovic et al., 1991; Tuler and Kasperson, 2010). But, case in point, using risk assessment methods when strong knowledge about the probabilities and outcomes does not exist has also been credited as being irrational and unscientific (Ewing et al., 1999; Stirling, 2007). For over 40 years now, nuclear waste management has been a case of "competing rationalities" of risk between the optimistic view of technocratic rationalists and the cautionary view of concerned public and scientists (Lee, 1980).

3. Objectives

These issues discussed in the previous section illustrate some of the reasons why the U.S. nuclear waste management program has, so far, been unable to make sustained progress toward the safe disposal of radioactive waste from commercial reactors. Yet, long-proposed recommendations by national and international experts and observers clearly indicate that decision in the U.S. program should be based on new grounds—from *seeking the social acceptance of a technically rational choice* to *negotiating the technical feasibility of a societal choice*. That is, social acceptability cannot be forced upon but, rather, needs to result from a process of continuous interaction between science and society based on trustful relations (La Porte and Metlay, 1996). If one accepts to apply this principle to nuclear waste management, then a decision-making process must be designed that accounts for mechanisms to effectively co-create these solutions.

The present paper provides a methodological framework for the comparison of alternative spent fuel management strategies based on socio-technical dimensions of analysis and multiple perceptions of social impacts by the different interested parties. Specifically, the socio-technical multi-criteria evaluation (STMCE) framework seeks to respond to multiple needs of the U.S. program:

(1) **Increasing the pool of perspectives**. In any decision problem in environmental and public policy, it is crucial to account for the diversity of perspectives from the various interested socio-technical actors, especially in situations where stakes are high, facts are uncertain, and values are in dispute over what the "best" solution is (Funtowicz and Ravetz, 1993b). So far, in nuclear waste management in the U.S., the technical and scientific analyses that are carried out—and how the decision problem is framed in the first place—do not start from public concerns but from

technical considerations (Ramana, 2018). Yet, to be successful, the framing of nuclear waste management strategies as well as the design of geological disposal and interim storage systems should reflect national, state, and local community concerns and preferences (Bonano et al., 2011). In the STMCE approach, all types of socio-technical actors with potential interest in the outcome of the decision can be considered in the problem framing and structuring—from localities to tribes, citizen groups, local and national NGOs, state governments and agencies, utilities, vendors, regulators and federal government and agencies. In addition, the relative level of interest (or stakes) of all concerned actors can be assessed (either by the analyst or by the actors themselves through a participatory exercise), thus allowing to attribute (or not) weights to their perceived impacts of each solution. By including in the analysis a broader range of perspectives from all potentially interested socio-technical actors, the analytical and decision-making process becomes more inclusive and thus more trustworthy.

(2) Supporting host communities. Institutional trust is improved when potentially impacted parties receive support that allows them to hire their own experts who will conduct and publish their own reviews (Reset Steering Committee, 2018). In the U.S. program, this would allow potential host communities, defined as both local communities and states on the one hand or tribal nations in the U.S. context, to make their own judgement on proposed solutions and, thus, increase their negotiating power with the federal government. More importantly, if the technical feasibility of a solution proposed by the implementer is confirmed through an independent review process, it would dramatically increase the social acceptability of this solution. This paper thus seeks to support potential host communities by offering a tool for the rapid appraisal and comparison of alternative spent fuel management strategies.

(3) **Searching for compromise solutions**. In nuclear waste management, like in other complex decision problems in environmental and public policy, there is a need to search for compromise solutions that are not necessarily the "best" solutions either technically or socially. It is now well accepted that a workable appoach to nuclear waste management is towards finding solutions that can be demonstrated to provide adequate levels of both safety and social and political acceptance (Bonano et al., 2011). Yet, in practice, there is a lack of frameworks and methods that can be consistently used to assess the technical and social performance of proposed alternatives, as well as that can help effectively co-create solutions that are both technically feasible and socially accepted. In the STMCE framework, we acknowledge the existence of the equally important technical and societal dimensions in the description of a decision problem. Specifically, one can compare the performance of long-term spent nuclear fuel management strategies based on technical dimensions, societal dimensions, and their combination. In addition, the method includes a coalition formation process based on the perceived impact of the solutions proposed. This process supports the negotiation between parties over proposed alternatives and the identification of potential compromise solutions.

(4) **Reallocating power among parties**. The reallocation of power among the parties involved in the U.S. program has been already recommended by independent national and international experts (Reset Steering Committee, 2018). In particular, the national managing organization (at the moment the U.S. DOE) should engage with localities, tribes, and states to co-design a decision-making process and

establish appropriate control mechanism over this process. In the STMCE method, the reallocation of power is made through the use of a proportional veto function. The proportional veto function consists in giving a coalition of actors the ability to veto any subset of alternatives proportionally to the fraction of socio-technical actors it contains. This rule allows to eliminate any "extreme" solution that would be considered feasible only by a too small number of parties relatively to the set of socio-technical actors included. This approach thus reallocates power among parties where communities, tribes and states can have a strong, but conditional, veto power, so the decision will be made only among non-extreme solutions.

4. Framework

4.1. Defining the decision problem

Decision problems in nuclear waste management can be defined (1) at the local level, searching for solutions to remove spent nuclear fuel from a specific reactor site to another site either within or outside the state (for an example, see (Diaz-Maurin and Ewing, 2020a)); (2) at the state and regional levels, searching for strategies of nuclear waste management for several reactor sites within a state or a group of states; or (3) at national level, defining an integrated strategy of nuclear waste management that matches the solutions being proposed at local, regional and state levels. Of course, in either case, the decision problems would overlap each other. What is considered as a feasible solution at the local level may not be considered as acceptable at the higher, state or national, levels (Section **2**). To be effective, an integrated nuclear waste management strategy in the U.S. requires to be defined across the various local, state and national levels (Bonano et al., 2018; Rechard et al., 2015). Ideally, adopting a multi-scale integrated analysis approach, a national strategy would be defined through an iterative process that works in parrallel—and in interaction—with many other processes tasked with finding solutions at the lower level (Diaz-Maurin and Ewing, 2020b). Here, we focus on developing a framework and method for their use in a single multi-criteria decision problem.

4.2. Social multi-criteria evaluation

Multi-criteria decision analysis (MCDA) emerged as a sub-discipline of operational research also known as "the science of decision making" (Gass, 1983; Hillier and Lieberman, 2015). MCDA provides a framework for stakeholders to structure their thoughts about the pros and cons of different decision options. Formally, a MCDA method can be defined as "an aggregate of all dimensions, objectives (or goals), criteria (or attributes) and criterion scores used […]. This implies that what formally defines a multi-criteria method is the set of properties underlying its aggregation convention" (Munda, 2008, p. 6). Because the types and properties defining the aggregation convention can vary broadly, many MCDA approaches and methods are available to decision makers that can be applied to a virtually infinite number of specific decision problems often requiring the method to be adapted to each situation (Doumpos et al., 2019; Greco et al., 2016). Despite their differences, MCDA methods all aim to address the trade-offs between decision options by means of a mathematical convention that explicitly evaluates multiple conflicting criteria. However, as pointed by Munda (2008, p. 7): "In general, in a multi-criterion problem, there is no solution optimizing all the criteria at the same time (the so-called ideal or utopia solution) and therefore compromise solutions have to be found." This is particularly true of decision problems that convey potential health and environmental risks such as the remediation and management of hazardous substances.

To address this issue, the *social multi-criteria evaluation* approach has been developed for policy evaluation and conflict management in environmental and public policy decisions (Munda, 2019). This approach has already demonstrated its applicability in different typologies of decision problems and in various geographical and cultural contexts (Greco and Munda, 2017). These include economic development of regions and cities, rural electrification, food production, water resources management, aquatic systems protection, coastal zone management, environmental management in arid regions. For a recent review of real-world applications of the social multi-criteria evaluation approach, see Munda (2019).

One of the main advantages of social multi-criteria evaluation—in contrast to MCDA—is its ability to deal with various conflicting evaluations by achieving the comparability of incommensurable dimensions and values. In particular, the social multi-criteria evaluation approach extends the multiple criteria decision support to also include the concept of *social actor*, thus allowing for an integrated analysis of the problem at hand (Munda, 2008, 2004). However, unlike other participatory or stakeholder engagement approaches, Munda's approach considers public participation as a necessary *but not a sufficient condition* for successful evaluation (Munda, 2004). In addition to participation, transparency also increases the chances of successful public policy decisions (Stiglitz, 2002). A social multi-criteria evaluation process will be transparent if, in representing a given decision problem, the assumptions used, the interests and values considered are declared (Munda, 2004). Munda's social multi-criteria evaluation also seeks to overcome the pitfalls of technocratic approaches to decision support by allowing the integration of different methods of sociological research. That is, social multi-criteria evaluation primarily aims at searching for compromise solutions by highlighting distributional conflicts among options and social actors. By searching for compromise solutions rather than optimal solutions, social multi-criteria evaluation acknowledges that scientific knowledge and technological systems are themselves social constructions (Bijker et al., 2012; Jasanoff, 2006).

In operational terms, the social multi-criteria evaluation process consists of seven main steps that are presented in **Fig. 1**. The process starts with a description of the relevant social actors (**step 1**), which can include an institutional analysis. Then, the process defines the social actors' values, desires and preferences (**step 2**) performed either through focus groups, interviews or questionnaires. This is an essential, yet very difficult, step of the social multi-criteria evaluation process because of the ambiguity of capturing what people really think as well as the difficulty of considering a statistically representative set of members for each relevant social actor. The process accounts for such ambiguity by introducing the notion of *fuzzy uncertainty* in the analysis. The generation of policy options and selection of evaluation criteria (**step 3**) are based on the information collected in step 2. Ideally, this should be a process of co-creation resulting from a dialogue between analysts and relevant social actors. Although the definition of the evaluation criteria is mainly the task of the analysts, they should provide a technical translation of the social actors' needs, preferences and desires. The construction of the multi-criteria impact matrix (**step 4**) is, by far, the most data intensive step of a social multi-criteria evaluation process, especially when it deals with a broad range of dimensions of analysis (*e.g.*, technical, economic, safety, environmental dimensions). The multi-criteria impact matrix synthesises the performance of each alternative according to each criterion. Then, the construction of a social impact matrix (**step 5**) allows one to complete the multi-criteria impact matrix based on the criteria, although the *criterion scores* (*i.e.*, the expected outcome of each option are assigned a numerical score on a strength of preference scale for each criterion, generally extending from 0 to 100) are not determined directly by the social actors. The social impact matrix ensures that the technical translation, operationalized by the analysts in the multi-criteria evaluation, is checked against an assessment of the socio-technical actors' preferences. Combining a technical multi-criteria impact (or evaluation) matrix with a social impact matrix is a desired property of a social multi-criteria evaluation process (Greco and Munda, 2017; Munda, 1995).

The next step applies a mathematical procedure (or algorithm) (**step 6**) that aggregates the criterion scores and generates a final ranking of the proposed alternatives. Many aggregation methods exist, each with its own advantages and disadvantages (Greco et al., 2016). Finally, the sensitivity and robustness analysis (**step 7**) seeks to look at the sensitivity of the ranking to the exclusion/inclusion of criteria, criterion weights and dimensions (Saltelli et al., 2008). Although this is mainly a technical step, it also includes a social component, as the inclusion/exclusion of a given dimension, or set of criteria, reflects the social debate and deliberation among social actors (Greco and Munda, 2017).

Although Munda's approach is a step-wise process, it differs from other multi-criteria frameworks that typically work iteratively towards a final (optimal) alternative. In the social multi-criteria evaluation approach, the iteration concerns the overall process by searching for compromise solutions once distributional conflicts between the technical performance and social impact have been highlighted by the analysis. In addition, the seven steps proposed by Munda are not fixed. Indeed, a central tenet of social multi-criteria evaluation is to allow flexibility and adaptability to the actual decision problem.

In the next section, we extend Munda's framework to the socio-technical dimensions of commercial nuclear waste management in the U.S.

4.3. Socio-technical approach to nuclear waste management

There is now a growing consensus that nuclear waste management decisions must go through two types of filters: technical filters and social filters (Metlay and Ewing, 2014; US NWTRB, 2015). This is explained by the need to site facilities, such as geologic repositories for disposal and interim facilities for storage, that must be both technically sound and socially accepted. Moreover, decades of siting efforts worldwide have shown that one cannot design and implement any nuclear waste management strategy and policy without considering the two technical and social dimensions as equally important (US NWTRB, 2009). In a decision process, it does not matter which one of the technical or social filters is met first as long as both are satisfied.

One challenge in any decision-support framework for nuclear waste management is that these two views are generally shared by different sets of *socio-technical actors*. Scientists, engineers, vendors, and utilities involved in developing management strategies tend to focus on the technical dimensions of the proposed solutions; whereas local communities, elected officials and state agencies will tend to focus on social (or societal) dimensions. At first glance, it could thus seem appropriate not to mix the two dimensions. Afterall, engineers are those in charge of addressing technical aspects of proposed solutions but have little to say about their societal implications. Likewise, local communities cannot tell much about the technical details of proposed solutions, but they form part of the social groups that could be potentially affected by these solutions. Yet, in a decision problem, a solution may be either technically sound or socially desirable, but not necessarily both. A decision-aid framework therefore must be designed that account for the two technical and societal views and accommodate for the existence of tradeoffs between the two views so that the socio-technical performance of proposed options can be evaluated and compared. Moreover, by the time decision over a management strategy is made, the two technical and societal views will have been unavoidably mixed.

The interdependence of the two technical and social dimensions has already been discussed (Diaz-Maurin and Ewing, 2018; US NWTRB, 2015). For instance, solutions for which the technical suitability can be demonstrated by relatively simple analyses may improve their social acceptance; whereas, in site selection processes, specific site-suitability criteria are often added to account for the views of the public, thus, ultimately providing a societal content to the definition of technical suitability. In another example, the hypothesis by the U.S. National Academy of Sciences of a fundamental geologic regime remaining stable up to about one million years was used as a technical basis for introducing the one-million-year compliance period in the Yucca Mountain standards; thus responding to the societal demands for a longer regulatory period in the long-term safety demonstration (National Research Council, 1995). Yet, it turned out that the National Academy's hypothesis was challenged later by the results of the safety assessment performed to demonstrate compliance with this standard (Diaz-Maurin and Ewing, 2018).

The STMCE method presented in the next section goes beyond this process by performing several multi-criteria evaluations according to technical and societal dimensions of analysis—and their combination. This allows one to highlight potential performance gaps between the technical and societal dimensions through the multi-criteria evaluation of options. In addition, potential conflicts between the preferences of the concerned actors are highlighted by the social impact analysis that translates the perceived impact of each option for each socio-technical actor.

5. Method description

5.1. Multi-criteria analysis technique and features

5.1.1. Selection of multi-criteria analysis technique

Formally, nuclear waste management can be considered as a *discrete multi-criteria problem* for which a finite number of feasible options is known—from storage at reactor sites, to interim storage at another site and/or to disposal in a deep geologic repository. A multi-criteria approach to nuclear waste management will thus consist in ranking these feasible options based on a set of evaluation criteria. Among the main techniques proposed to solve a discrete multi-criteria problem, the multi-attribute utility (or value) theory and outranking methods have been the most popular (Greco and Munda, 2017). We provide in Appendix **A** a review of previous applications using both techniques to the problem of nuclear waste management. In this paper, we use the outranking technique for the design of the STMCE method.

Outranking methods are based on the concept of *partial comparability*. They consist in comparing criteria by means of partial binary relations based on indexes of concordance/discordance and then to aggregate these relations (Greco and Munda, 2017). Various approaches exist to generate and treat outranking relations depending on the type of decision problem at hand. Typical outranking methods seek to eliminate alternatives that are "dominated" by other in a particular comparison domain (DCLG, 2009). They thus attribute weights to criteria so they have more influence than others on the ranking of options. However, the disadvantage of weighing criteria in a social multi-criteria evaluation process is that socio-technical actors will unavoidably disagree about which criteria to weight more than others. In turn, their disagreement will make it more difficult to have the multi-criteria analysis method accepted and implemented. In the STMCE method, we avoid this problem by considering all criteria under the *equal weighting* assumption (Munda, 2009).

Different criteria can be used to select a multi-criteria analysis technique for decision support. Such criteria may include the internal consistency and logical soundness of the technique, its transparency, its ease of use, the amount of data required not being inconsistent with the importance of the issue considered, a realistic amount of time and manpower resource required for the analysis process, the ability of the technique to provide an audit trail, and whether it offers some software availability, where needed (DCLG, 2009). Outranking methods typically do not rank high on these criteria. However, outranking methods are comparatively better to address social conflicts and to account for the political realities of decision making; thus, they can be an effective tool in nuclear waste management. Recall that our objective is not to develop a multi-criteria analysis method for the exclusive use of decision-makers, *e.g.* the government. Rather, the STMCE method seeks to be used as an exploration and facilitation tool engaging with the various concerned parties in nuclear waste management to highlight potential performance and preference gaps between options and how coalitions of actors over compromise solutions can form.

5.1.2. Main features

A multi-criteria analysis method must exhibit desirable properties if it is to be used in a social multi-criteria evaluation process (**Table 1**). Based on our objectives (Section **3**), we discuss how STMCE addresses each one of these desirable properties:

1. **Compensation:** STMCE is based on a *partial compensation* of criteria that avoids the problem of trade-offs between the technical and societal dimensions by performing two separate multi-criteria evaluations as well as a combined evaluation. This allows one to reveal distributional conflicts and support the search for compromise solutions.
2. **Importance coefficient:** Even in social decisions, weights are never importance coefficients, *they are always trade-offs* seeking the complete compensation between values and criteria (Munda, 2008). STMCE avoids this issue by: *(1)* explicitly considering *indifference/preference thresholds* in the multi-criteria evaluation (Munda, 2004), and *(2)* introducing weights only as *importance coefficients* and not as trade-offs in the social impact analysis (Munda, 2009).
3. **Mixed information:** The STMCE method uses an impact (or evaluation) matrix that may include quantitative, qualitative or both types of information. Specifically, information can be crisp, stochastic or fuzzy measurements of the performance of an alternative with respect to an evaluation criterion (Munda, 2012). The ability to handle mixed information is very flexible for real-world applications, especially for evaluating the performance of alternatives from a socio-technical perspective.
4. **Simplicity:** One important feature of the STMCE method is the relative simplicity of its mathematical procedure. This ensures the transparency of the overall multi-criteria process and allows socio-technical actors to use the analytical tool to

generate their own rankings. To run a STMCE analysis, the user only needs to prepare a multi-criteria impact matrix and a social impact matrix (*e.g.*, a spreadsheet) to be loaded into STMCE.

5. **Hierarchy:** As in AHP, STMCE can include hierarchical relations across the various dimensions of analysis and criteria. This can be useful in complex systems such as geologic repositories that can be described across temporal, spatial and functional scales (Diaz-Maurin and Ewing, 2018). However, since the multi-criteria evaluation is based on a *no criterion weighting* approach, assigning the same weight to all the criteria does not guarantee that all dimensions of analysis (*e.g.*, management, occupational safety, public safety, economic) will have the same weight. This would be the case only under the condition that all dimensions have the same number of criteria. Yet, forcing dimensions to have the same number of criteria would inevitably introduce redundancy (if criteria are added) or reduce exhaustiveness (if criteria are removed), which is an undesirable property of any multi-criteria evaluation. An alternative approach can be to assign the same weight to each dimension and then to distribute proportionally each weight among the criteria. As one understands, the question of weighting criteria inherently implies trade-offs. Assigning the same weight to all criteria implies that different dimensions are weighted differently, whereas assigning different weights to criteria would guarantee that all the dimensions are equally weighted. In STMCE, criteria are not weighted ab can work with both approaches.
6. **Discrete decision problem:** The STMCE method is used to evaluate long-term spent fuel management options framed as a discrete multi-criteria decision problem where feasible options are known. One important principle of STMCE is that, like

in Munda's approach, *dominated* alternatives shall not be eliminated from the evaluation. Indeed, as the evaluation seeks compromise solutions rather than optimal solutions, having a ranking of alternatives will be more useful than simply knowing what the "best" option is. In fact, in the case of spent fuel management in the United States, having a federal geologic repository is evidently the best option from the perspective of the permanent isolation of the waste. Yet, it is also the most controversial solution from a political and social point of view because of the issues associated with selecting a site and demonstrating its long-term safety (Reset Steering Committee, 2018; US NWTRB, 2015). Given the current stalemate of the U.S. disposal program, it may be more preferable from the perspective of local communities and states to implement a spent fuel management strategy that ranks second (and so, not necessarily technically "bad") but that may reduce social conflicts and help to achieve the ethical imperative of handling radioactive waste (Carter, 1987).

7. **Thresholds:** As mentioned, STMCE considers explicit *indifference/preference thresholds* in the multi-criteria evaluation. When comparing alternatives, an indifference threshold determines the difference in the criterion performance, at which they can be considered to be equally good (Wątróbski et al., 2019). However, in STMCE, it is possible to define strict preference and indifference areas, in place of the notion of "weak preference" (Roy, 1996) where an agent hesitates between indifference and preference (Munda, 2008). This can be justified by the long time scale involved in any scenario of spent nuclear fuel management—from decades of (interim) storage to over a hundred of years before geological disposal is achieved and the repository is closed. Over such period of time, one understands that there is

as much uncertainty about the present preferences as there is about the future outcomes (Shrader-Frechette, 2000). For this reason, STMCE does not consider *fuzzy uncertainty* on the threshold values. However, STMCE introduces fuzzy uncertainty on the qualitative measurements by means of linguistic variables; as well as *stochastic uncertainty* on the quantitative measurements.

8. **Conflict analysis:** In the social impact analysis, STMCE uses the semantic distance between the linguistic variables (*e.g.*, "Good", "Bad", "Very bad") of any pair of socio-technical actors as a *conflict indicator* (Munda, 2008). The semantic distance allows one to perform a fuzzy cluster analysis in which similarities/diversities among socio-technical actors are identified, thus coalitions (clusters) of multiple actors can form (Section **5.3.1**). In addition, STMCE can perform several multi-criteria evaluations for different dimensions of analysis (sets of criteria). For instance, in the spent fuel management decision problem, STMCE would first rank scenarios according to the two technical and societal impact matrices and then integrate both dimensions in one matrix. This will allow one to highlight potential conflicts in the ranking of alternatives.

5.2. Multi-criteria evaluation procedure

5.2.1. Aggregation convention

The socio-technical multi-criteria evaluation method consists of three complementary evaluations based on (1) a set of technical criteria, (2) a set of societal criteria, and (3) their combination. Each one of the multi-criteria evaluations is based on the same aggregation convention. We adapted the aggregation convention originally developed by Munda (2012, 2008). The multi-criteria evaluation consists of (1) the pairwise comparison of alternatives according to a set of criteria , and (2) the generation of an ordinal ranking of alternatives using the aggregated criterion scores.

Formally, let us consider a set of evaluation criteria $G = g_m, m = 1,2, \dots, M$, and a finite set $A = a_n, n = 1,2, \dots, N$ of potential alternatives (options). Let us now start with the simple assumption that the performance (*i.e.*, the criterion score) of an alternative a_n with respect to a judgement criterion g_m is based on an *interval or ratio* scale of measurement. In order to rank alternatives, let us introduce an *indifference threshold* that indicates the degree of difference up to which two options are considered equivalent and, consequently, the degree of difference from which a preference relation exists. By defining a positive indifference threshold q, we can now define the resulting *threshold model* as:

$$\begin{cases} a_j P a_k \Leftrightarrow g_m(a_j) > g_m(a_k) + q \\ a_j I a_k \Leftrightarrow \left|g_m(a_j) - g_m(a_k)\right| \leq q \end{cases} \tag{1}$$

where a_j and a_k belong to the set A of alternatives and g_m to the set G of evaluation criteria.

In the threshold model, $a_j P a_k$ means that alternative j is preferred over alternative k if the difference in the criterion scores between the two alternatives is greater than the indifference threshold q. Otherwise, the difference between the criterion scores is considered to be not significant and there is no preference between the two alternatives (*i.e.*, $a_j I a_k$).

Based on these indifference and preference relations between two alternatives, we can now construct an outranking matrix $E \in \mathbb{R}^{M \times M}$ as:

$$e_{jk} = \sum_{m=1}^{M} \left(w_m(P_{jk}) + \frac{1}{2} w_m(I_{jk}) \right) \tag{2}$$

where w_m belongs to a set of weights $W = w_m, m = 1,2, \dots, M$ that can serve as importance coefficients of the set of evaluation criteria G. However, in the analysis all the criteria are considered to have the same importance, so that no weighting coefficient is used (*i.e.*, $w_m = \frac{1}{M}$ and $\sum_{m=1}^{M} w_m = 1$). By construction, it follows that $e_{jk} + e_{kj} = 1$.

The aggregated score r_j for a given alternative j is obtained by taking the sum of all the row entries in the outranking matrix E as:

$$r_j = \sum_k e_{jk} \tag{3}$$

The ranking of a given alternative j can then be determined by the order of r_j in the set of aggregated scores $R = r_n, n = 1,2, \dots, N$. The alternative with the highest aggregated score will be ranked first.

5.2.2. Monte Carlo simulation

A sensitivity and robustness analysis is used to generate the distribution of the possible rankings considering stochastic uncertainty on the criteria scores. For this, we use a Monte Carlo simulation to repeatedly run the multi-criteria evaluation based on randomly generated samples of criteria scores (Section **5.2.1**). This method allows us to determine the most likely ranking of alternatives, given a range of values for the criterion scores.

For each Monte Carlo simulation, each criterion score is sampled from some unknown distribution, where the only known values are the score's mean, minimum, and maximum. We assume that all criterion scores are normally distributed. While the mean for each distribution is known, the standard deviation is not given and must be estimated. We apply the "Three-Sigma Rule" that states that approximately 99.73% of all values of a normally distributed parameter fall within three standard deviations of the mean (Duncan, 2000). We can thus estimate the standard deviation as:

$$\sigma = \frac{HCV - LCV}{6} \tag{4}$$

where HCV (Highest Conceivable Value) and LCV (Lowest Conceivable Value) represent the maximum and minimum values provided for the criterion score, respectively.

To formalize the Monte Carlo sampling, let C be the set of criterion scores. Let then x_i, μ_i, LCV_i, HCV_i be the sampled value, mean, minimum, and maximum for criterion score $i \in C$, respectively. We can thus define the percentage deviation from the mean of the sampled value x_i as:

$$d_i = \begin{cases} \frac{|x_i - \mu_i|}{|\mu_i - LCV_i|} & \text{if} |x_i - \mu_i| < 0 \\ \frac{|x_i - \mu_i|}{|\mu_i - HCV_i|} & \text{else} \end{cases} \tag{5}$$

The procedure can also conduct post-sampling adjustments on the sampled values of criteria in two cases. First, when a normal distribution cannot be considered because the criterion values are fixed ("either/or" condition), the randomly generated values are set to the closest known values (mean, minimum or maximum). Second, when criteria correlated with one another, we consider the value sampled from one score's distribution to be conditional on the value obtained from a correlated score's distribution. We consider only linear correlations (direct or inverse) controlled by linear adjustment to the sampled values of correlated criteria.

Formally, the post-sampling adjustment for criterion score i is equal to the sum of deviations from its correlated criterion scores. Let $J_i = j: corr(i,j) \neq 0; i,j \in C$ be the criterion scores that are correlated with i. The post-sampling adjustment is defined as $\mathrm{adj}_i = \sum_{j \in J} d_j$. We can now define the final value after post-sampling adjustment as:

$$x_{i,\mathrm{adj}} = \begin{cases} x_i + \mathrm{adj}_i |\mu_i - LCV_i| & \mathrm{if adj}_i < 0 \\ x_i + \mathrm{adj}_i |\mu_i - HCV_i| & \mathrm{else} \end{cases} \tag{6}$$

We thus obtain a set C' of randomly sampled and adjusted criterion scores that can be used in the multi-criteria evaluation.

We conduct the Monte Carlo sampling in `R` (R Core Team, 2019) using the function `set.seed` that can reproduce the same sequence. That is, the `runif` function in `R` does not involve randomness *per se*, but is a deterministic sequence based on a random starting point. For instance, the seed number "2020" always returns the following sequence for the first four random variables:

```
> set.seed(2020)
> runif(4)
[1] 0.6469028 0.3942258 0.6185018 0.4768911
```

Each multi-criteria evaluation is thus performed n times, where n is the number of random samples of criteria scores required to obtain convergence of the results. The number of Monte Carlo random samples is determined empirically.

5.3. Social impact and conflict analysis

5.3.1. Fuzzy cluster analysis

To contrast the results of the multi-criteria evaluation, we perform an analysis of the social impact of the alternatives on the interests of the socio-technical actors. For this, we adapted the same framework as proposed by Munda (2008, 1995). The impact of each alternative on each socio-technical actor is evaluated by the analysts based on their assessment of how they are impacted. This step can be done by reviewing available material and eventually by asking opinions through focus groups, interviews or questionnaires.

The impacts are recorded by means of seven *linguistic variables*: “Very bad”, “Bad”, “More or less bad”, “Moderate”, “More or less good”, “Good”, and “Very good”. Formally, let X represent the set of possible impacts. With this, we can obtain a social impact matrix $S \in X^{P \times N}$, where P is the number of socio-technical actors and N is the number of alternatives.

To make comparisons between linguistic variables, we compute their semantic distances using *fuzzy sets*. Fuzzy sets are based on the idea of introducing a degree of membership of an element with respect to some sets (Munda, 1995). Fuzzy sets are necessary in order to introduce some level of uncertainty within linguistic variables. That is, the measurement scale based on linguistic variables is not purely ordinal. *Fuzzy uncertainty* refers to the degree of ambiguity in the information about the system that generates fuzziness in the evaluation of the impact of alternatives on the socio-technical actors’ interests.

Specifically, a semantic rule M is used to associate a linguistic variable with its meaning, and incorporates a compatibility (membership) function $\mu: X \to [0,1]$ to represent the degree of membership. For instance, μ_{good} shows the degree to which a numerical score is compatible with the concept of *good* and equivalently μ_{good} may be viewed as the membership function of the fuzzy set *good*. **Fig. 2** shows the membership functions defining the fuzzy set for the seven linguistic variables used.

We then use the semantic distance S_d between any pair of socio-technical actors as a conflict indicator (Munda, 2009). Let μ_1 and μ_2 be membership functions. Let $f(x) = k_1\mu_1(x)$ and $g(y) = k_2\mu_2(x)$, where k_1 and k_2 are constants obtained by rescaling μ_1 and μ_2, respectively, such that:

$$\int_{-\infty}^{+\infty} f(x)dx = \int_{-\infty}^{+\infty} g(y)dy = 1. \tag{7}$$

Furthermore, $f(x) \in X = [x_L, x_U]$ and $g(y) \in Y = [y_L, y_U]$. S_d is then defined as:

$$S_d\big(f(x), g(y)\big) = \iint_{x,y} |x - y| f(x)g(y)dydx \tag{8}$$

In the case when the intersection of the two membership functions is empty, we have:

$$S_d\big(f(x), g(y)\big) = |E(x) - E(y)| \tag{9}$$

where $E(x)$ and $E(y)$ are the expected values of the two membership functions.

When the intersection between the two fuzzy sets is non-empty, their semantic distance is actually computationally intractable by means of iterated integration (Munda, 1995). Thus, we use a Monte Carlo type numerical procedure as in Munda (1995). The procedure is as follows:

Algorithm 1: Numerical procedure to compute semantic distance

1. Draw a random number r_0 $(0 \leq r_0 \leq 1)$
2. $x_1 = r_0 x_L + (1 - r_0) x_U$
3. Draw a random number z_0 $\left(0 \leq z_0 \leq \max f(x)\right)$
4. If $z_0 > f(x_1)$ return to step 1; else move to next step
5. Draw a random number r_1 $(0 \leq r_1 \leq 1)$
6. $y_1 = r_1 y_L + (1 - r_1) y_U$
7. Draw a random number z_1 $\left(0 \leq z_1 \leq \max g(y)\right)$
8. If $z_1 \leq g(y_1)$ compute $|x_1 - y_1|$; else return to step 5

This procedure is repeated $n = 1000$ times, and the mean of all the computed terms is approximately equal to the distance between the two fuzzy sets. That is:

$$S_d\big(f(x), g(y)\big) \approx \frac{1}{n} \sum_{i=1}^{n} |x_i - y_i| \tag{10}$$

In the analysis, a generalization of the Minkowski p-metric with a Euclidean value metric $p = 2$ (partial compensation) is applied (Munda, 2009). That is:

$$S_d(f(x), g(y)) \approx \frac{1}{n} \left(\sum_{i=1}^{n} |x_i - y_i|^2\right)^{1/2} \tag{11}$$

By using the semantic distance described in Eq. (9) and (11) as a conflict indicator of the preferences among the socio-technical actors, we construct a similarity matrix for all possible pairs of actors. The similarity matrix $s \in [0,1]^{P \times P}$, where P is the number of socio-technical actors, is constructed by means of a simple transformation as:

$$s_{ij} = \frac{1}{1+d_{ij}}, 1 \leq i, j \leq P \tag{12}$$

From the similarity matrix, we can then create a dendrogram to visualize the level of similarity between the socio-technical actors based on their expressed option preferences. This allows the socio-technical actors to learn the extent to which they agree on their preferences over different alternatives. For this, a fuzzy cluster algorithm can be used that synthesizes similarities/diversities among socio-technical actors (Munda, 2009).

To generate the dendrogram, we use the `hclust` function that is the default hierarchical clustering method in `R` (R Core Team, 2019). This clustering method defines the distance between two clusters to be the maximum distance between their individual components. The hierarchical clustering process consists in making pair-wise comparisons of all elements of the similarity matrix s. At every step of the clustering process, the two nearest clusters are merged into a new cluster. The process is repeated until the whole data set is agglomerated into one single cluster.

5.3.2. Weighting actors

In order to rank the alternatives, we first weight the socio-technical actors based on the assessment of their relative level of stakes. Any weighting of social groups requires a normative justification (Munda, 2008). In the socio-technical multi-criteria evaluation (Section **5.2**), we used an *equal weighting* assumption between criteria and dimensions. Because different dimensions are associated with different groups in society (Munda, 2008), if the selected criteria maximize exhaustiveness *and* minimize redundancy, then the equal weighting assumption is justified. However, when ranking alternatives based on the social impacts one must consider that not all socio-technical actors have the same levels of interest and influence in the decision problem, *independently from how they may be impacted by each alternative*. The weighting of socio-technical actors can thus be justified by the need to apply some type of importance/relevance coefficient to the concerned socio-technical actors, so that not all the impact evaluations will be treated equally in the ranking—contrary to the fuzzy cluster analysis (Section **5.3.1**).

Munda (2009) attributed weights as importance coefficients to the various social actors. Formally, a vector Λ of weights is attached to the set of the P social actors, indicating their relative importance: $\Lambda = \{\lambda_p\}$, $\mathrm{p} = 1,2,\ldots,\mathrm{P}$, with $\sum_{p=1}^{P} \lambda_p = 1$. Yet, in this approach, even if weights are introduced as importance coefficients, the vector Λ is defined *ad hoc* by the analyst and, thus, can be contested by the concerned parties. In the STMCE method, we use another approach to attribute weights to the socio-technical actors using an explicit method to extract their relative importance.

In strategic management, *power* (or influence) refers to the ability of individuals or groups to persuade, induce or coerce others into following certain courses of action; whereas *interest* (or stake) refers to ownership, right, wealth, benefit, risk, or any other tangible or intangible aspects that a given stakeholder considers as relevant and potentially affected, positively or negatively, by a given issue or decision (Johnson et al., 2008). We use a power/interest matrix of the socio-technical actors as a mean to generate weights. A power/interest matrix (also called "stakeholder map") is a 2-dimensional plot in which socio-technical actors are positioned according to their estimated level of power and interest (Olander and Landin, 2005). In the power/interest matrix, the x-axis represents the level of influence (power) the actor has on the decision and the y-axis represents the actor's level of interest (stakes) in the impact of that decision; the range of both axes is $[0,1]$. The power/interest matrix provides an intuitive way of positioning the socio-technical actors relatively to each other, allowing the analysts to obtain a natural and explicit weighting system. To avoid the issue of having to compensate power and interest (that are incommensurate), we consider weights only in relation the relative levels of interest (stakes) between actors (x-axis). Our weighting system is thus derived from the relative positions of actors along the x-axis of the power/interest matrix.

Formally, the weighting system for the socio-technical actors is as follows:

1. We start with measuring the level of interest from the power/interest matrix. Let $z \in \mathbb{R}^P$, where P is the number of socio-technical actors, be a vector that captures this information.
2. We calculate a distance matrix $D \in \mathbb{R}^{P \times P}$, where $D_{ij} = z_i - z_j$. That is, we obtain a matrix of the relative distances in interest level between the different socio-technical actors.
3. We then average the relative distances for each socio-technical actor in relation to the others as: $r_p = \frac{1}{m} \sum_j D_{ij}, -1 \leq r_p \leq 1$.
4. Finally, we obtain the weight of the socio-technical actor as: $\lambda_p = 1 + r_p, 0 \leq \lambda_p \leq 2$.

One can confirm that the average weight of the socio-technical actors is $\frac{1}{P} \sum_p \lambda_p = 1$. A value of $r_p = 0$ would imply an equal weighting assumption (*i.e.*, $\lambda_p = 1$). The weighting system consists in applying a deviation around this value.

This weighting system can improve the social impact analysis by giving a degree of importance to socio-technical actors based on their estimated relative level of stakes in the decision problem and independently from how they may be impacted by each alternative. However, it requires the construction of a power/interest matrix of all actors for which estimated levels of interest may be affected by ambiguity and disagreement. An alternative weighting system can consist in estimating the stakes of each socio-technical actors by means of linguistic variables and treated as a fuzzy set, like for estimating the impacts of each alternatives (Section **5.3.1**).

5.3.3. Ranking alternatives

We can now combine the weights obtained for the socio-technical actors with the social impact matrix S, that represents each actor's perceived impact from the alternatives. Like in Section **5.2.1**, we first build an outranking matrix $E \in \mathbb{R}^{N \times N}$ as:

$$e_{jk} = \sum_{p=1}^{P} \left(\lambda_p(P_{jk}) + \frac{1}{2} \lambda_p(I_{jk}) \right) \tag{13}$$

Again, to get the ranking of alternatives, we simply take the sum of all the row entries for a given alternative in the outranking matrix to get an aggregate score. For a given alternative j, the aggregated score $r_j = \sum_k e_{jk}$. The ranking is then determined by the order of the aggregate scores.

The process described above is similarly performed for the K coalitions formed by the dendrogram. The coalitions are extracted from the dendrogram using the `cutree` function in `R`. The number of coalitions K is determined by the user after inspecting the results of the dendrogram. So, in addition to the ranking of alternatives for all socio-technical actors, K rankings are similarly made for each coalition.

Last, we also calculate the number of options that a coalition can veto for all K coalitions. Here, we wish to identify the options that are considered "extremely bad" by certain groups so that we can better identify the stable solutions. We follow Moulin's (1981) theorem, which says that any group with x percent of socio-technical actors has the ability to veto up to x percent of alternatives. This takes the form of a proportional veto function, which is defined as (Munda, 2009):

$$V_{P,N}(c_i) = \left(N \cdot \frac{|c_i|}{P}\right) - 1 \tag{14}$$

where (x) is the largest integer bounded below by x. Recall that P is the number of socio-technical actors, N is the number of alternatives, and c_i is the i'th group out of the K coalitions.

6. Numerical example

We now provide a numerical example to illustrate the output generated by the STMCE method. For this, we use the case of a decommissioned nuclear power plant in San Onofre, California. The San Onofre Nuclear Generating Station (SONGS), located 50 miles north of San Diego, California, stores 3,855 spent fuel assemblies (approx. 1,609 metric tons)—the largest spent fuel inventory stored at a all-unit shutdown power plant in the country (Carter, 2018). The reactors at SONGS were shut down in 2013 and spent fuel assemblies are progressively being moved from water pools to dry casks located on two dedicated storage areas. Although storage in dry casks is considered as safe as storage in pools (National Research Council, 2006), this is not a permanent solution, and spent fuel assemblies will eventually have to be moved to another site.

For reasons of space, no details about the data used to generate the outputs are provided. In fact, an STMCE application to an actual situation of spent fuel management requires to introduce a large amount of technical and contextual information in order to perform the analysis. The scope of this paper is to present the STMCE method that we illustrate with a numerical example using published data. We do not discuss the results either. The interested reader will find the full study of the STMCE method applied to the case of San Onofre, California, in Diaz-Maurin and Ewing (2020a).

6.1. Multi-criteria evaluations

Let us consider 8 scenarios of long-term spent fuel management at SONGS (**Table 2**). We evaluate the socio-technical performance of each scenario against 22 indicators (**Table 3**). This problem can be synthesised in the evaluation matrix described in **Table 4**.

Let us now compare each pair of options according to each single indicator. For this, we apply the threshold model described in Eq. (1). By introducing the indifference and preference relations between alternatives, we then obtain the outranking matrix as described in Eq. (2). Finally, by applying Eq. (3), a ranking is obtained for each one of the three multi-criteria evaluations performed (**Table 5**).

We then perform 500 Monte Carlo simulations varying each indicator of the evaluation matrix within its range of possible values (**Table 4**). Recall that the random variable generation uses the `R` function `set.seed` which can produce the same sequence; hence, the Monte Carlo simulation is replicable. **Fig. 3** shows the results of the sensitivity/uncertainty analysis for the three multi-criteria evaluations.

6.2. Social impact analysis

Let us now consider a social impact matrix showing the perceived outcome of each one of the 8 scenarios according to the 20 socio-technical actors considered (**Table 6**).We can then compare each pair of options according to each single actor's linguistic variable. For this, we apply the semantic distance described in Algorithm 1 and Eq. (11). We then compute the fuzzy indifference relations to obtain the similarity matrix as described in Eq. (12). **Fig. 4** presents the dendrogram obtained by applying the fuzzy clustering analysis to the social impact matrix (**Table 6**). From this dendrogram, we can identify 4 coalitions C_i formed by:

- C_1 = actors 1–5, 17;
- C_2 = actors 6–12, 19, 20;
- C_3 = actors 13–16; and
- C_4 = actor 18.

We can then rank the alternatives for each one of the four coalitions. The ranking procedure of alternatives based on the social impacts uses the same *equal weighting* assumption as in the multi-criteria evaluations (Section **6.1**). **Table 7** presents the rankings of scenarios at SONGS based on the social impacts for all actors combined and by coalitions.

We can now apply the proportional veto function to the SONGS case as described in Eq. (14). We obtain that coalition C_1 can veto the "do nothing" (1) option, whereas coalition C_2 can veto the "do nothing" (1), in-state direct disposal (4), and out-of-state direct disposal (5) options. However, coalitions C_3 and C_4 cannot veto any option because they contain only 4 actors ($4/20 = 0.2 < 1$) and 1 actor ($1/20 = 0.05 < 1$), respectively.

7. Discussion

In this section, we discuss the advantages and limitations of the STMCE framework and method for nuclear waste management as presented in this paper.

- **Purpose**

Any normative model suggesting how individuals should make multi-criteria evaluations or choices can be subject to criticism (DCLG, 2009). In its attempt at "rationalizing" the dimensions of choice when the "irrational", as some put it, often strongly affects outcomes in nuclear waste management (Bergmans et al., 2015; Tuler and Kasperson, 2010), STMCE is no immune to such criticism. For instance, because it uses mathematical procedures, STMCE can seem still attached to the idea that one can "solve" the waste problem (Ramana, 2018). But STMCE is not limited to a quantitative evaluation method. STMCE is embedded in a decision-support framework of the same name that takes the form of a social multi-criteria evaluation process. A large body of research now recognizes that decisions in nuclear waste management, to be successful and accepted, must go through a participatory process (Bergmans et al., 2015; Brunnengräber and Di Nucci, 2019)—although participation is *not a sufficient condition* for a successful social multi-criteria evaluation process (Munda, 2019). STMCE offers an analytical tool that supports—but does not replace—discussion, deliberation and decision. Because it requires participation of actors, the STMCE framework thus does not pretend to make policy recommendations. Clearly, decision-makers and other concerned socio-technical actors are better placed than analysts to evaluate impact of proposed alternatives and make decisions. The value of STMCE therefore is in providing a logically sound foundation for gathering and using all of the information about relevant aspects of the decision that should be included in such decision-making process. That is, STMCE provides evaluations and highlights conflicts, but it does not intend to substitute for the decision-making process itself. Because it highlights conflicts between actors' perspectives and identifies potential compromise solutions, we believe STMCE can be an important step forward in nuclear waste management policy in the U.S.

- **Scope**

The paper focuses on the nuclear waste management situation in the United States. As such, we did not review the siting processes used in the nuclear waste programs of other countries. As shown in Section **2**, the U.S. program exhibits very specific characteristics—most notably the influences of national politics, the complex role of states, and the quantitative approach to safety—to which the method has been tailored. Countries with most advanced nuclear waste disposal programs, such as Finland, Sweden and France, all have a very different political structure (Metlay, 2016). Moreover, as explained, STMCE is not a siting process method *per se* but, rather, an analytical and decision-support method that provides a procedures to evaluate the socio-technical performance and social conflict of alternative strategies of nuclear waste management.

Second, the paper focuses on spent fuel from U.S. commercial nuclear reactors. It does not discuss other types of waste such as the high-level radioactive legacy waste and DOE-owned spent nuclear fuel from defense programs. While the framework presented in this paper could in principle be applied to other waste types, the decision-making process is different as regard military waste. Most of these waste are being stored and disposed of on land owned by the federal government so a public siting process is, in most cases, not required.

Last, the paper does not explicitely discuss the consent-based siting approach that has been proposed by the federal government (US DOE, 2017, 2016b). Yet, the consent-based siting approach has not been implemented in the U.S., despite independent experts made it a central recommendation since almost a decade (Blue Ribbon Commission, 2012; Metlay, 2013; Reset Steering Committee, 2018).

- **Approach**

The social multi-criteria evaluation approach is not well known in the nuclear waste communities, especially among the engineers and mathematicians carrying risk assessments. In fact, the STMCE approach is a departure from conventional multi-criteria decision analysis (MCDA) methods that typically search for optimal solutions through a mathematical framework and are implemented by scientists hired by decision-makers in a "speak truth to power" approach. In contrast, STMCE is an approach that primarily seek to reallocate power among parties, highlight socio-technical conflicts on the proposed alternatives and search for compromise solutions. Simplicity, transparency and reproducability are important features of the STMCE approach—as must be any use of "models" for public policy (Saltelli et al., 2020). The paper provides a discussion of multi-criteria frameworks and justifies our choice of the social multi-criteria evaluation framework against MCDA (Section **4.2**). Moreover, the social multi-criteria evaluation approach—used as the foundation of STMCE—is a proven methodology that has been tried and applied in many real-world environmental and public policy problems (Munda, 2019).

- **Method acceptability**

Among the various multi-criteria techniques available the outranking technique—used in STMCE—is well suited to indirectly capture some of the political realities of decision making (DCLG, 2009). Yet, the outranking approach can be dependent on some arbitrary definitions on what constitutes "outranking" and how the threshold values are set and can be subject to manipulation by the decision-makers. This can become a difficulty in implementing the technique because potentially concerned parties will try to influence on the choice of criteria and threshold values considered. The STMCE partially avoids this issue by performing the downgrading of options not according to the criteria (in the multi-criteria evaluation) but through the use of a proportional veto principle in the social impact analysis.

In a real-world situation, the STMCE method is likely not to be consensually viewed as authoritative. In fact, our objective is not to have STMCE accepted by the decision-makers and then applied to a decision problem framed by them. Otherwise, there would be no value in applying STMCE over other social multi-criteria evaluation and MCDA approaches. Rather, we see STMCE as a bottom-up, independent approach that would provide a measure of the gaps between the performance of options against criteria, and provide also a measure of the conflicts that exist between the perceptions of actors over the different options. This provides a new set of information that may be considered by the stakeholders in the deliberation and decision-making process. Empowering social-actors, especially localities, tribes and states in their negotiation with the federal government and regulatory agencies, is a core objective of STMCE.

Last, when applying STMCE to a real-world situation, socio-technical actors must be able to quickly and fully understand how the method works before they can participate to the selection of alternatives and criteria as well as to the assessment of preferences and impacts of alternatives. For this reason, a STMCE frramework can be conducted only through a step-wise, iterative process that spans several months or years. In fact, such process must allow the so-called "extended peer community" (Funtowicz and Ravetz, 1993b)—which includes decision-makers and other concerned socio-technical actors—to critically review the assumptions of the analysis. Such quality control process, in turn, will add to the credibility and legitimacy of the methodology and, thus, to the thruthworthyness of the process by the parties.

- **Method implementability**

At a minimum, the social multi-criteria engagement process will require actors to participate in framing the decision problem, identifying alternatives, deciding on the criteria and threshold values and generating the social impact matrix. Yet, this process can be difficult to implement because of the difficulty to capture the preferences of the decision-makers and other concerned actors in a consistent fashion. In fact, there has been significant research and numerous applications on situations where the preferences of the decision maker (*e.g.*, a government agency) depend on the separate preferences of the actors, as well as other criteria. The extent to which a decision-maker or any actor cares about the decision is based on the potential consequences of the alternatives.

To structure any social multi-criteria evaluation therefore requires significant work defining the decision problem, decide on a set of alternatives for the decision, and list all the relevant criteria for their assessment. Naturally, the actors should be involved in the process. In addition, there is the necessity to establish useful measures for each criterion. To thoroughly structuring the decision to be faced, the analysts must therefore spend a significant amount of time with each actor to help them understand and express their preferences accurately. (As explained in Section **5.3**, the use of linguistic variables coupled with a fuzzy set approach can facilitates this step.) Moreover, we recall that the STMCE approach is by nature an iterative process (**Fig. 1**). Such issues must be considered in any application of the STMCE approach.

8. Conclusions

This paper presented a socio-technical multi-criteria evaluation (STMCE) framework and method supporting the search for compromise solutions by highlighting conflicts and supporting their resolution. The approach seeks to support local communities and states in the search of alternative management strategies for spent fuel that, in the absence of federal interim storage or geologic disposal capacity, is stranded at 15 decommissioned reactor sites across the country (Reset Steering Committee, 2018).

This paper provided (1) a discussion about the issues faced by the nuclear waste management program in the U.S.; (2) a review of existing multi-criteria analysis methods; (3) a detailed description of the STMCE framework and method; (4) a numerical examples that illustrates the outputs generated by the method; and, finally, (5) a discussion about its advantages and limitations. Despite some limitations, the STMCE approach responds to our stated objectives of (1) increasing the pool of perspectives through the introduction of the concept of socio-technical actor in the analysis; (2) supporting host communities by offering an independent, transparent and replicable tool for the comparison of the socio-technical impact of alternatives; (3) searching for compromise solutions by performing a coalition formation process; and (4) reallocating power among parties through the application of the proportional veto principle.

The STMCE application has been applied to the case of the spent fuel management at a decommissionned nuclear power plant in San Onofre, California (Diaz-Maurin and Ewing, 2020a). Apart from commercial spent fuel and high-level nuclear waste management, the STMCE framework can be used in other decision problems of the nuclear fuel cycle with socio-technical implications. In particular, it can be useful for (i) the selection of sites for disposal of low- and intermediate-level nuclear waste; (ii) the selection of remediation strategies for radioactively contaminated soils; (iii) the performance comparison of nuclear waste repositories in different geologic settings (Diaz-Maurin and Ewing, 2019b); as well as, (iv) the choice of new nuclear fuel designs and reactor types with waste management considerations.

Acknowledgment

The authors acknowledge the assistance of Hilary C. Sun, from the Computer Science Department at Stanford University, during the early development of the method presented in this paper. We also thank Giuseppe Munda, from the Joint Research Centre at the European Commission, as well as D. Warner North, from NorthWorks, San Francisco, CA, USA, for useful comments, criticism and discussions in the preparation of this paper. The views expressed in this paper, as well as, the possible errors or misconceptions are the sole responsibility of the authors.

Funding

The research leading to this document received funding from the European Union's Horizon 2020 research and innovation program under the Marie Sklodowska-Curie Individual Fellowship program (grant agreement no. 739850), the MacArthur Foundation under CISAC's Nuclear Security Fellowship program (2017-2019), and the VPUE Department and Faculty Grants program from Stanford's Office of the Vice Provost for Undergraduate Education (2017-2019).

References

Alley, W.M., Alley, R., 2012. Too Hot to Touch: The Problem of High-Level Nuclear Waste. Cambridge University Press, Cambridge, UK.

Bergmans, A., Sundqvist, G., Kos, D., Simmons, P., 2015. The participatory turn in radioactive waste management: deliberation and the social–technical divide. Journal of Risk Research 18, 347–363. https://doi.org/10.1080/13669877.2014.971335

Bijker, W.E., Hughes, T.P., Pinch, T. (Eds.), 2012. The Social Construction of Technological Systems, Anniversary Edition. MIT Press, Cambridge, MA.

Blue Ribbon Commission, 2012. Report to the Secretary of Energy. Blue Ribbon Commission on America's Nuclear Future, Washington, DC.

Bonano, E., Swift, P., Appel, G., Meacham, P., 2011. Can Repository Scientists and Social Scientists Work Together to Find Solutions to Nuclear Waste Management Problems? A Repository Scientist's Perspective. Risk, Hazards & Crisis in Public Policy 2, 1–18. https://doi.org/10.2202/1944-4079.1068

Bonano, E.J., Kalinina, E.A., Swift, P.N., 2018. The Need for Integrating the Back End of the Nuclear Fuel Cycle in the United States of America. MRS Advances 3, 991–1003. https://doi.org/10.1557/adv.2018.231

Bredehoeft, J.D., England, A., Stewart, D., Trask, N., Winograd, I., 1978. Geologic disposal of high-level radioactive wastes: Earth-science perspectives, U.S. Geological Survey Circular 779. U.S. Department of the Interior, U.S. Geological Survey, Alexandria, VA, USA.

Brunnengräber, A., Di Nucci, M.R. (Eds.), 2019. Conflicts, Participation and Acceptability in Nuclear Waste Governance: An International Comparison, Energy Policy and Climate Protection book series (EPKS). Springer VS, Wiesbaden.

Carter, J., 2018. Spent Nuclear Fuel and High-Level Radioactive Waste Inventory Report (No. FCRD-NFST-2013-000263, Rev. 5). Savannah River Site (SRS), Aiken, South Carolina, USA. https://doi.org/10.2172/1462174

Carter, L.J., 1987. Nuclear Imperatives and Public Trust: Dealing with Radioactive Waste. Resources for the Future, Inc., Washington, DC.

Davis, L.E., Knopman, D., Greenberg, M.D., Miller, L.E., Doll, A., 2012. Choosing a New Organization for Management and Disposition of Commercial and Defense High-level Radioactive Materials (No. MG-1230-DOE). RAND Corporation, Santa Monica, CA.
DCLG, 2009. Multi-criteria analysis: a manual. UK Department for Communities and Local Government, London, UK.
Diaz-Maurin, F., 2018. Chronic long-term risk of low-level radiation exposure: Bridging the lay/expert divide. Bulletin of the Atomic Scientists 74, 335–339. https://doi.org/10.1080/00963402.2018.1507792
Diaz-Maurin, F., 2014. Going beyond the Nuclear Controversy. Environmental Science & Technology 48, 25–26. https://doi.org/10.1021/es405282z
Diaz-Maurin, F., Ewing, R.C., 2020a. Socio-technical evaluation of long-term spent nuclear fuel management options: The case of San Onofre, California. EarthArXiv. https://doi.org/10.31223/X5459S
Diaz-Maurin, F., Ewing, R.C., 2020b. Integration of the Back-end of the Nuclear Fuel Cycle: An Overview. MRS Advances 5, 253–264. https://doi.org/10.1557/adv.2020.101
Diaz-Maurin, F., Ewing, R.C., 2019a. Probabilistic Performance Assessment vs. the Safety Case Approach. MRS Advances 4, 987–992. https://doi.org/10.1557/adv.2018.681
Diaz-Maurin, F., Ewing, R.C., 2019b. Multi-scale, multi-criteria evaluation of nuclear waste repositories in different geologic settings, in: Goldschmidt Conference Abstracts. Presented at the Goldschmidt Annual International Conference, 18–23 August 2019, Geochemical Society and European Association of Geochemistry, Barcelona, Spain, p. 798.
Diaz-Maurin, F., Ewing, R.C., 2018. Mission Impossible? Socio-Technical Integration of Nuclear Waste Geological Disposal Systems. Sustainability 10, 4390. https://doi.org/10.3390/su10124390
Diaz-Maurin, F., Kovacic, Z., 2015. The unresolved controversy over nuclear power: A new approach from complexity theory. Global Environmental Change 31, 207–216. https://doi.org/10.1016/j.gloenvcha.2015.01.014
Doumpos, M., Figueira, J.R., Greco, S., Zopounidis, C. (Eds.), 2019. New Perspectives in Multiple Criteria Decision Making: Innovative Applications and Case Studies, Multiple Criteria Decision Making. Springer International Publishing, Cham, Switzerland. https://doi.org/10.1007/978-3-030-11482-4_11
Duncan, J.M., 2000. Factors of Safety and Reliability in Geotechnical Engineering. Journal of Geotechnical and Geoenvironmental Engineering 126, 307–316. https://doi.org/10.1061/(ASCE)1090-0241(2000)126:4(307)
Ewing, R.C., 2006. Performance Assessments: Are They Necessary or Sufficient?, in: MacFarlane, A., Ewing, R.C. (Eds.), Uncertainty Underground: Yucca Mountain and the Nation’s High-Level Nuclear Waste. MIT Press, Cambridge, MA, pp. 71–83.
Ewing, R.C., Tierney, M.S., Konikow, L.F., Rechard, R.P., 1999. Performance Assessments of Nuclear Waste Repositories: A Dialogue on Their Value and Limitations. Risk Anal 19, 933–958. https://doi.org/10.1111/j.1539-6924.1999.tb00452.x
Flynn, J., Kasperson, R., Kunreuther, H., Slovic, P., 1992. Time to rethink nuclear waste storage. Issues in Science and Technology 8, 42–48.

Funtowicz, S.O., Ravetz, J.R., 1993a. Science for the post-normal age. Futures 25, 739–755.
Funtowicz, S.O., Ravetz, J.R., 1993b. Science for the post-normal age. Futures 25, 739–755. https://doi.org/10.1016/0016-3287(93)90022-L
Gass, S.I., 1983. Feature Article—Decision-Aiding Models: Validation, Assessment, and Related Issues for Policy Analysis. Operations Research 31, 603–631. https://doi.org/10.1287/opre.31.4.603
Greco, S., Ehrgott, M., Figueira, J.R. (Eds.), 2016. Multiple Criteria Decision Analysis: State of the Art Surveys, 2nd ed, International Series in Operations Research & Management Science. Springer, New York, NY. https://doi.org/10.1007/978-1-4939-3094-4_27
Greco, S., Munda, G., 2017. Multiple criteria evaluation in environmental policy analysis, in: Spash, C.L. (Ed.), Routledge Handbook of Ecological Economics. Routledge, pp. 311–320.
Greenberg, M., 2012. Nuclear Waste Management, Nuclear Power, and Energy Choices: Public Preferences, Perceptions, and Trust. Springer Science & Business Media.
Greenberg, M.R., 2009. NIMBY, CLAMP, and the Location of New Nuclear-Related Facilities: U.S. National and 11 Site-Specific Surveys. Risk Analysis 29, 1242–1254. https://doi.org/10.1111/j.1539-6924.2009.01262.x
Hillier, F.S., Lieberman, G.J., 2015. Introduction to Operations Research, 10th ed. McGraw-Hill Education.
Jasanoff, S., 2006. States of knowledge: the co-production of science and the social order, 1st ed. Routledge.
Jasanoff, S., 1990. The fifth branch: Science advisers as policymakers. Harvard University Press, Cambridge, MA, USA.
Johnson, G., Scholes, K., Whittington, R., 2008. Exploring corporate strategy, 8th ed. Financial Times Prentice Hall, Essex, England, UK.
La Porte, T.R., Metlay, D.S., 1996. Hazards and Institutional Trustworthiness: Facing a Deficit of Trust. Public Administration Review 56, 341–347. https://doi.org/10.2307/976375
Lee, K.N., 1980. A Federalist Strategy for Nuclear Waste Management. Science 208, 679–684. https://doi.org/10.1126/science.208.4445.679
Leiss, W., 1995. "Down and Dirty:" The Use and Abuse of Public Trust in Risk Communication. Risk Analysis 15, 685–692. https://doi.org/10.1111/j.1539-6924.1995.tb01340.x
Metlay, D., 2013. Consent-based siting: what have we learned. Radwaste Solutions 28–36.
Metlay, D., 2000. From tin roof to torn wet blanket: predicting and observing groundwater movement at a proposed nuclear waste site, in: Prediction: Science, Decision Making, and the Future of Nature. Island Press, Covelo, CA, pp. 199–228.
Metlay, D., Ewing, R., 2014. Safety Cases and Siting Processes, in: The Safety Case for Deep Geological Disposal of Radioactive Waste: 2013 State of the Art, Symposium Proceedings. OECD Publishing, Paris, France, pp. 319--324.
Metlay, D.S., 2016. Selecting a Site for a Radioactive Waste Repository: A Historical Analysis. Elements 12, 269–274. https://doi.org/10.2113/gselements.12.4.269
Moulin, H., 1981. The Proportional Veto Principle. The Review of Economic Studies 48, 407–416. https://doi.org/10.2307/2297154

Munda, G., 2019. Multi-criteria Evaluation in Public Economics and Policy, in: Doumpos, M., Figueira, J.R., Greco, S., Zopounidis, C. (Eds.), New Perspectives in Multiple Criteria Decision Making: Innovative Applications and Case Studies, Multiple Criteria Decision Making. Springer International Publishing, Cham, Switzerland, pp. 297–313. https://doi.org/10.1007/978-3-030-11482-4_11
Munda, G., 2012. Intensity of preference and related uncertainty in non-compensatory aggregation rules. Theory Decis 73, 649–669. https://doi.org/10.1007/s11238-012-9317-4
Munda, G., 2009. A conflict analysis approach for illuminating distributional issues in sustainability policy. European Journal of Operational Research 194, 307–322. https://doi.org/10.1016/j.ejor.2007.11.061
Munda, G., 2008. Social Multi-Criteria Evaluation for a Sustainable Economy. Springer Berlin Heidelberg, Berlin, Heidelberg.
Munda, G., 2004. Social multi-criteria evaluation: Methodological foundations and operational consequences. European Journal of Operational Research 158, 662–677. https://doi.org/10.1016/S0377-2217(03)00369-2
Munda, G., 1995. Multicriteria Evaluation in a Fuzzy Environment: Theory and Applications in Ecological Economics, Contributions to Economics. Physica-Verlag Heidelberg.
National Research Council, 2006. Safety and Security of Commercial Spent Nuclear Fuel Storage: Public Report. The National Academies Press, Washington, DC. https://doi.org/10.17226/11263
National Research Council, 1995. Technical Bases for Yucca Mountain Standards. The National Academies Press, Washington, DC. https://doi.org/10.17226/4943
NDC, 2020. Socioeconomic impacts from nuclear power plant closure and decommissioning: Host community experiences, best practices and recommendations. The Nuclear Decommissioning collaborative, Inc.
Olander, S., Landin, A., 2005. Evaluation of stakeholder influence in the implementation of construction projects. International Journal of Project Management 23, 321–328. https://doi.org/10.1016/j.ijproman.2005.02.002
Oreskes, N., Shrader-Frechette, K., Belitz, K., 1994. Verification, Validation, and Confirmation of Numerical Models in the Earth Sciences. Science 263, 641–646. https://doi.org/10.1126/science.263.5147.641
Peterson, P.F., 2017. Spent Nuclear Fuel is not the Problem [Point of View]. Proceedings of the IEEE 105, 411–414. https://doi.org/10.1109/JPROC.2017.2661498
Porter, T.M., 1995. Trust in Numbers: The Pursuit of Objectivity in Science and Public Life. Princeton University Press, Princeton, NJ, USA.
R Core Team, 2019. R: A Language and Environment for Statistical Computing (Version 3.5.1). R Foundation for Statistical Computing, Vienna, Austria.
Ramana, M.V., 2019. Why Technical Solutions are Insufficient, in: Brunnengräber, A., Di Nucci, M.R. (Eds.), Conflicts, Participation and Acceptability in Nuclear Waste Governance: An International Comparison Volume III, Energiepolitik Und Klimaschutz. Energy Policy and Climate Protection. Springer Fachmedien Wiesbaden, Wiesbaden, pp. 21–38. https://doi.org/10.1007/978-3-658-27107-7_2
Ramana, M.V., 2018. Technical and social problems of nuclear waste. WIREs Energy Environ 7, e289. https://doi.org/10.1002/wene.289

Ramana, M.V., 2013. Shifting strategies and precarious progress: Nuclear waste management in Canada. Energy Policy 61, 196–206. https://doi.org/10.1016/j.enpol.2013.05.085
Rechard, R.P., Price, L.L., Kalinina, E.A., Bonano, T., Jenkins-Smith, H., 2015. Integrating Management of Spent Nuclear Fuel from Generation to Disposal in the United States (SAND2015-3428C).
Reset Steering Committee, 2018. Reset of America’s Nuclear Waste Management Strategy and Policy. Stanford University, Stanford, CA.
Robinson, S.E., Stoutenborough, J.W., Vedlitz, A., 2017. Understanding Trust in Government: Environmental Sustainability, Fracking, and Public Opinion in American Politics, Routledge Studies in Public Administration and Environmental Sustainability. Routledge, New York, NY.
Rossignol, N., Parotte, C., Joris, G., Fallon, C., 2017. Siting controversies analysis: framework and method for questioning the procedure. Journal of Risk Research 20, 1253–1274. https://doi.org/10.1080/13669877.2014.983948
Roy, B., 1996. Multicriteria Methodology for Decision Aiding, Nonconvex Optimization and Its Applications. Springer Science & Business Media.
Saltelli, A., Bammer, G., Bruno, I., Charters, E., Fiore, M.D., Didier, E., Espeland, W.N., Kay, J., Piano, S.L., Mayo, D., Jr, R.P., Portaluri, T., Porter, T.M., Puy, A., Rafols, I., Ravetz, J.R., Reinert, E., Sarewitz, D., Stark, P.B., Stirling, A., Sluijs, J. van der, Vineis, P., 2020. Five ways to ensure that models serve society: a manifesto. Nature 582, 482–484. https://doi.org/10.1038/d41586-020-01812-9
Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S., 2008. Global Sensitivity Analysis: The Primer. John Wiley & Sons, Ltd.
Saraç-Lesavre, B., 2018. Budgeting the Future: Negotiating the Values of a Contemporary Liberal Democracy, in: Materiality and Managerial Techniques, Technology, Work and Globalization. Palgrave Macmillan, Cham, pp. 57–76. https://doi.org/10.1007/978-3-319-66101-8_3
Shrader-Frechette, K., 2000. Duties to future generations, proxy consent, intra-and intergenerational equity: The case of nuclear waste. Risk Anal 20, 771–778.
Shrader-Frechette, K.S., 1993. Burying uncertainty: Risk and the case against geological disposal of nuclear waste. University of California Press, Berkeley and Los Angeles, California, USA.
Slovic, P., Layman, M., Flynn, J.H., 1991. Risk Perception, Trust, and Nuclear Waste: Lessons from Yucca Mountain. Environment: Science and Policy for Sustainable Development 33, 6–30. https://doi.org/10.1080/00139157.1991.9931375
Stiglitz, J.E., 2002. New perspectives on public finance: recent achievements and future challenges. Journal of Public Economics 86, 341–360.
Stirling, A., 2007. Risk, precaution and science: towards a more constructive policy debate. EMBO reports 8, 309–315. https://doi.org/10.1038/sj.embor.7400953
Tuler, S., Kasperson, R., 2010. Social distrust: Implications and recommendations for spent fuel and high level radioactive waste management. Blue Ribbon Commission on America’s Nuclear Future, Washington, DC.
US DOE, 2017. Draft Consent-Based Siting Process for Consolidated Storage and Disposal Facilities for Spent Nuclear Fuel and High-Level Radioactive Waste. U.S. Department of Energy, Washington, D.C.

US DOE, 2016a. Designing a Consent-Based Siting Process: Summary of Public Input (No. Final Report). U.S. Department of Energy, Washington, D.C.
US DOE, 2016b. Integrated Waste Management and Consent-Based Siting. U.S. Department of Energy, Washington, D.C.
US GAO, 2014. Spent Nuclear Fuel Management: Outreach Needed to Help Gain Public Acceptance for Federal Activities That Address Liability (Report to Congressional Requesters No. GAO-15-141). U.S. Government Accountability Office.
US NWTRB, 2015. Designing a Process for Selecting a Site for a Deep-Mined, Geologic Repository for High-Level Radioactive Waste and Spent Nuclear Fuel - Detailed Analysis. United States Nuclear Waste Technical Review Board, Arlington, VA.
US NWTRB, 2009. Survey of National Programs for Managing High-Level Radioactive Waste and Spent Nuclear Fuel: A Report to Congress and the Secretary of Energy. United States Nuclear Waste Technical Review Board, Arlington, VA.
Vandenbosch, R., Vandenbosch, S.E., 2007. Nuclear waste stalemate: Political and scientific controversies, Geology / Nature and Environment. University of Utah Press.
Wątróbski, J., Jankowski, J., Ziemba, P., Karczmarczyk, A., Zioło, M., 2019. Generalised framework for multi-criteria method selection. Omega 86, 107–124. https://doi.org/10.1016/j.omega.2018.07.004
Wynne, B., 1992. Misunderstood misunderstanding: social identities and public uptake of science. Public Underst Sci 1, 281–304. https://doi.org/10.1088/0963-6625/1/3/004

Tables

Table 1. Evaluation of some multi-criteria methods according to desirable properties for social multi-criteria evaluation. Source: after Munda (2008, Table 5.5), except for STMCE (this paper).

	Comp.	Imp. Coef.	Mix. Inf.	Simpl.	Hier.	Discr. Prob.	Tresh.	Confl. Anal.
AHP	High	No	No	Low	Yes	No	No	No
ELECTRE	Low	Not clear	Partly	Low	No	Yes	Yes	No
NAIADE	Medium	No	Yes	Low	No	Yes	Yes	Yes
PROMETHEE	High	No	No	Medium	No	Yes	Yes	No
STMCE	Medium	Partly[1]	Partly[2]	Medium	Yes[3]	Yes	Yes[4]	Yes

Abbreviations used: Comp., compensation; Confl. Anal., conflict analysis; Discr. Prob., discrete decision problem; Hier., hierarchy; Imp. Coef., importance coefficient; Mix. Inf., mixed information; Simpl., simplicity; Thresh., thresholds. Notes: (1) in the conflict analysis only; (2) across the multi-criteria evaluation and social impact (conflict) analysis only; (3) hierarchy of dimensions in the multi-criteria evaluation; (4) indifference thresholds only (no fuzzy set preference/indifference as full stochastic uncertainty analysis is performed in multi-criteria evaluation).

Table 2. Scenarios of long-term spent fuel management at SONGS (source: Diaz-Maurin and Ewing, 2020a).

ID	Scenario	Pathway
1	Do nothing	Spent fuel storage at SONGS for 200 years (t0 = 2020) + repackaging every 50-100 years
2	In-state interim storage	20-40 years in dry casks at SONGS + shipment to an interim storage facility in California + storage 160-180 years at interim storage facility
3	Out-of-state interim storage	20-40 years in dry casks at SONGS + shipment to an interim storage facility in south-east or north-west location + storage 160-180 years at interim storage facility
4	In-state direct disposal	20-40 years in dry casks at SONGS + shipment to a geologic repository in California
5	Out-of-state direct disposal	20-40 years in dry casks at SONGS + shipment to a geologic repository in another state
6	In-state interim storage and disposal	20-40 years in dry casks at SONGS + shipment to an interim storage facility in California + 20-40 years storage at interim storage facility + permanent disposal at a geologic repository at same or other location in California
7	In-state interim storage and out-of-state disposal	20-40 years in dry casks at SONGS + shipment to an interim storage facility in California + 20-40 years storage at interim storage facility + shipment to and permanent disposal at a geologic repository in another state
8	Out-of-state interim storage and disposal	20-40 years in dry casks at SONGS + shipment to an interim storage facility in south-east or north-west location + 20-40 years storage at interim storage facility + permanent disposal at a geologic repository at same or other location

Table 3. Indicators and indifference threshold values for the socio-technical evaluation of scenarios at SONGS (source: Diaz-Maurin and Ewing, 2020a).

Ind. #	Indicator description	Unit	Indifference threshold
Technical dimension			
1.1	Repackaging of canisters during onsite storage	Number of canisters	82
1.2	Repackaging of storage casks during onsite storage	Number of storage casks	8.2
1.3	Repackaging of canisters before transport	Number of canisters	19
1.4	Loading/unloading to/from transportation casks	Number of load./unload.	109
1.5	Repackaging of canisters during offsite storage	Number of canisters	67
1.6	Repackaging of storage casks during offsite storage	Number of storage casks	7.4
1.7	Total cumulative individual worker dose of normal operations during onsite storage	rem	43
1.8	Total cumulative individual worker dose of normal operations during interim storage	rem	18
1.9	Total cumulative individual worker dose from loading/unloading casks for transport	rem	2.1
1.10	Collective dose to workers during transport	person-rem	93
1.11	Total individual worker dose from normal surface operations during geologic disposal	mrem	0.29
Societal dimension			
2.1	Duration of onsite storage at SONGS (after 2020)	Years	30
2.2	Duration of storage in California until in-state disposal or transport off state (after 2020)	Years	30
2.3	Duration of isolation in a geologic disposal facility (before 2220)	Years	30
2.4	Public radiation exposure risk during onsite storage at SONGS	Ci-person-year (x10^15)	2.0
2.5	Public radiation exposure risk during interim storage in California	Ci-person-year (x10^14)	0.7
2.6	Public dose during transport	mrem	0.033
2.7	Total cost of onsite storage at SONGS	M$	390
2.8	Total cost of interim storage and/or disposal in California	M$	484
2.9	Total cost of transport	M$	5.4
2.10	Total economic impact compensation during storage in California	M$	804
2.11	Financial risk from postponed investment costs of disposal (incl. repository closure)	B$-year	46

Table 4. Evaluation matrix of the SONGS case (source: Diaz-Maurin and Ewing, 2020a).

Ind. #	Scenario 1	2	3	4	5	6	7	8
Technical dimension								
1.1	246 [123, 492]	0 [0, 88]	0 [0, 88]	6 [0, 246]	6 [0, 246]	0 [0, 88]	0 [0, 88]	0 [0, 88]
1.2	25 [12, 49]	0 [0, 9]	0 [0, 9]	1 [0, 25]	1 [0, 25]	0 [0, 9]	0 [0, 9]	0 [0, 9]
1.3	0 [0, 0]	0 [0, 113]	0 [0, 113]	0 [0, 113]	0 [0, 113]	0 [0, 113]	0 [0, 113]	0 [0, 113]
1.4	0 [0, 0]	246 [246, 326]	246 [246, 326]	246 [246, 326]	246 [246, 326]	246 [246, 652]	492 [492, 652]	246 [246, 652]
1.5	0 [0, 0]	246 [123, 404]	246 [123, 404]	0 [0, 0]	0 [0, 0]	6 [0, 198]	6 [0, 198]	6 [0, 198]
1.6	0 [0, 0]	21 [9, 44]	21 [9, 44]	0 [0, 0]	0 [0, 0]	0 [0, 9]	0 [0, 9]	0 [0, 20]
1.7	188 [136, 271]	31 [17, 98]	31 [17, 98]	56 [15, 186]	56 [15, 186]	31 [17, 98]	31 [17, 98]	31 [17, 98]
1.8	0 [0, 0]	66 [35, 111]	66 [35, 111]	0 [0, 0]	0 [0, 0]	19 [5, 53]	19 [5, 53]	19 [5, 53]
1.9	0 [0, 0]	2.9 [1.9, 5.1]	2.9 [1.9, 5.1]	1.6 [1.1, 2.9]	1.6 [1.1, 2.9]	3.5 [2.3, 12.3]	7 [4.6, 12.3]	3.5 [2.3, 12.3]
1.10	0 [0, 0]	58 [0, 83]	172 [68, 278]	66 [45, 83]	93 [68, 111]	58 [45, 83]	87 [68, 100]	305 [68, 555]
1.11	0 [0, 0]	0 [0, 0]	0 [0, 0]	1.5 [1.2, 1.8]	1.5 [1.2, 1.8]	0.6 [0.5, 0.7]	0.6 [0.5, 0.7]	0.6 [0.5, 0.7]
Societal dimension								
2.1	200 [200, 200]	30 [20, 40]	30 [20, 40]	60 [20, 100]	60 [20, 100]	30 [20, 40]	30 [20, 40]	30 [20, 40]
2.2	200 [200, 200]	200 [200, 200]	30 [20, 40]	60 [20, 100]	60 [20, 100]	90 [40, 140]	90 [40, 140]	30 [20, 40]
2.3	0 [0, 0]	0 [0, 0]	0 [0, 0]	140 [180, 100]	140 [180, 100]	110 [160, 60]	110 [160, 60]	110 [160, 60]
2.4	9.9 [7.8, 13.1]	1.7 [1.1, 2.3]	1.7 [1.1, 2.3]	3 [1.1, 5.4]	3 [1.1, 5.4]	1.7 [1.1, 2.3]	1.7 [1.1, 2.3]	1.7 [1.1, 2.3]
2.5	0 [0, 0]	3.5 [4.5, 2.5]	0 [0, 0]	0 [0, 0]	0 [0, 0]	1.3 [0.6, 1.6]	1.3 [0.6, 1.6]	0 [0, 0]
2.6	0 [0, 0]	0.029 [0.003, 0.1]	0.029 [0.003, 0.1]	0.029 [0.003, 0.1]	0.029 [0.003, 0.1]	0.058 [0.006, 0.2]	0.058 [0.006, 0.2]	0.058 [0.006, 0.2]
2.7	2271 [2135, 2541]	300 [200, 497]	300 [200, 497]	607 [200, 1271]	607 [200, 1271]	300 [200, 497]	300 [200, 497]	300 [200, 497]
2.8	0 [0, 0]	2241 [2006, 2611]	0 [0, 0]	657 [287, 1333]	0 [0, 0]	1537 [761, 2902]	880 [474, 1569]	0 [0, 0]
2.9	0 [0, 0]	6.6 [0, 11.5]	11.2 [3.4, 21.1]	7.6 [3.6, 11.5]	6 [3.4, 8.5]	5.9 [4.4, 9]	4.2 [2.4, 5.8]	14.7 [1.8, 32.1]
2.10	4826 [0, 4826]	724 [0, 4826]	724 [0, 965]	1448 [0, 2413]	1448 [0, 2413]	724 [0, 3379]	724 [0, 3379]	724 [0, 965]
2.11	132 [57, 275]	132 [57, 275]	132 [57, 275]	2 [0, 17]	2 [0, 17]	3 [0, 21]	3 [0, 21]	3 [0, 21]

Note: Values are indicated as Median [Minimum, Maximum].

Table 5. Ranking of scenarios for the multi-criteria evaluations performed at SONGS (source: Diaz-Maurin and Ewing, 2020a).

Scenario	Technical view	Societal view	Combined
(1) Do nothing	2	7	6
(2) In-state interim storage	6	8	8
(3) Out-of-state interim storage	8	5	7
(4) In-state direct disposal	1	3	2
(5) Out-of-state direct disposal	3	1	1
(6) In-state interim storage and disposal	4	6	4
(7) In-state interim storage and out-of-state disposal	7	4	5
(8) Out-of-state interim storage and disposal	5	2	3

Note: Scenarios are ranked from 1 (most performing) to 8 (least performing).

Table 6. Social impact matrix of scenarios on the socio-technical actors at SONGS (source: Diaz-Maurin and Ewing, 2020a).

Actor ID*	Scenario 1	2	3	4	5	6	7	8
1	Very bad	Very good	Very good	More or less good	More or less good	Very good	Very good	Very good
2	Very bad	Very good	Very good	More or less good	More or less good	Very good	Very good	Very good
3	Very bad	Good	Very good	Good	Very good	More or less good	Good	Very good
4	Very bad	Good	Very good	More or less good	Good	More or less good	Good	Very good
5	Very bad	Good	Very good	Good	Very good	More or less good	Good	Very good
6	Very bad	Very good	Very good	Good	Good	Very good	Very good	Very good
8	Very bad	Very good	Very good	Good	Good	Very good	Very good	Very good
10	Very bad	Very good	Very good	Good	Good	Very good	Very good	Very good
13	Very bad	Bad	Very good	More or less bad	Very good	Bad	Good	Very good
14	Very bad	Bad	Very good	More or less bad	Very good	Bad	Good	Very good
15	Bad	Bad	Very good	Bad	Very good	Very bad	Bad	Very good
16	Bad	Bad	Very good	Bad	Very good	Very bad	Bad	Very good
17	Very bad	More or less good	Very good	Good	Very good	More or less good	Good	Very good
18	Very good	Good	Very good	Very bad	Very bad	Bad	Bad	Very good
19	Moderate	Very good	Very good	Very good	Very good	Very good	Very good	Very good
20	Very bad	Very good	Very good	Very good	Very good	Very good	Very good	Very good

Table 7. Mean ranking of scenarios from social impact analysis at SONGS (source: Diaz-Maurin and Ewing, 2020a).

Scenario	**All**	**Coalition 1**	**Coalition 2**	**Coalition 3**	**Coalition 4**
(1) Do nothing	8	8	8	7	1
(2) In-state interim storage	4	5	1	6	4
(3) Out-of-state interim storage	1	1	1	1	1
(4) In-state direct disposal	7	7	6	5	7
(5) Out-of-state direct disposal	5	3	6	1	7
(6) In-state interim storage and disposal	6	6	1	8	5
(7) In-state interim storage and out-of-state disposal	3	4	1	4	5
(8) Out-of-state interim storage and disposal	1	1	1	1	1

Note: Scenarios are ranked from 1 (most performing) to 8 (least performing). Tied scenarios are ranked with highest value of the concerned positions.

Figures

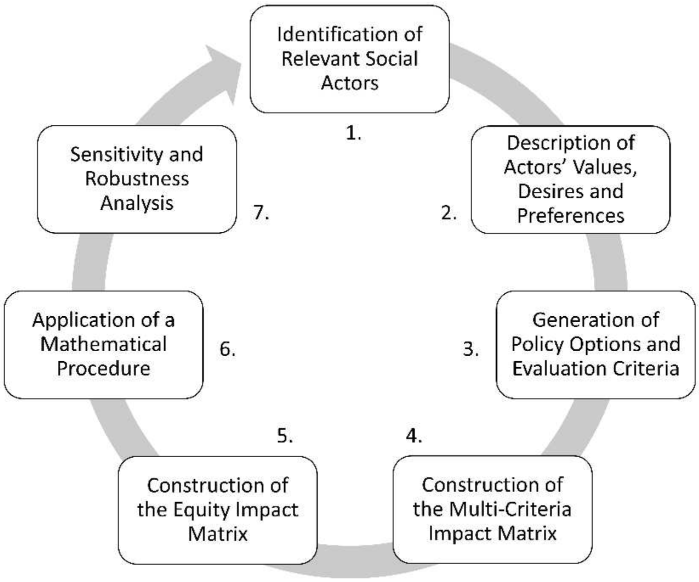

Fig. 1. Main steps of Munda's social multi-criteria evaluation process (adapted from Munda, 2009).

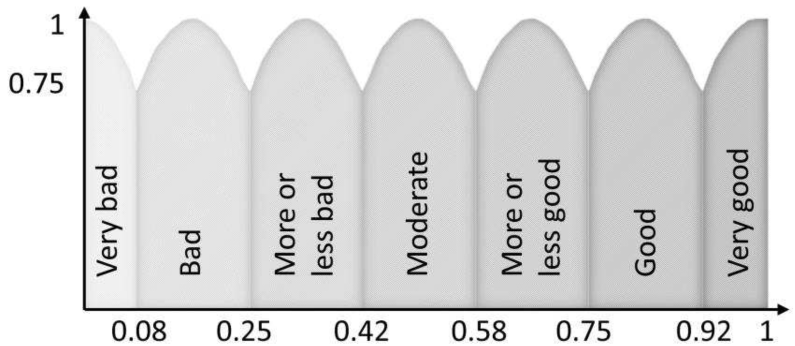

Fig. 2. Membership functions of the linguistic variables (adapted from Munda, 2009). Note: Each membership function assumes a standard deviation $\sigma = \frac{1}{6}$ so that fuzziness exists only between linguistic variables that are directly adjacent.

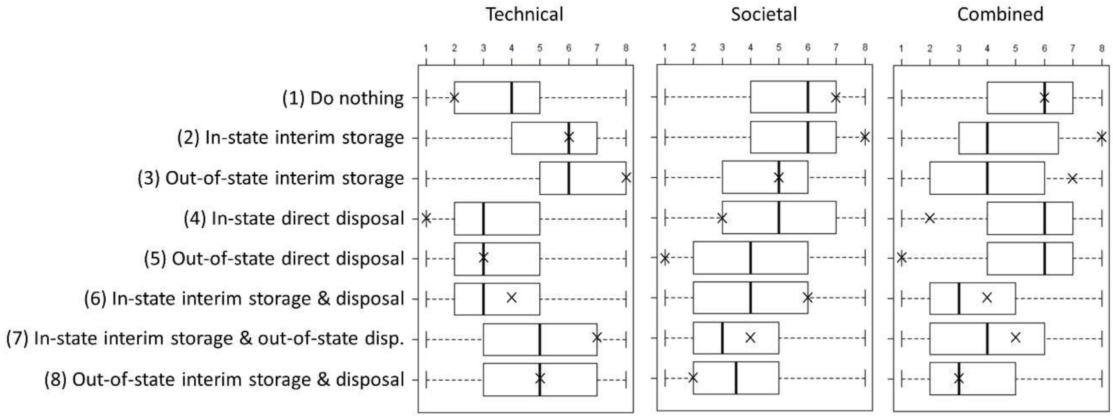

Fig. 3. Ranking of the scenarios at SONGS from the Monte Carlo simulation for 500 random samples. Note: Scenarios are ranked from 1 (highest performance) to 8 (lowest performance). The box contains points within the 25–75 percentile (Q1–Q3) range, dotted lines are points within 1.5 times the interquartile range (IQR), white circles (not shown in figure) are suspected outliers either 1.5xIQR or more above Q3 or 1.5xIQR or more below Q1, the black line is the median, and the cross is the mean value from **Table 5**.

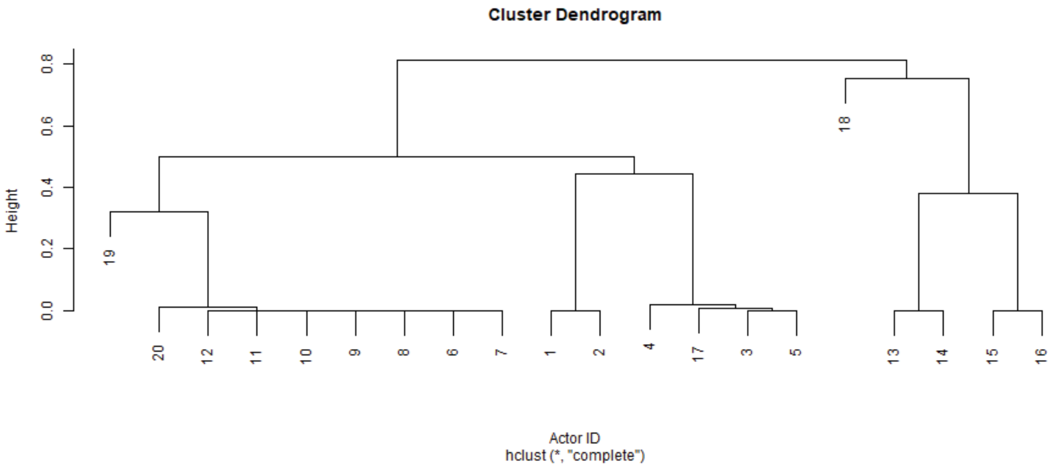

Fig. 4. Dendrogram of the coalition formation process at SONGS (source: Diaz-Maurin and Ewing, 2020a).

Appendix A. Supplementary Method

We review the different existing multi-criteria analysis techniques and discuss their previous applications to the nuclear waste management decision problem. We focus on their relevance to nuclear waste management from a social conflict resolution perspective. A detailed review of existing multi-criteria analysis techniques is available from the UK Department for Communities and Local Government (2009).

Using a comprehensive bibliometric database of over 30,000 scientific articles about nuclear waste management published during the 1979–2017 period (Diaz-Maurin et al., 2019), we could identify only very few papers applying multi-criteria analysis techniques in this area. This can be explained by the fact that nuclear waste management is mainly the responsibility of governments that generally do not publish their methods and results in the scientific literature.

Formally, nuclear waste management can be considered as a *discrete multi-criteria problem* for which a finite number of feasible options is known—from storage at reactor sites, to interim storage at another site and/or to disposal in a deep geologic repository. A multi-criteria approach to nuclear waste management will thus consist in ranking these feasible options based on a set of evaluation criteria. An alternative approach could be to frame nuclear waste management as a continuous decision problem with multiple objectives at once and no clear way of deciding which one should be the objective function and the rest be represented as constraints (DCLG, 2009). The main objective of such approach, called multiple objective decision-making (MODM), thus is the search for *efficient* solutions. In practice, like with MAUT, this technique consists of maximizing the decision maker's overall goal (objective) as a function of the decision variables while this objective function is limited by the other functional constraints characterizing the operating environment. Yet, MODM methods, like standard MCDA techniques searching for *optimal* solutions, focus on the perspectives of the decision-makers; thus, they exclude from the analysis the concept of social actor that is crucial in nuclear waste management decision problems. We exclude continuous multi-criteria analysis methods. We also exclude from this review other standard multi-criteria analysis techniques, such as non-compensatory direct estimation methods and linear additive models, that do not address decision problems from a social conflict resolution perspective involving multiple actors (Section **4.2**).

A.1. Discrete multi-criteria analysis techniques

Among the main techniques proposed to solve a discrete multi-criteria problem, the multi-attribute utility (or value) theory (MAUT) and outranking methods have been the most popular (Greco and Munda, 2017). MAUT methods seek to determine a utility (or value) function defined on the set of feasible alternatives and, then, to maximize this function (Keeney and Raiffa, 1976; Keeney and von Winterfeldt, 1994; Merkhofer and Keeney, 1987). To be operational, the function maximization in MAUT must assume the complete compensation of criteria and dimensions. The compensation assumption requires the method to resolve any trade-off appearing between non-equivalent dimensions of analysis. Yet, in practice, trade-offs between criteria and dimensions cannot be easily determined due to the unavoidable incommensurability of values and ambiguity of preferences, particularly across different social actors. In social decisions, trade-offs must rather be negotiated between social actors and, *then*, translated by the analysts. In its simplest and most common analytical form, MAUT uses a linear aggregation rule. Among the applications of MAUT, the analytic hierarchy process (AHP) developed by Saaty

(1980) is the most popular. Concerns have been raised about the theoretical foundations of the AHP and some of its properties, especially regarding the problem of *rank reversal*. Rank reversal occurs when, by simply adding another option to the list of options being evaluated, the ranking of two other options, although unrelated to the new one, can be reversed (DCLG, 2009).

In contrast, outranking methods are based on the concept of *partial comparability*. Among the many methods available, ELECTRE (Roy, 1996) and PROMETHEE (Brans et al., 1986) are the most commonly used. Outranking methods consist in comparing criteria by means of partial binary relations based on indexes of concordance/discordance and then to aggregate these relations (Greco and Munda, 2017). Several approaches exist to generate and treat outranking relations depending on the type of decision problem at hand. Outranking methods also differ about the type of data inputs they can use; either quantitative, qualitative—precise or imprecise—or mixed data (DCLG, 2009). Among available outranking methods for environmental management and policy, the NAIADE method originally developed by Munda (1995) is of particular relevance to the nuclear waste management decision problem. NAIADE uses an impact matrix that may include crisp, stochastic or fuzzy measurements of the performance of an alternative with respect to an evaluation criterion (Greco and Munda, 2017). The STMCE approach presented in this paper extends the original NAIADE method (Munda, 1995) for the aggregation convention and Munda's more recent work (Munda, 2012) that introduces weights as importance coefficients both for criteria and social groups. The main issue with outranking methods concerns its dependence on the arbitrary definitions of what precisely constitutes outranking and how the threshold values are set can be manipulated by the decision makers (DCLG, 2009). To address this issue, the social multi-criteria evaluation process—and by extension the STMCE method presented in this paper—must include the participation of concerned socio-technical actors in the problem framing, the selection of alternatives, criteria and threshold values, as well as for the assessment of the social impact of each alternative.

A.2. Previous applications

We now discuss previous applications of discrete multi-criteria analysis methods to nuclear waste management issues in the United States and in other countries, as summarized in **Table A.1**.

Applications using MAUT methods

In 1982, Saaty published a study applying his newly developed AHP method to the comparison of different high-level nuclear waste disposal concepts proposed by the U.S. DOE (Saaty and Gholamnezhad, 1982). As this application was made from the sole perspective of the U.S. DOE, it allowed the analysts to assume the complete compensation of the performance of health, safety, and environmental impacts with costs and political considerations. Moreover, they also assigned weights to each disposal strategy considered in order to translate the priorities and preferences of DOE. The analysis concluded on geological disposal being the best alternative available over, in decreasing order of performance, space disposal, very deep borehole disposal, island disposal, and sub-seabed disposal. As deep, mined geologic repositories was considered by the scientific community as the best technical solution for the disposal of radioactive materials since the late 1950s (National Research Council, 1957), it is not clear whether this application had any impact on the U.S. waste disposal strategy. This example shows that, to be effective, the MAUT approach requires that trade-offs can be decided upon *internally*. This may be the case of entrepreneurial or technocratic decisions for which a decision-maker can be clearly identified and will take responsibility for the decision outcome; but it will hardly be the case in environmental management and public policy affected by social, political and legal conflicts, such as commercial spent fuel management in the United States.

A few years later, in 1985, with many sites under consideration for a geologic repository, the U.S. DOE performed a multi-attribute utility analysis (MUA) to rank sites (US DOE, 1986). DOE's MUA method was a direct application of the MAUT approach. After reviewing a draft of the MUA method, the National Research Council's Board on Radioactive Waste Management (BRWM) emphasized that the MUA methodology would be best applied only as a decision-aiding tool complemented by additional factors and judgements before making a final decision about what sites to characterize through a performance assessment (US NWTRB, 2015). The BRWM eventually considered the approach appropriate to integrate technical, economic, environmental, socioeconomic, and health and safety issues, despite stating that it had not reviewed the data and judgments on which the conclusions of the MUA would be based. A technical critique of DOE's MUA method was eventually published that listed limitations typical of multi-criteria analysis methods (Merkhofer and Keeney, 1987) and that Keeney and von Winterfeldt (1994) attempted to resolve in a refined MUA methodology.

Following the BRWM review, DOE then applied its proposed MUA method to compare five sites—three salt sites, the Hanford site in Washington state and the Yucca Mountain site in Nevada. These sites were evaluated against pre- and post-closure performance outcomes. After applying a composite aggregation, the MUA method ranked the Yucca Mountain site first, followed by the three salt sites, and then, lagging behind, by the Hanford site (US DOE, 1986). The Secretary of Energy then recommended President Reagan to select three sites for in-depth characterization, including the Hanford site. Yet, as the debate moved to political and legal grounds, the Secretary recommendations were challenged in Congress. At one instance, a Committee investigation found that DOE had modified the weighting on the various components—effectively assigning low weighting to post-closure safety—which the Committee interpreted as supporting the selection of the Hanford site over the three salt sites. Members of Congress insisted that the decision to select a geologic repository shall be based on the soundest scientific and technical judgments possible, to which the DOE responded that the MUA method was by no means capable of providing "scientific evidence" that would somehow be devoid of "judgment" (US NWTRB, 2015). In this view, DOE did not have to necessarily select the top-ranked sites identified by the MUA.

The multi-attribute evaluation process carried out by DOE in 1985-86 was only a step in a lengthy site selection process that, as it turned out, was subsequently replaced by the 1987 Nuclear Waste Policy Act Amendments, which narrowed the scope of DOE's investigation to a single site, Yucca Mountain in Nevada. Yet, it reveals the different possible interpretations about the role of a multi-criteria analysis in a decision-making process. This example illustrates the importance of being explicit—and transparent—about the purpose of a multi-criteria analysis rather than focusing on developing a sophisticated method.

Applications using outranking methods

In the 1990s, with the development of outranking methods in Europe, the PROMETHEE and ORESTE methods were applied to nuclear waste management. The first application by Briggs and colleagues (1990) treated the full nuclear waste management process (interim storage, transport and geologic disposal) for all types of radioactive waste materials (LLW/ILW, HLW and SNF). However, the method focused only on the financing methods as a mean to rank sites, without an assessment of their technical suitability. Moreover, because PROMETHEE methods are based on a complete compensation assumption (**Table 1**), the authors acknowledged that different alternatives could only be assessed against a small number of strongly conflicting criteria, because otherwise too many trade-offs would be introduced in the analysis. In a second application, Delhaye and co-workers (1991) proposed the ORESTE method as an alternative to PROMETHEE but it is essentially the same as the first application (both papers have one author in common) and focuses on the financing of nuclear waste management options. The third application by Petraš (1997) focused on the selection of sites for the surface disposal facilities of low- and intermediate-level nuclear waste (LLW/ILW); hence it does not include interim storage and *geologic* disposal. As LLW and ILW represent larger volumes as compared with high-level waste (HLW) and spent nuclear fuel (SNF), the study was performed from a land use management perspective; hence not from a social conflict resolution approach.

Applications using other methods

In their conceptual study, Atherton and French (1998) proposed a discounted utility theory (DUT) approach as a way to address long-term nuclear waste management. The DUT method is a normative discounting model to account for the value of the decision maker's relationship to the different time frames. Such approach that deals with multiple time periods thus seems particularly relevant to nuclear waste management requiring to make decisions with consequences over long periods of time—from decades for interim storage to thousands of years for geologic disposal. However, the major problem with this approach is that it is impossible—at least very difficult—to make a judgement about the values of future generations and, especially, how to deal with the trade-offs between present values and future outcomes. This approach, that focuses on maximizing utility, thus faces issues of inter- and intra-generational ethics about how to treat technological risk and duties to future generations (Shrader-Frechette, 2000).

More recently, Morton and colleagues (2009) reviewed the multi-criteria decision analysis of different management options by the UK's Committee on radioactive waste management (CoRWM). In the process of defining its MCDA method, CoRWM found itself focusing on the trade-off between flexibility and burden of ongoing maintenance of storage. This trade-off between short-term and long-term objectives is a common issue in nuclear waste management. Yet, in the case of CoRWM, it is unclear whether and how it resolved the problem of trade-offs—a crucial issue for any MCDA. As it appears, the CoRWM decision analysis experience, so far, focused on discussing the role option assessment using MCDA approach should have in decision process, but did not get to the point of applying or developing such methods (Morton et al., 2009).

In parallel, Xu (2009) proposed a different method that is based on the evidential reasoning (ER) decision approach to assess two potential repository options for low- and medium-level short-lived waste in Belgium. Yet, like MAUT methods, the ER decision approach searches for the maximization of a utility function for each criterion and then performs a linear weighted aggregation of these functions. As such, the ER approach implies a total linear compensation among criteria that is not a desirable property in social multi-criteria evaluation (**Table 1**).

Finally, most recently, Schwenk-Ferrero and Andrianov (2017) proposed a MCDA framework for the comparison of nuclear waste management strategies based on a hierarchical objective structure. The authors reviewed different MCDA methods (such as MAVT/MAUT, AHP, TOPSIS, PROMETHEE) and selected the MAVT approach as their reference method for their application thus applying weights as tradeoffs between the criteria. As explained, MAVT is not an appropriate approach for the comparison of nuclear waste management strategies from a social multi-criteria evaluation perspective.

References

Atherton, E., French, S., 1998. Valuing the future: a MADA example involving nuclear waste storage. Journal of Multi-Criteria Decision Analysis 7, 304–321. https://doi.org/10.1002/(SICI)1099-1360(199811)7:6<304::AID-MCDA225>3.0.CO;2-0

Brans, J.P., Vincke, Ph., Mareschal, B., 1986. How to select and how to rank projects: The PROMETHEE method. European Journal of Operational Research, Mathematical Programming Multiple Criteria Decision Making 24, 228–238. https://doi.org/10.1016/0377-2217(86)90044-5

Briggs, Th., Kunsch, P.L., Mareschal, B., 1990. Nuclear waste management: An application of the multicriteria PROMETHEE methods. European Journal of Operational Research 44, 1–10. https://doi.org/10.1016/0377-2217(90)90308-X

DCLG, 2009. Multi-criteria analysis: a manual. UK Department for Communities and Local Government, London, UK.

Delhaye, C., Teghem, J., Kunsch, P., 1991. Application of the ORESTE method to a nuclear waste management problem. International Journal of Production Economics 24, 29–39. https://doi.org/10.1016/0925-5273(91)90150-R

Diaz-Maurin, F., Sun, H.C., Yu, J., Ewing, R.C., 2019. Evolution and Structure of the Scientific Basis for Nuclear Waste Management. MRS Advances 4, 959–964. https://doi.org/10.1557/adv.2018.636

Greco, S., Munda, G., 2017. Multiple criteria evaluation in environmental policy analysis, in: Spash, C.L. (Ed.), Routledge Handbook of Ecological Economics. Routledge, pp. 311–320.

Keeney, R.L., Raiffa, H., 1976. Decisions with multiple objectives: preferences and value trade-offs. Wiley New York.

Keeney, R.L., von Winterfeldt, D., 1994. Managing Nuclear Waste from Power Plants. Risk Analysis 14, 107–130. https://doi.org/10.1111/j.1539-6924.1994.tb00033.x
Merkhofer, M.W., Keeney, R.L., 1987. A Multiattribute Utility Analysis of Alternative Sites for the Disposal of Nuclear Waste. Risk Analysis 7, 173–194. https://doi.org/10.1111/j.1539-6924.1987.tb00981.x
Morton, A., Airoldi, M., Phillips, L.D., 2009. Nuclear Risk Management on Stage: A Decision Analysis Perspective on the UK's Committee on Radioactive Waste Management. Risk Analysis 29, 764–779. https://doi.org/10.1111/j.1539-6924.2008.01192.x
Munda, G., 2012. Intensity of preference and related uncertainty in non-compensatory aggregation rules. Theory Decis 73, 649–669. https://doi.org/10.1007/s11238-012-9317-4
Munda, G., 1995. Multicriteria Evaluation in a Fuzzy Environment: Theory and Applications in Ecological Economics, Contributions to Economics. Physica-Verlag Heidelberg.
National Research Council, 1957. The Disposal of Radioactive Waste on Land. The National Academies Press, Washington, DC. https://doi.org/10.17226/2345
Petraš, J.C.E., 1997. Ranking the Sites for Low- and Intermediate-Level Radioactive Waste Disposal Facilities in Croatia. International Transactions in Operational Research 4, 237–249. https://doi.org/10.1111/j.1475-3995.1997.tb00080.x
Roy, B., 1996. Multicriteria Methodology for Decision Aiding, Nonconvex Optimization and Its Applications. Springer Science & Business Media.
Saaty, T.L., 1980. The analytic hierarchy process. McGraw Hill, New York.
Saaty, T.L., Gholamnezhad, H., 1982. High-Level Nuclear Waste Management: Analysis of Options. Environ Plann B Plann Des 9, 181–196. https://doi.org/10.1068/b090181
Schwenk-Ferrero, A., Andrianov, A., 2017. Nuclear Waste Management Decision-Making Support with MCDA. Science and Technology of Nuclear Installations 2017, 20. https://doi.org/10.1155/2017/9029406
Shrader-Frechette, K., 2000. Duties to future generations, proxy consent, intra-and intergenerational equity: The case of nuclear waste. Risk Anal 20, 771–778.
US DOE, 1986. A Multiattribute Utility Analysis of Sites Nominated for Characterization for the First Radioactive-Waste Repository: A Decision-Aiding Methodology (No. DOE/RW-0074). Washington, DC.
US NWTRB, 2015. Designing a Process for Selecting a Site for a Deep-Mined, Geologic Repository for High-Level Radioactive Waste and Spent Nuclear Fuel - Detailed Analysis. United States Nuclear Waste Technical Review Board, Arlington, VA.
Xu, D.-L., 2009. Assessment of nuclear waste repository options using the ER approach. Int. J. Info. Tech. Dec. Mak. 08, 581–607. https://doi.org/10.1142/S021962200900351X

Table A.1. Comparison of previous applications of multi-criteria analysis methods for nuclear waste management.
Abbreviations used: AHP, analytic hierarchy process; card., cardinal; deter., deterministic; CoRWM, UK's Committee on radioactive waste management; DUT, discounted utility theory; ER, evidential reasoning; fuz., fuzzy; HLW, high-level waste; ILW, intermediate-level waste; LLW, low-level waste; MAUT, multi-attribute utility theory; MAVT, multi-attribute value theory; MCDA, multi-criteria decision analysis; MUA, multi-attribute utility analysis; ord., ordinal; SNF, spent nuclear fuel; STMCE, socio-technical multi-criteria evaluation; unspec., unspecified.

Reference	**Country**	**Level**	**Process**	**Waste type**	**Social actors**	**Method**	**Linear compensation effect**	**Type of aggregation**	**Type of preferential information**
Saaty and Gholamnezhad (1982)	USA	National	Disposal	HLW/SNF	No	AHP	Partial	Single criterion	Deter., card., non-deter.
U.S. Department of Energy (1986)	USA	National	Disposal	HLW/SNF	Ad hoc	MUA	Partial	Single criterion	Deter., ord.
Briggs et al. (1990)	unspec.	National	Storage, disposal	LLW/ILW, HLW/SNF	No	PROMETHEE	Partial	Outranking	Deter., card., ord.
Delhaye et al. (1991)	unspec.	National	unspec.	unspec.	No	ORESTE	Partial	Outranking	Deter., ord.
Keeney and von Winterfeldt (1994)	USA	National	Disposal	HLW/SNF	No	MUA	Partial	Single criterion	Deter., ord.
Petraš (1997)	Croatia	National	Disposal	LLW/ILW	No	PROMETHEE	Partial	Outranking	Deter., card., ord.
Atherton and French (1998)	UK	National	Storage, disposal	unspec.	No	DUT	Partial	Single criterion	Deter., ord.
CoRWM in Morton et al. (2009)	UK	National	Storage, disposal	LLW/ILW, HLW/SNF	Ad hoc	unspec.	unspec.	unspec	unspec.
Xu (2009)	Belgium	National	Disposal	LLW/ILW	Yes	ER	Total	Single criterion	Deter., card., non-deter., ord.
Schwenk-Ferrero and Andrianov (2017)	unspec.	Local, multi-national, regional	Storage, disposal	HLW/SNF	Ad hoc	MAVT	Partial	Single criterion	Deter., ord.
Diaz-Maurin et al. (2020)—this paper	USA	Local, state, regional	Storage, disposal	HLW/SNF	Yes	STMCE	Partial	Outranking	Deter., card., non-deter., ord., fuz.