Use of Multi-Criteria Decision Analysis for Energy Planning

By

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A thesis submitted

in partial fulfillment of the requirements

for the degree of

Master of Science

(Natural Resources and Environment)

at the University of Michigan

May 2015

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ABSTRACT

This paper uses a Multi-Criteria Decision Analysis (MCDA) to examine tradeoffs in electricity generation technologies on the basis of cost, greenhouse gas emissions, water consumption, and land use. Using a life cycle basis, the analysis compares electricity produced from coal, natural gas, nuclear energy, hydropower, solar energy via photovoltaics, solar energy via concentrating solar technology, onshore wind, offshore wind, geothermal energy and biomass. Attributional life-cycle analysis values for overall water consumption and greenhouse gas emissions associated with each generation technology are used, along with the levelized cost of electricity and levelized avoided cost of electricity' as metrics for cost, and generation weighted land-use efficiency values for evaluation of land-footprint. Two objective scoring methods are used to determine whether scoring methodology influences the results of the MCDA. The results are consistent under the two scoring schemes, indicating that the results are robust to different objective methods of evaluation under an MCDA framework. Different weighting alternatives for determining the relative importance of the four objective functions are also considered to determine the sensitivity of the results to stakeholder preferences. If a heavy emphasis was given to costs, geothermal energy tends to dominate because of its lowest levelized cost of electricity. On the other hand, when a low weights is given to costs, wind power and nuclear energy emerge superior under a number of weighting schemes. Lastly, the results from the MCDA methods are compared to a Benefit Cost Analysis (BCA) to test for consistency, and it is found that the optimal solutions are different under the latter due to the high weights that are implicitly given to costs under a BCA. Even after a price on greenhouse gas emissions is factored into the BCA, it favors the technologies with a low levelized cost over ones that have lower greenhouse gas emissions, demonstrating that an MCDA is better at explicitly recognizing tradeoffs and incorporating stakeholder preferences into decision making. Thus, the suitability of MCDA for making more informed, context specific decisions is discussed, and the merits offered by an MCDA in contrast to a BCA are presented.

ACKNOWLEDGEMENTS

I would like to sincerely thank my advisers Dr. Shelie Miller, and Dr. Jeremiah Johnson.

Shelie has been a great adviser, and I appreciate her constant guidance and support throughout the thesis. I have learned a lot, both from her course, as well as through my interactions with her over the last two years.

Jeremiah, with his tremendous knowledge when it comes to power systems, has also been very helpful, and has given me invaluable inputs that have helped guide the thesis.

I would also like to thank Dr. Greg Keoleian; a lot of the knowledge about energy systems applied in this thesis has been through my learning in the course on energy systems offered by him.

This thesis is a part of a larger project REFRESCH (Researching Fresh Solutions to the Energy/Water/Food Challenge in Resource Constrained Environments), and has been funded by the REFRESCH team, interactions with which have greatly helped me grow my awareness of water-energy issues.

Contents

1. INTRODUCTION

This paper uses a Multi-Criteria Decision Analysis (MCDA) approach to carry out an evaluation of the various generation technologies that could be potentially used for fulfilling the growing needs of the power sector based on different criteria that are important to consider when making energy planning decisions. Generation from coal, natural gas, nuclear energy, hydropower, solar energy (photovoltaics as well as concentrating solar power), wind (onshore and offshore), geothermal energy and biomass is compared. The criteria considered are- minimization of system costs, water footprint, carbon dioxide equivalent emissions, and land intensity of the chosen energy technology. There are studies on the water-energy nexus in the context of the electricity generation sector that have examined the effect of a carbon price on water consumption by the power sector in the US, and indicated that the water consumption may increase due to the incentives to shift to hydro and nuclear generation, as well as due to the incorporation of carbon capture and storage technologies, all of which are water intensive.[1] There has also been extensive research on the water-energy nexus, especially in the context of the wastewater sector and evaluation of energy use in the water sector, as well as on the energy sector's carbon dioxide emissions independently. However, most of the research has focused on evaluating the impacts of a certain energy generation portfolio scenarios on the water sector, rather than using the impacts as a metric to aid decision making. In this paper, we aim to look at the suitability of an MCDA approach to make more informed decisions, rather than evaluate the impacts of different decisions that are made solely on the basis of economics. There is no study optimizing the life cycle water consumption, emissions, as well as land use of new generation, along with costs from a big picture perspective, and that is the question this paper aims to answer.

1.1. Tradeoffs associated with Energy Planning Decisions:

Costs are an important factor in energy planning. To compare the various options for power generation that could be used to meet increasing energy needs, the associated costs of energy generation are attempted to be minimized using their 'Levelized Cost of Electricity', in combination with their 'Levelized Avoided Cost of Electricity', where possible.

Water and energy are intricately interrelated because of the utilization of energy for the water sector, and also the indispensable role of water in the energy sector. Even though the dependence of these sectors on each other has been recognized, there haven't been any widespread coherent policies that take into account the impact of one sector on another while making decisions.[2]

Water use in the energy sector may occur during different stages, such as extraction and processing of resource fuel, as would be in case of coal, or even during operations and maintenance, as would be common in the case of consumption attributed to renewable energy generation technologies. Water footprint of the power sector depends on several factors including, but not limited to, the fuel mix of the chosen generation fleet, the type of power plant in question, as well as the physical characteristics such as the water stress in the region the plant is located.[3]

The inter-dependencies between water and energy are well established in the United States, and different steps have been taken to address the same, such as the creation of a 'Water-Energy-Technology-Team' by the Department of Energy,[4] and the introduction of a bill in the U.S.Senate related to this issue.[5]

In addition to having a large water footprint, the power sector is a major emitter of greenhouse gas emissions, which are the main drivers of climate change, and play a role in influencing the hydrological cycle, thereby giving us another consideration closely tied to the water-energy nexus that could be used for energy planning.[6] With a changing regulatory landscape requiring reduction of greenhouse gas emissions, it becomes important to factor minimization of the emissions footprint of chosen electricity generation technologies for energy planning decisions in the power sector. This study attempts to capture the importance of the emissions profile of electricity generation by having ‘reduction of greenhouse gas emissions’ as one of the objectives.

Production of electricity requires land to be dedicated for generation. This can have implications for emissions if the land developed for power is by destruction of forests. It can also have an impact on species that have that land as a habitat. Land footprint of power generating technologies can also be a concern in geographically constrained regions. Thus, factoring in land use of the different electricity generation technologies is important while making energy planning decisions.

1.2. Multi-Criteria Decision Analysis Framework:

For the purpose of this research, the energy-water nexus in the electricity generation sector is studied, along with the carbon emissions, land use, and economic metrics that may factor into electricity expansion decisions. Given this context, an MCDA seems to be a suitable tool for the analysis of the tradeoffs associated with each generation technology.

The criteria used in this study are important considerations for the power sector, when looking at California’s 15-year drought as a case in point. Historically, hydropower has been the primary source of clean and renewable energy in California.[7] Hydroelectric power generation in California peaked in the 1950s,[8] but has declined in prominence over the past half century due to falling water levels with hydropower production accounting for only 9 percent of statewide electricity generation in 2013.[9] Much of this decline is due to drought, and highlights how electricity generation is closely tied to water availability. These dry conditions not only limit hydropower generation, requiring generation from other sources to make up for the shortfall, but also result in increasing electricity demand as increasingly hot temperatures are recorded during the summer, setting new peak demand records.[10] The limited availability of hydropower is forcing some utilities to buy back-up generation in the form of natural gas, putting the ability of regulated entities to meet the state's renewable portfolio standard at risk. California set an accelerated renewable portfolio standard in 2011, which requires investor-owned utilities, electric service providers, and community choice aggregators to procure 33 percent of their energy from renewable sources by 2020. CO_2 emissions from power generation, which had been falling steadily over 2007-2011, now appear to be rising as a result of the lack of hydroelectric power, according to the state's Air Resources Board.[11] This brings to light the link between carbon dioxide, water availability and power generation, and is part of the rationale behind this study, that aims to look at the entire system, instead of individual criterion for optimization.

With renewables being increasingly suggested as energy options to be pursued for reduction in emissions as well as water-footprint when compared to conventional generation sources, there is concern about some of the issues associated with renewable energy, such as their higher land footprint compared to conventional generation alternatives. To capture that, minimization of the land footprint of the chosen energy mix is one of the objectives considered in this study.

Multi-criteria decision analysis (MCDA) methods are extremely valuable, especially in the case of decision making for sustainable energy, because of their ability to incorporate multiple criteria that aren’t restricted to economics alone.[12] Compared to previously used single criteria approaches aimed at identifying the most efficient options at a low cost, MCDA gives us the opportunity to factor in environmental concerns such as water stress, land-use, and carbon dioxide emissions, which are a part of the objectives of this study, to obtain an integrated decision making solution.[13]

The MCDA method has already been used successfully in the areas of renewable energy planning and resource allocation when it comes to dissemination of various energy options, electric utility planning, and planning for different energy projects, as evidenced by literature.[14] Wimmler et al[15] have given an exhaustive list of the different cases where MCDA has been used to make decisions related to energy planning. The paper shows different methods like the Analytical Hierarchy Process, MAUT, MACBETH, PROMETHEE and others have been used for many different contexts, and no method seems to dominate.[16]

The Multi-Criteria Decision Analysis approach used in this study falls under the broad category of 'Compensatory Methods', which implies that tradeoffs between different performance parameters are allowed.[17] Under that broad category, this paper uses a 'Simple Additive Weighted Model' to evaluate different technology options considered relative to each other. Mathematically, this can be summarized as:

Equation 1:

$$S(a) = \sum_{i=1}^{m} w_i \, s_i(a)$$

where w_i is the weight assigned to criteria 'i', and $s_i(a)$ is a partial score function that is representative of the performance of option 'a' for the same criteria 'i'.[18] *S(a)* may be either maximized or minimized depending on whether the chosen scoring method is structured to make high or low values preferable. The score function is an objective measure of how an alternative performs with respect to each criterion. The weight factor is a subjective measure that indicates the relative value of each criterion in an overall decision. Weights depend on stakeholder values and may vary across individuals, regions, situations, and time. Hence, the weights as well as the scores will determine the overall performance of the different technologies considered for energy generation. There are multiple methods that can be used to calculate scores. This paper examines two scoring methods to determine whether different scoring methods yield similar results.

Weights are determined by the decision maker's preferences based on value judgments. For instance, if a decision maker cares deeply about carbon-dioxide reductions, they would lay a heavy weight on the corresponding objective. Alternatively, in an arid region facing water scarcity issues, minimization of water consumption within the region may be a priority. This paper focuses on the sensitivity of different methodological choices to the results of an MCDA of electricity generation. The paper explores ranges of weights that may lead to selection of different alternatives; however it does not use weights explicitly derived from stakeholders, as preferences are context-specific and require higher resolution data particular to a given decision.

The multi-objective optimization methods used in this study have been widely used in similar settings such as sustainability evaluation of power plants and determination of optimal renewable energy technologies' mix, which involve high investment costs, longer project durations accompanied by high uncertainty, and conflicting objectives.[19] MCDA can provide guidance to energy management questions due to its integrated operational evaluation and decision support approach, and hence seems suitable for the multi-objective optimization question this paper aims to answer.

The model developed in this study can be used to evaluate the tradeoffs involved with our energy choices, when it comes to their impacts on water, land, and emissions, as well as their overall costs. It primarily aims to study the different energy alternatives that come out to be superior if certain objectives are prioritized over the others, and helps in explicitly recognizing the tradeoffs involved with these choices.

This paper constructs a generic model that is intended to show how MCDA could be used to select a preferred technology for a marginal increase in electricity generation, given stakeholder preferences for cost, GHG emissions, land use, and water consumption. The performance of each technology is determined for each of these criteria, and objective scores are assigned to them using two calculation methods. A range of weighting schemes is applied to determine the effect different preferences have on the results. The results of the MCDA are compared to benefit-cost analysis to determine whether the two methods yield similar results.

2. MATERIALS AND METHODS

Using a Multi-Criteria Decision Analysis framework described earlier, a constrained optimization is carried out for the four objective functions of cost minimization, water-consumption minimization, carbon dioxide equivalent emissions minimization, and the minimization of land intensity of power generation. Rather than making specific recommendations about individual electricity generation options, the purpose of this paper is to examine the robustness of MCDA, determining whether different methodological choices yield similar results. The model represents a generic model using U.S. average data; it would need to be tailored to specific regions by using geographically explicit data and constraints associated with the specific system. For example, data regarding costs and capacity factors of renewable energy technologies are highly variable and need to be tailored to be representative of the specific decision-making context. Similarly, geothermal is included within the analysis, but may not be a viable technology alternative for most regions.

While comparing the alternative technologies for power generation, there is no distinction made among the resources in terms of their dispatchability, variability, and provision of ancillary services to the grid. Ancillary services are support services in the power system needed for power quality, reliability, and security,[20] and conventional generation is expected to be different in terms of these services offered to the grid when compared to renewable generation.

Hence, it is possible to have wind power as superior for meeting the objectives considered in the study, but it might not be feasible to meet all the new power requirements by wind alone despite its abundance due to the constraints of the system. Although some aspects of the variability of renewable energy resources is captured in the metrics used for costs associated with these technologies, as is the case with LACE incorporating the capacity value of each resource, the treatment of all forms of generation in terms of their power availability is a simplification used in this paper.

“A set of solutions in a MCDA problem is Pareto efficient (also called non-dominated), if their elements are feasible solutions such that no other feasible solution can achieve the same or better performance for all the criteria being strictly better for at least one criterion. This is a necessary condition to guarantee the rationality of any solution to an MCDA problem.”[21] A Pareto or tradeoff frontier in the context of this analysis is a set of technologies such that among those technologies, improvements in any objective are not possible without compromises in other objectives by a change in choice of technology. In this study, the Pareto frontier is comprised of Geothermal energy, which has the lowest cost, nuclear energy, which has the lowest land footprint, and wind energy, which corresponds to the smallest life cycle emissions as well as water consumption value. These three technologies are also referred to as ‘non-inferior’ technologies.

The details of the approach are described in the following sections.

2.1. System Framework Under An MCDA Approach:

2.1.1. System Variables:

Ten electricity generation technologies are chosen for this analysis. Decision variables are defined as the amount of electricity generated from coal (E_c), natural gas, (E_{ng}), solar PV (E_{spv}), concentrated solar power (E_{scsp}), onshore wind (E_{onw}), offshore wind (E_{offw}), nuclear (E_{nuc}), hydropower (E_{hyd}), geothermal (E_{geo}), and biopower (E_{bio}). The assumption made is that the generation from any of the technologies is not large enough to change the overall LCOE-LACE value for the technology, which might be true for renewable energy technologies with high levels of penetration.

2.1.2. Criteria Considered Under The MCDA Framework:

The grand objective function is calculated as a weighted scored sum of the individual objective functions of water stress minimization, carbon dioxide minimization, costs minimization, and land intensity minimization as follows, by using equation 1 for the 4-objective system used in this study.

The individual objective functions, and the scoring and weighting schemes used to transform them into the grand objective function are explained in more detail in the subsequent sections.

There are multiple objectives that are considered to determine the best energy pathway, namely:

2.1.2.1. Minimizing costs associated with the implementation of the proposed system

Objective Z1:

Levelized cost of electricity (LCOE) is a convenient way of contrasting between power generation options, and reflects the costs associated with building a new power plant of a given type, financing costs, its fixed as well as variable operation and maintenance costs, fuel costs, and the capacity factor of the plant.[22] It can be thought of as the revenue required to make a project under consideration viable. However, the LCOE does not take into account important considerations such as the capacity value of new generation, the existing resource mix of the region under consideration, as well as the projected utilization rate of the proposed new generation.[23] In order to capture the economic benefit of a new generation project to the system, the 'Levelized Avoided Cost of Electricity' (LACE) can be used in combination with the LCOE to give an idea of the net economic benefit from a proposed project.[24] A sensitivity analysis is carried out to test for the impact of using just LCOE versus LCOE-LACE as a metric on the results. The technology rankings do not change with or without the inclusion of LACE, as will be seen in the subsequent sections.
Even though there is significant variation in LCOEs and LACEs by region, in this paper we focus only on the broad level average cost comparisons at the country scale for the US by using average $/MWh data. Using the average LCOE and LACE values provided by the EIA, and the differences between them as metrics to reflect costs of electricity of various generation technologies, the objective function for cost minimization is (ignoring subsidies for the purpose of the analysis). LACE varies according to the existing technology within the electricity portfolio; therefore, the values obtained from the analysis can only be applied to the next marginal increase in generation. Beyond marginal increases in electricity generation, the model will need to take into account the system dynamics associated with a changing LACE factor.

2.1.2.2. Minimizing the life-cycle water footprint

Objective Z2:

In order to minimize water stress, the water footprint of various electricity generation technologies is used to calculate the life-cycle water consumption associated with each technology. Data provided by Meldrum at al[25] is used. Most of the water consumption in power generation comes from power plant cooling, with thermoelectric power plant cooling responsible for 3-4% of all U.S. water consumption, owing to the water intensive closed-loop cooling systems (also known as wetcooling system) predominantly in use.[26] Water use in electricity generation is either due to water withdrawal or consumption, wherein withdrawal involves returning the water to its source, while consumptive water use is where the water is transformed into an unusable state, and does not become a part of the water cycle of the region in question.[27] In this paper, we only look at the consumptive use of water for electricity generation.

The Meldrum et al study reports water use across different stages encompassing everything from component manufacturing, fuel cycle that involves various sub-stages like refining and transport, as well as the water use in power plant operation and decommissioning, with a sensitivity analyses for the assumptions made about different parameters such as heat rates and efficiency.[28] This dataset is chosen because it seems to be the most recent review paper that harmonizes consolidated data from different primary estimates of water use in electricity generation in the United States in existing literature.[29]

The values for the lifecycle water footprint of biopower and hydropower are not given in this paper, due to the wide range of estimates in literature for water use in both those cases, and the difficulty with harmonizing those.[30] To arrive at numbers for those two cases, separate estimates from other sources are used.

Due to lack of data available regarding life cycle water consumption of hydropower, operational water consumption is used, as it comprises the majority of the life cycle water consumption for hydropower[31].

Most of the water consumption for hydropower comes from evaporative losses from the reservoir, and because the reservoir is used for purposes other than just electricity generation, there is debate about whether all of it should be attributed to electricity generation.[32] However, consistent with the data available, for the purpose of this study, we used the US average for the consumptive use of hydropower, which assumes that the evaporative losses from the reservoir are due to the primary aim of electricity generation from it.

Similarly, for biopower, there is a large variation in literature estimates. The water consumption associated with the generation of electricity from biomass can vary based on whether hybrid poplar, maize, sugar beet or soybean is used, as well as whether the crop is assumed to be rain fed or irrigated.[33] Biopower water consumption can also be very sensitive to the geography of the region the crop is being grown in, and dependent on the climatic factors of the agricultural area,[34] making it hard to arrive at a single representative number for its water consumption value.

For determining the water footprint of biopower facilities, a consumption value of 553 gal/MWh, as reviewed from 4 different sources in Macknick et al[35] is used. Like hydropower, only the operational water consumption associated with biomass is used, and does not take into account upstream water use. If that is factored in, the water consumption value for biomass would be higher. This then can be assumed to be the lower limit for consumptive water use of biopower.

While this study uses life cycle water consumption as the basis of analysis, decision makers may only be interested in water consumption specific to their region. In that case, the analysis can be tailored to include only region-specific water consumption that impacts local scarcity.

2.1.2.3. Minimizing the life-cycle greenhouse gas emissions

Objective Z3:

The Life-Cycle Analysis data published by the 'Intergovernmental Panel on Climate Change'[36] (publicly available at: http://en.openei.org/apps/LCA/) is used. The published report reviews and harmonizes data from more than 200 papers and harmonizes it to give estimates for lifecycle carbon dioxide equivalent footprint of each generation technology.[37] Even though there are some differences in estimates across different papers in literature estimating life-cycle emissions associated with different types of power generation, the overall ranking of technologies on a climate basis is broadly consistent for all except biopower. There is significant difficulty in establishing greenhouse gas emissions associated with biopower due to the wide variety of estimates in literature. While some crops such as switchgrass used for biopower production can be considered to have zero or negative net carbon dioxide emissions when planted in degraded agricultural lands,[38] there are other cases where significant emissions result due to land use changes that may occur.[39,40] The estimates published by the IPCC report are used for biopower in order to have consistency with the estimates for the other sources, even though land-use change emissions are not accounted for in the report,[41] acknowledging the wide range of estimates in literature and the difficulty with harmonizing and attributing land use change emissions to biopower.

2.1.2.4. Minimizing the land-intensity

Objective Z4:

Very few studies have quantified the life-cycle land use associated with all the generation technologies. It is very challenging to quantify life-cycle land use associated with electricity generation due to the large level of uncertainty involved.[42] Moreover, median and average values are unable to capture the distribution of the estimates, as is seen to be the case for evaluating the land-footprint associated with solar PV and solar CSP.[43] A report published by the IEA qualitatively estimates the potential land impacts of various generation technologies,[44] but it is hard to tell the relative ranking of the different technologies. Similarly, an NREL report quantifies the direct and indirect land impacts from solar PV and solar CSP, and shows that the value is higher for PV compared to CSP, but mentions that the categories have small sample sizes.[45] It is also relatively easier to quantify direct land impacts, as compared to indirect ones.[46] Therefore, for the purpose of this paper we only focus on the direct land impacts of electricity generation, due to the large variation involved in indirect impacts stemming from differences in boundaries, locations, as well as limited sample sizes. This simplification is assumed to be appropriate, as direct land footprint is most likely to be of concern to individual stakeholders.

For this paper, data published in McDonald et al[47] is used to determine the land footprint associated with each generation technology. The paper makes available the generation weighted land use efficiency for conventional as well as renewable energy generation technologies based on energy growth projections by EIA.[48] Fthenakis et al have also published a comprehensive life-cycle land use of electricity generation technologies,[49] and the order of technologies in terms of their land use efficiency remains broadly consistent with the data used for this paper. In their paper, there is large variation in estimates based on the location of the plant in question, highlighting how single values for land impacts of technologies are difficult to arrive it without information on the exact site being considered.

The actual full cycle land impacts of each technology will be higher than the ones used in this paper, and the values in this analysis could be considered to be the lower end of land impact estimates.

2.1.2.5. *Summary of generation technologies considered. The median value is used in calculations. The range is given in parentheses below*

(Refer to Appendix A for more detail)

Table 1 - Summary of associated costs, greenhouse gas emissions, land-use and water footprint of chosen technologies

Generation Technology	Median GHG emissions in kg CO2/MWh[50,51]	Mean Water consumption in gallons/MWh[52,53]	Average LCOE in 2012 $/MWh[54]	Average LACE in 2012$/MWh[55]	Mean Land Use Intensity (kilometer square/TWh/yr)[56,57]
Coal (Tower cooling)	820 (740-910)	553	95.6 (87-114.4)	62.2 (54.6-70.6)	9.7 (2.5-17)
NG (Tower cooling, Combined cycle)	490 (410-650)	215	64.4 (59.6-73.6)	62.9 (54.5-74.2)	18.6***
Solar (PV)	48 (18-180)	100	130 (101.4-200.9)	73.4 (50.8-89.6)	36.9***
Solar (CSP, Tower cooling, Trough technology)	27 (8.8-63)	1050	243.1 (176.8-388)	73.3 (48.2-82.3)	15.3***
Wind (onshore)	11 (7-56)	2	80.3 (71.3-90.3)	55.7 (51.7-66.4)	72.1***
Hydro (In stream and reservoir technology)	24 (1-2200)	4491*	84.5 (61.6-137.7)	59.9 (54.1-69.5)	54***
Nuclear (tower cooling)	12 (3.7-110)	777	96.1 (92.6-102)	61.7 (54.6-70.5)	2.4 (1.9-2.8)
Geothermal	38 (6-79)	292	47.9 (46.2-50.3)	60.9 (58.3-62.4)	7.5 (1-13.9)
Biomass	230 (130-420)	553*	102.6 (92.3-122.9)	63.3 (54.5-74.5)	543.4 (433-654)
Wind Offshore	12 (8-35)	2**	204.1 (168.7-271)	62.3 (55.1-73.7)	72.1***

*Operational water consumption data used, due to lack of availability for full cycle.[58]

**Assumed to be the same as onshore wind, due to lack of distinction made in the dataset.[59]

*** Ranges not explicitly mentioned in the source.

2.1.3. Scoring

Two objective scoring rubrics are used to evaluate the robustness of results to different scoring methodologies. These scoring schemes mathematically convert the performance of each technology in each criteria used into scores. As is common with MCDA methods, both scoring schemes use a scale of 0 to 1 to translate each objective into a comparable scale.[60] In one scoring scheme, the superior options receive higher scores, whereas in the other scoring scheme, lower scores are preferable.

The scoring schemes used are described in the following sections:

2.1.3.1. Scoring Method 1: "Higher Preferred"

The first scoring method calculates each technology's performance relative to the technology that performs the best for each of the criterion. The technology that has the best performance on each criterion receives a score of 1, whereas the worst performer scores a 0 on that criterion. All other technologies receive scores between 0-1, which can be interpreted as the percentage of the best that is achieved by the technology with respect to that objective. In practice, it is common to use percentage scales where the extremes 0 and 1 represent a real or hypothetical worst or best, and is the rationale behind this scoring scheme.[61]

The equation summarizing this scoring scheme can therefore be expressed as:

Equation 2:

$$\textbf{Score } (\mathbf{S_i}) = (\textbf{Max } \mathbf{Z_j} - \mathbf{Z_{ij}}) / (\textbf{Max } \mathbf{Z_j} - \textbf{Min } \mathbf{Z_j})$$

Where Score (S_i) is the score of generation technology i,

Max Z_j is the maximum value attained by objective j with the given set of generation technologies,

Min Z_j is the minimum value attained by objective j with the given set of generation technologies,

And Z_{ij} is the value of the objective function j with generation technology i.

Using this scoring scheme, it can be seen that the best technology for the single objective under consideration will get a score of 1, whereas the worst will get a score of 0.

2.1.3.2. Scoring Method 2: "Lower Preferred"

The second scoring method calculates each technology's performance relative to the technology that performs the worst for each of the criterion. In this scheme, a lower score is preferred and the technology that performs the worst for each criterion receives a score of 1. The upper boundary of the scoring range is 1, but it is not necessary for the alternatives to span the entire range between 0-1.

The equation summarizing this scoring scheme can be expressed as:

Equation 3:

$$\textbf{Score } (\mathbf{S_i}) = \mathbf{Z_{ij}} / \textbf{Max } \mathbf{Z_j}$$

Where Score (S_i) is the score of generation technology i, Max Z_j is the minimum value attained by objective j with the given set of generation technologies,

And Z_{ij} is the value of the objective function j with generation technology i.

Using these two scoring schemes, the different objective functions (Zs) can be mathematically transformed into scores (corresponding Ss), which are then used for further analysis to study the effect of weighting schemes. The paper tests whether results of the analysis are significantly affected by the different scoring schemes.

2.1.4. Weighting

Whereas scores are objective measures that translate performance on each criterion to a commensurate scale, weights are subjective values that indicate the extent to which a stakeholder values each criterion. This paper shows how different weighting schemes may lead to different preferred technologies. A rigorous stakeholder engagement process coupled with region specific data is necessary to determine the best options for a region and such an undertaking is outside the scope of this paper.

The raw scores can be considered to be the results that are obtained in an equal weighting scenario. However, decisions are unlikely to be made by giving equal importance to all criteria. To understand the relationship between the weights attributed to the different objectives and the changes in recommendations from the different points on the Pareto frontier, additional weighting schemes are explored.

2.2. Comparison of an MCDA Approach to a Benefit-Cost Analysis:

The results of the analysis for the two scoring schemes are compared to one another as well as a traditional benefit cost analysis to test for variations and differences in results using different methods, and examine possible underlying causes in any discrepancies.

In order to conduct a benefit-cost analysis, the LCOE and LACE data is used as a cost metric, with an additional cost that would be levied for carbon emissions.

For calculating the costs associated with carbon dioxide equivalent emissions, ‘Social Cost of Carbon’ values provided by the EPA[62] are multiplied by the emissions associated with every technology to find out an associated dollar value.

Three cost scenarios are considered- High, Medium and Low.

In the High scenario, the upper value for the social cost of carbon given by the EPA is used, while in the Low scenario, the lowest bound for the same is considered to be the cost of greenhouse gas emissions.

3. THEORY AND CALCULATIONS

3.1. Multi-Criteria Decision Analysis

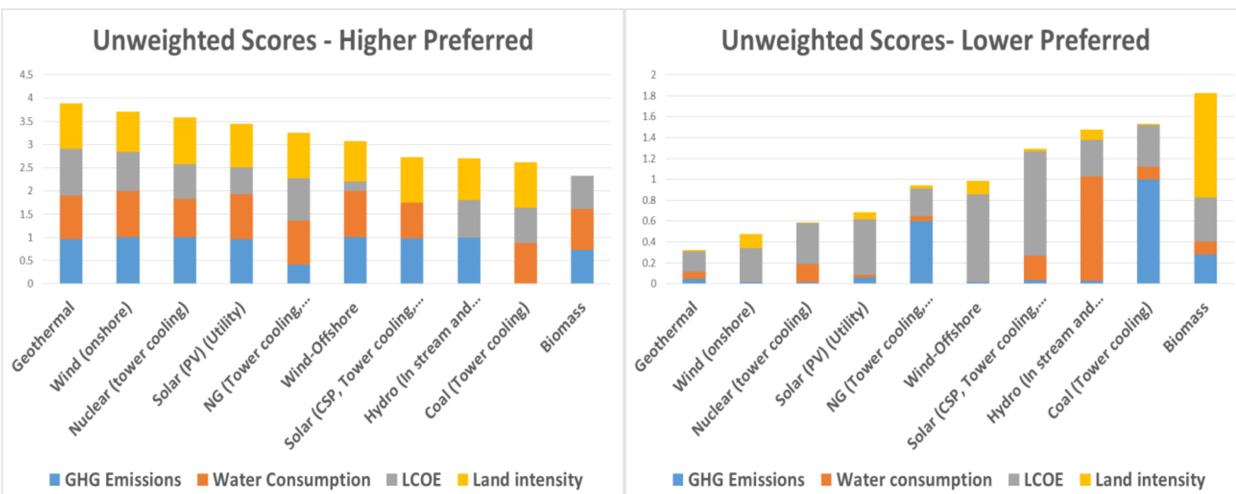
3.1.1. Scoring

Using the two scoring schemes, the performance of each generation technology for each of the objective functions is calculated individually at first. These can be thought of as the solutions to single objective functions, and the optimal solutions for these form the extremes of the Pareto frontier, as is defined in the preceding sections. Alternatively, the scores of technologies for each criterion can be interpreted as the performance of the points if the weight given to that particular objective function is 1, while the weights corresponding to the other objective functions are 0.

The results when using LCOE as a metric are compared to those from using LCOE in combination with LACE, and the ranking of each technology remains the same in both the cases.

Because the ranking of technologies does not change with or without the use of LACE as a metric to compute costs, LCOE alone is used as a metric as a proxy for costs, and the decomposition of scores is studied to evaluate the merits and demerits of a particular technology. Conventional generation and renewable energy technologies are both compared and contrasted and their ranking under the two scoring schemes is shown in the following graphic:

Figure 1: Scores of the Technologies under the two scoring methodologies (Equal Weighting).



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For the left half, a higher score indicates a better performance, and a greater degree of meeting objectives, whereas on the right side, a lower score is preferred because it implies a lower overall impact on resources. As seen, geothermal is the most superior under both schemes, whereas biomass performs poorly. Moreover, the overall ranking of technologies is the exact same in both cases. This implies that the overall ranking of the technologies under the two methods are consistent, at least under the case of equal weighting of objectives. The consistency of the methods under other weighting schemes is explored in the later sections of the paper.

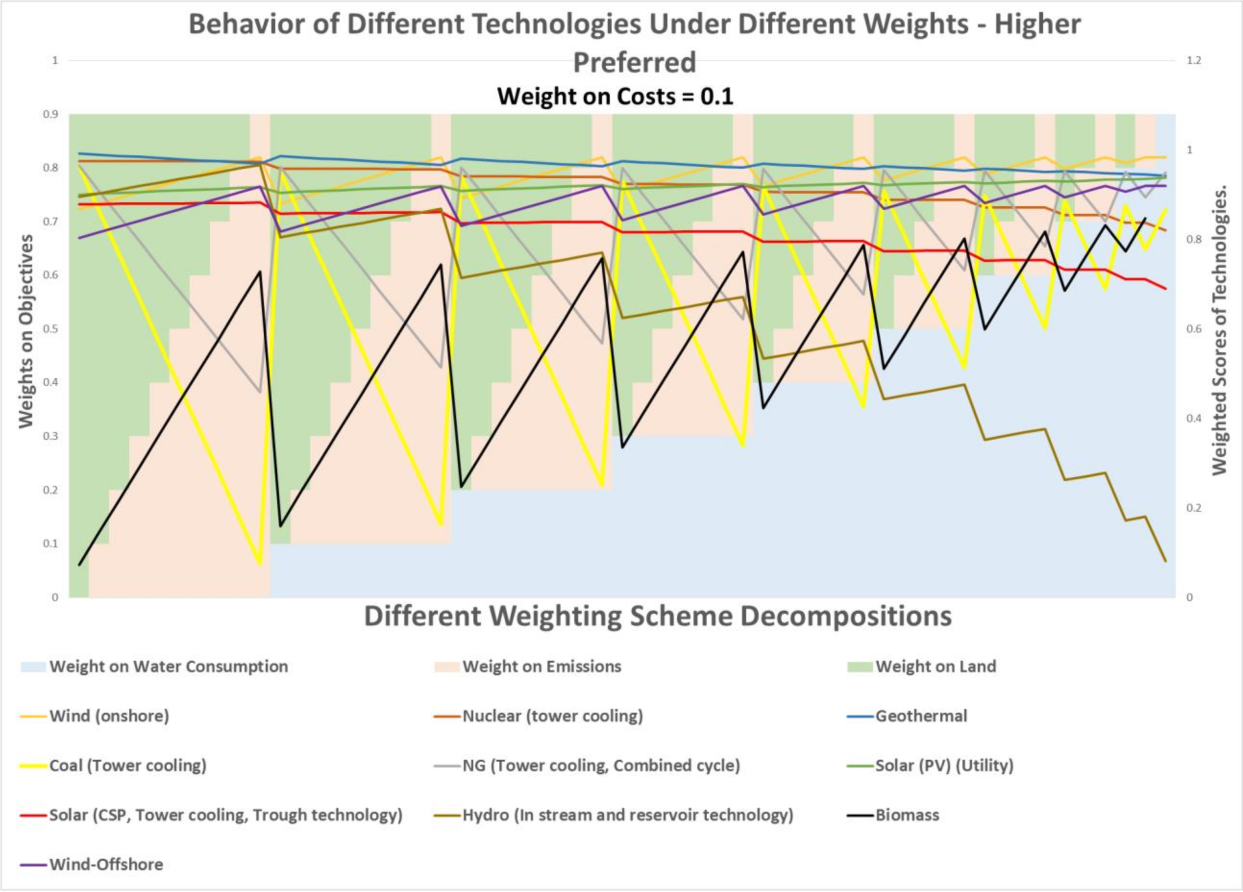
3.1.2. Weighting

For the purpose of this study, a number of 'hypothetical' weighting schemes are used, and their effect on the overall scores for each technology are studied, to identify critical weighting points that could lead to a switch in preferred technology.

For this, the weight for the costs criterion is held constant, and the remaining weight is distributed among the other three criteria of water consumption, greenhouse gas emissions, and land-footprint in various ways. This process is repeated for two values of the weight allocated to costs, and the recommendation changes from the weighted scores are then observed.

The following figure illustrates the weighting combinations that allocate different priority weights to water consumption, emissions, and land intensity, while holding the weight given to costs as a constant 0.1, superimposed with each of the scoring schemes.

Figure 2: Weighted 'Higher Preferred' Scores of the technologies when superimposed with the weighting schemes.



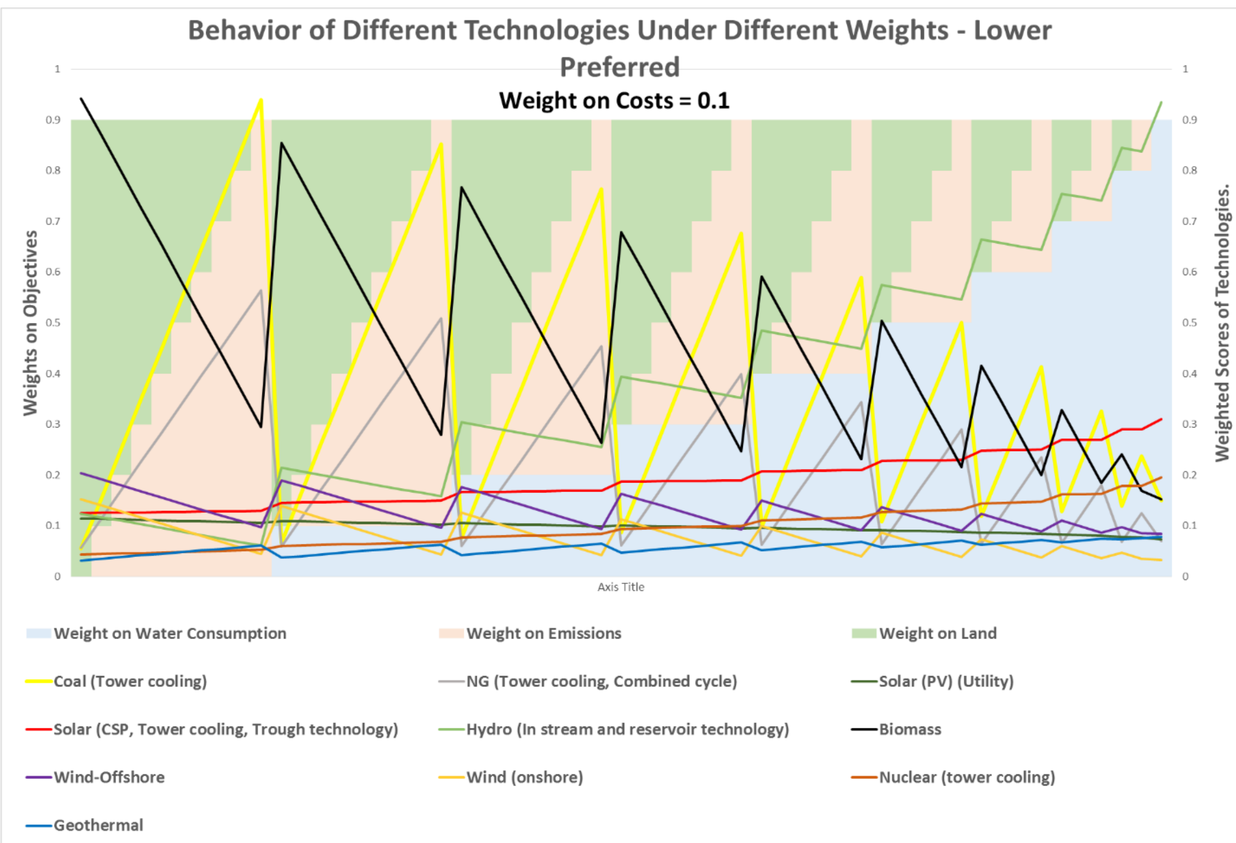
This figure shows how the performance of the technologies (as measured by their weighted scores) changes under the different weighting scheme combinations. The weighting scheme diagram shows that the combinations can be thought of as a collection of 'blocks', where each block has a constant weight assigned to water consumption as an objective. Thus, as we move from the left to right in the chart (as the 'blue' portion of the primary axis increases), the weight allocated to water consumption is gradually increasing, making it a higher priority.

Within each block of constant water consumption weight allocation, the remaining weightage is allocated to land on the left, and emissions on the right. This means, within each block, as we move from the left to right, we increase the priority given to emissions over land intensity.

Geothermal energy is the cheapest, wind power has the lowest carbon dioxide equivalent emissions, and nuclear energy has the lowest land footprint. Therefore, these three form the extremes of the Pareto frontier, which means that when switching from any of these technologies to another, we are compromising on the objective function that these technologies are optimal for.

As seen from Figure 2, Wind, which is the best in terms of life cycle water consumption, starts getting a higher weighted score as we move from the left of the figure to the right. Similarly, nuclear sees an overall decline in weighted score as we prioritize water consumption (move from the left to the right of the figure). Within each block, the weighted score of wind power improves when emissions are prioritized over land footprint, whereas a reverse trend is seen for geothermal energy and nuclear energy, whose weighted scores lose to wind when it comes to emissions prioritization. A higher amplitude of ‘spikes’ in the figure would indicate a great different for a given technology in meeting two different objectives. For example, wind power seems to have the steepest drops and rises within in each block. This is because wind power is the best for emissions, but worst (among the Pareto frontier extremes) for land footprint.
The same overall results are seen when the weighting scheme is superimposed on the ‘Lower Preferred’ scheme, as illustrated in the following figure:

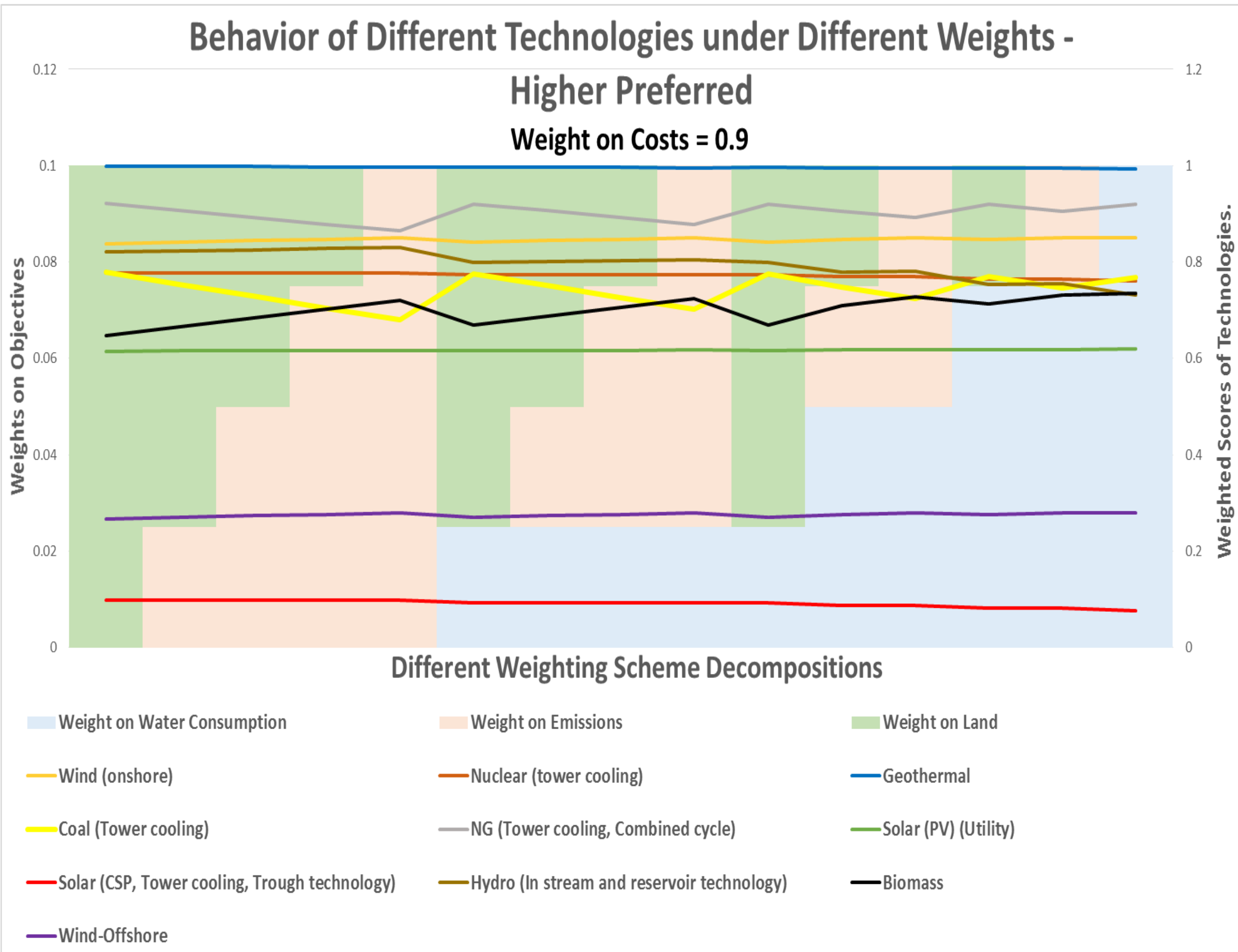
Figure 3: Weighted ‘Lower Preferred' Scores of the technologies when superimposed with the weighting schemes (Weight on costs = 0.1).



Here, a lower weighted score indicates lower impact on resources, and is a sign of better technology performance with the given weight on objectives. Again, the results are similar to those with the weighted scores under the 'Higher Preferred' scheme. Nuclear shows a higher impact when we move from left to right, as water consumption gets prioritized, while wind gets a lower score, indicating a superiority of wind when it comes to water consumption. Similarly, within each block, wind performs better when emissions are prioritized over land intensity, whereas geothermal and nuclear are better in terms of land intensity but worse in terms of emissions relative to wind.

It is highly unlikely that a weight of 0.1 would be given to costs, but the scheme indicates how different preferences could influence a decision, even though it is not representative of expected stakeholder preferences. A more likely scenario with a weight of 0.9 given to costs is considered, and the behavior of the technologies in terms of their weighted scores is studied under that scheme too.

Figure 4: Weighted 'Higher Preferred' Scores of the technologies when superimposed with the weighting schemes (Weight on costs = 0.9).

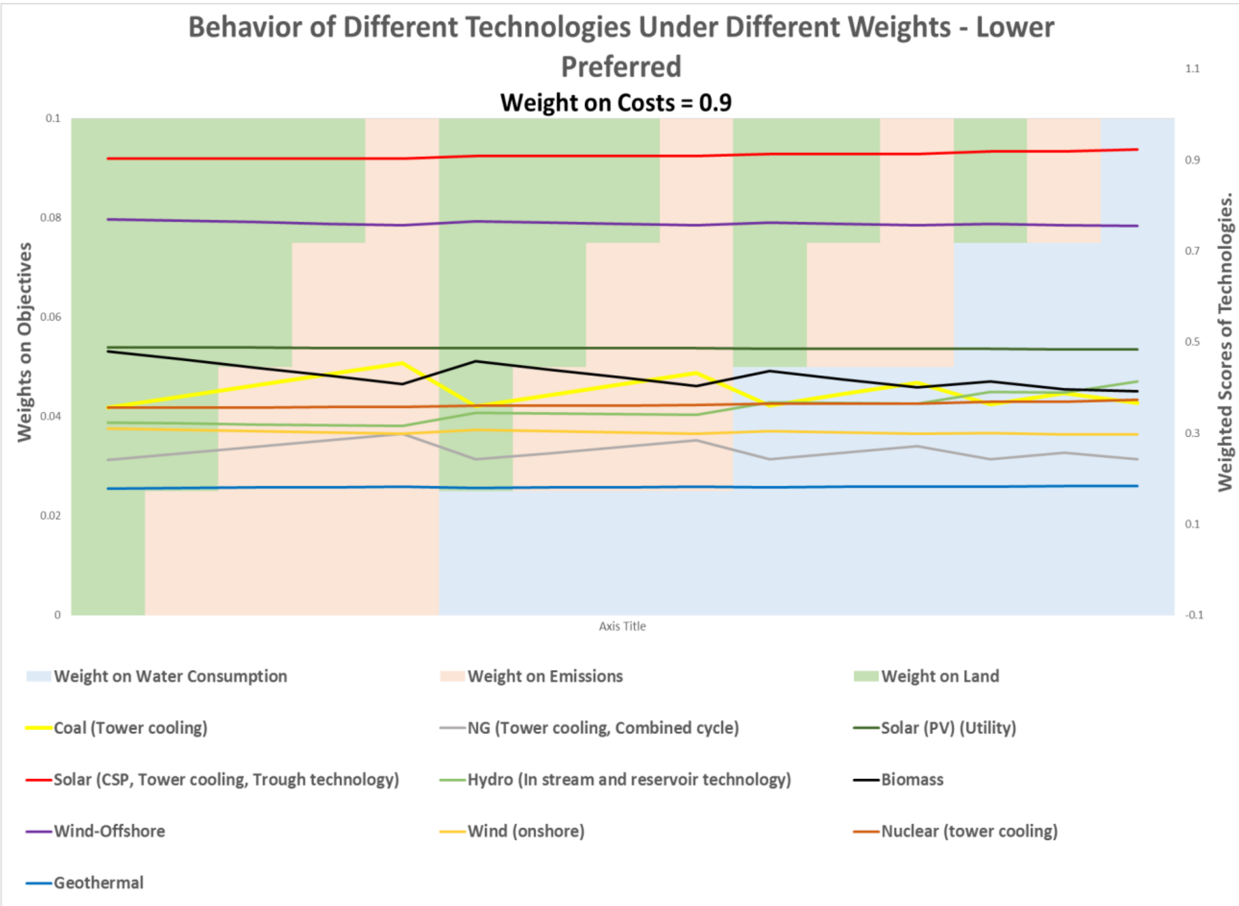


As seen, when 90% of the overall weight allocation is given to costs, the flexibility left for the prioritization of the other objectives is greatly reduced.

The figure shows that once costs are prioritized to 90%, there is no effect of changing the weights for the technology that gets the highest weighted score, which in this case is geothermal. The weights on the other three factors do not influence the relative rankings much.

An analogous analysis is done for the impact scoring scheme under the same weighting schemes, and the behavior of the weighted scores of the technologies is similar to the one observed under the 'Higher Preferred' scheme.

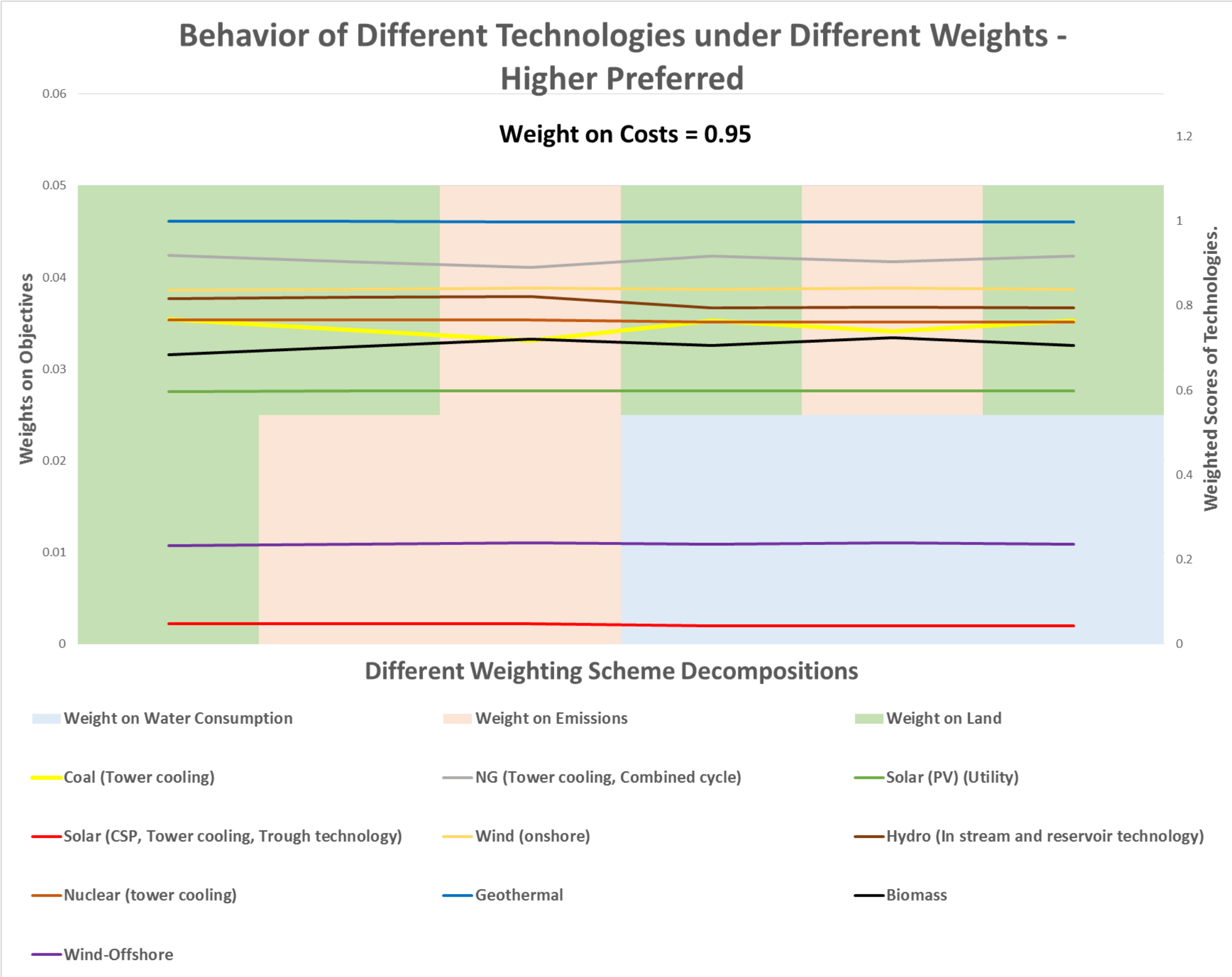
Figure 5: Weighted 'Lower Preferred' Scores of the technologies when superimposed with the weighting schemes (Weight on costs = 0.9).



Again, as expected, once a high weight is given to costs, geothermal power with its lowest weighted impact score, emerges to be superior no matter how the remaining 10% is distributed among the objective of water consumption, emission and land intensity.

At a weight of 95% given to costs, the tradeoffs between the technologies are no longer relevant to their overall ranking, as seen:

Figure 6: Weighted 'Higher Preferred' Scores of the technologies when superimposed with the weighting schemes (Weight on costs = 0.95).



Unless the costs are weighted at 95%, there are tradeoffs that color the performance of technologies, and do not give a single ranking order.

3.2. Benefit-Cost Analysis

A benefit cost analysis (BCA) is carried out to determine the similarities and differences in the results from a BCA compared to an MCDA approach. In a benefit cost analysis, preference weights can be thought of as being reflected in prices seen in the market, or by explicit techniques of welfare economics.[63] Therefore, there should be an equivalence between the two methods in terms of results, if a high weight is given to the 'costs' objective under an MCDA.

To verify that, LCOE is used as a proxy for costs associated with a given technology. The levelized cost of energy will have incorporated in it the costs of water and land, as these are costs associated with a project. However, the levelized cost of energy will not reflect the cost of emissions associated with each technology. For this purpose, Social Cost of Carbon (SCC) values published by the Environmental Protection Agency are used.[64] Three scenarios- High, Medium and Low are considered, and they correspond to the high, medium and low values estimated for the social cost of carbon, as determined by the discount rate used. It is important to note, however, that even though the LCOE reflects the costs of water and land requirements associated with a project, it does not account for the costs of land degradation, or the environmental costs of water consumption in a water-scarce region. In such a case, an MCDA retains the ability to capture these factors by corresponding values given to weights.

The emissions from each generation technology (t CO_{2eq} /MWh) are multiplied with the social cost of carbon ($/t CO_{2eq}) to get an associated carbon cost for each technology. The carbon cost added to the levelized cost of energy is then used for ranking the technologies from least cost to costliest.

The following table summarizes the results under the different social cost of carbon estimates:

Table 2 - Technology Ranking, Cheapest to Costliest

Low Scenario (SCC = $12*/metric ton of CO_{2eq})	**Medium Scenario (SCC = $39*/metric ton of CO_{2eq})**	**High Scenario (SCC = $61*/metric ton of CO_{2eq})**
Geothermal	Geothermal	Geothermal
NG (Tower cooling, Combined cycle)	Wind (onshore)	Wind (onshore)
Wind (onshore)	NG (Tower cooling, Combined cycle)	Hydro (In stream and reservoir technology)
Hydro (In stream and reservoir technology)	Hydro (In stream and reservoir technology)	NG (Tower cooling, Combined cycle)
Nuclear (tower cooling)	Nuclear (tower cooling)	Nuclear (tower cooling)
Biomass	Biomass	Biomass
Coal (Tower cooling)	Coal (Tower cooling)	Solar (PV) (Utility)
Solar (PV) (Utility)	Solar (PV) (Utility)	Coal (Tower cooling)
Wind-Offshore	Wind-Offshore	Wind-Offshore
Solar (CSP, Tower cooling, Trough technology)	Solar (CSP, Tower cooling, Trough technology)	Solar (CSP, Tower cooling, Trough technology)

**Constant 2011 dollars*

As seen from the table, in the low scenario, natural gas is the second cheapest, but as the price on carbon increases, it gets pushed down in the ranking order. Geothermal emerges to be most superior under the Benefit Cost Analysis because of its lowest LCOE, as well as its relatively low emissions. Nuclear energy and biomass see no change in ranking under all three scenarios, whereas hydropower and solar PV show an improvement in rankings with an increased cost associated with emissions.

4. RESULTS AND DISCUSSION

4.1. Suitability of MCDA methods, and differences in scoring schemes

Out of the three broad categories of 'Value Measurement Models', 'Goal, Aspiration and Reference Level Models', and 'Outranking Models' frequently used in MCDA methods,[65] this paper used a Value Measurement Model for comparison between the technology alternatives. This model is chosen over a 'Goal Programming' approach, because the optimization does not have predefined goals to be met in each criterion (for example, the study does not set carbon reduction goals that ought to be attained by the power sector, merely tries to minimize them keeping in mind the tradeoffs associated with carbon dioxide reduction). If there were predefined goals that the energy system needs to meet, a 'Goal, Aspiration and Reference Level Model' could be used, which would minimize the deviations from the desired goals.[66] Alternatively, constraints could be built into the model if there was a particular budget limit for energy investments, or a constraint on how much carbon could be emitted from new generation.

The results under the MCDA approach used in this paper are consistent in terms of the overall ranking of technologies with the two scoring methodologies employed, as is seen in Figure 1. The analysis also shows how the assignment of weights colors the performance of the technologies considered. The raw scores, i.e. just the sum of the scores of each of the technologies, without weighting, can be calculated and compared to the weighted scores under different weighting schemes for an estimation of the impact of weights on the overall performance of the technologies considered. It is observed that the weighted scores can differ significantly from the unweighted ones, and after weighting, the recommendations may be different from those seen after unweighted scoring. This finding is consistent with what has been shown in literature on the changes in recommendations due to different methods employed to conduct an MCDA, and that the changes in recommendation with changing weights should not be taken to be an indication that something is wrong with any of the methods used.[67,68]

Montis et al[69] have formulated a list of criteria to compare different MCDA methods and their suitability for sustainability issues, and have concluded that identification of a 'best' from the methods is not realistic, and that different methods can be applied just as successfully in different contexts.[70] However, they did not conduct a comparison of methods for the same decision making context, as is done in this study. It is important to note though, that both the methods used in these study fall in the category of Multi-Attribute Value theory, and the impacts of methodological differences within this category are being examined.

The two scoring schemes, 'Higher Preferred' and 'Lower Preferred', have associated merits and demerits. The 'Higher Preferred' scoring scheme sets the upper and lower bounds for each generation technology based on the best and worst possible performance in each category. This scheme uses relative metrics for the evaluation of each technology, and gives a ranking scale that reflects the performance of each technology in comparison to the best available and worst available technology, instead of an absolute metric. For example, wind power having a score of 1 does not imply that the carbon footprint of wind is an absolute 0, but rather that it has the lowest carbon footprint among all the technologies considered. In a context where stakeholders are interested in knowing about the absolute impacts of a particular option, this scoring scheme may not give the magnitude associated with each in the absolute sense, and instead, the 'Lower Preferred' scheme could be used, because even the technology with the lowest impact does not get a score of 0.

An issue with the ‘Lower Preferred’ scheme is that it seems to be sensible only with positive numerators and denominators. For the purpose of this research, it becomes challenging to use this scheme in the form of the above equation to calculate scores for costs, because the lowest LCOE – LACE value is negative (which indicates the technology has a positive net benefit to the system), making the technology scores negative and distorting the interpretation. To accommodate for a negative denominator, the scoring scheme could be altered by multiplying throughout by (-1), however, it seems more straightforward and easy to use the ‘Higher Preferred’ scheme when dealing with negative numbers.

The ‘Lower Preferred’ scheme seems to be more sensitive to weights because of the change in recommendations relatively more easily than that from ‘Higher Preferred’ method, when LCOE is used as metric for costs comparison. For example, when a weight of ‘0.1’ is given to the costs function, under all the combinations of the other three function weights, Lower Preferred Scores show ‘Geothermal’ to be optimal 56.3% of the times, whereas Higher Preferred weighted scores show ‘Geothermal’ to be optimal 65.4% of the times. It’s possible that the differences in weighting stem from the wide ranges in the raw data, and how each scoring scheme translates the extreme values numeric scores.

The scoring schemes, when combined with weighting, give different recommendations when LCOE is used as a metric for costs versus when LCOE-LACE is used, unlike the case of unweighted scoring, which gives the same optimal technology recommendation with both the scoring methods. (Refer to Appendix B.) For instance, as mentioned, Lower Preferred Scores show ‘Geothermal’ to be optimal 56.3% of the times when LCOE is used as a cost metric, and 10% weight is allocated to costs. However, when LCOE-LACE is used as a metric, even with a 10% weight on costs, ‘Geothermal’ emerges to be superior regardless of the alteration of weighting distribution under this scheme. This variation is higher in weighted ‘Lower Preferred’ scores than the variation in weighted ‘Higher Preferred’ scores, and the latter shows high consistency in results regardless of LCOE or LCOE-LACE being used as a proxy for costs. In this context, consistency is defined as the similarity when it comes to the recommendation, i.e. the technology that receives the best weighted score. (Refer to Appendix C for a complete list of Pareto optimal solutions with different weighting schemes.) It is important to note that further analysis would be needed to test if this consistency holds true beyond the best weighted scores technology, because it is possible that geothermal is an ‘outlier’ in its performance, and that the scoring schemes give very different technology preference orders after weighting for the remaining technologies. Comparing figures 2 and 3, as well as 4 and 5, it seems that the methods are broadly consistent with each other, and the weighted scores of technologies follow very similar trends under the two methods.

The analysis is repeated without geothermal energy, given that is likely to be a more location specific resource than the others, which would make the analysis without geothermal power more realistic. When geothermal is eliminated, power from natural gas is the cheapest available option. Hence, the extremes of the Pareto frontier are now natural gas, nuclear energy and wind power. Now, there seems to be a significant consistency across the two scoring schemes with respect to the technology that gets the best score, even after weighting, and the relative sensitivity of weighted ‘Lower Preferred’ to changing cost metrics is eliminated. (Refer to Appendix D for a complete list of Pareto optimal solutions with different weighting schemes, when geothermal is eliminated from the analysis.) Again, consistency here is specific to the recommendation similarity obtained from the two schemes.

A possible explanation could be the fact that the presence of negative scores is not suitable when working with 'Lower Preferred' scheme. To test if this is indeed the case, the LCOE-LACE value for geothermal in the dataset, which is originally negative, is artificially made positive by changing it from -$13/MWh to $0.1/MWh. The results after doing so are compared to the weighted Lower Preferred scores when solely LCOE is used, to see if there is now more consistency among the two. It is found that there is now a very high consistency between the weighted Impact Scores. Only two discrepancies are seen, and this could be a result of the changed value for 'LCOE-LACE', as opposed to the scoring scheme itself. (Refer to Appendix E for a complete list of Pareto optimal solutions when the LCOE-LACE value for Geothermal energy is artificially made positive.)

This would indicate that 'Lower Preferred' should not be used if there are negative scores that may result from the values in the dataset. In such a situation, a 'Higher Preferred' approach will be more robust. However, with positive values, both the schemes seem to be consistent in terms of unweighted as well as weighted scoring results, and both offer more benefits over a traditional Benefit-Cost Analysis approach when it comes to explicit recognition of tradeoffs, context specificity, and engagement with stakeholders for incorporation of subjective preferences.

4.2. MCDA versus BCA

The results are different under a traditional benefit-cost analysis, when compared to an equal scoring approach under MCDA. One possible explanation for this could be the fact that the Benefit-Cost analysis takes into account market clearing prices, which could be thought of as weights in the MCDA used, with a high emphasis on costs. This is verified if under high weights given to the costs function in an MCDA, the results from the MCDA become equivalent to those from a Benefit-Cost analysis. To do so, the results from the BCA were compared to the weighted scores with a high weight allocated to costs.

Under a weighting scheme that allocates 95% weight to costs, and distributes the remaining 5% among land, water and emissions, the results match up to those from the 'Low Scenario' of the Benefit-Cost Analysis. (Figure 6 vs Table 2 – Low Scenario)

Under this scheme, geothermal has the lowest costs, whereas Solar CSP, the highest, which determines them to be the most optimal and least optimal for both, the 'Higher Preferred' as well as 'Lower Preferred' weighted scoring schemes. However, under any weighting schemes where the preference allocated to costs is less than 95%, we get a great deal of flexibility when comparing the intermediate scored options using an MCDA approach, depending on whether we prioritize land, water or emissions, which is absent in a benefit cost analysis.

There are a large number of similarities in MCDA and BCA, as would be expected to some extent, because both are based in utilitarian theory, and often use linear aggregate models (Net Present Value in a BCA, and linear additive functions in MCDA such as the MAVT method used for this study).[71]

In order to get a fair comparison between the two methods, environmental economics techniques such as 'contingent valuation' and 'hedonic pricing' can be used to determine a dollar value of 'water scarcity', or 'land degradation', because even though the LCOE accounts for the cost of water associated with the project, and the leasing rate of land, it does not address the issue of pricing water or land quality. There is criticism, however, against trying to bracket environmental attributes into the category of market goods, and the use of consumer preferences seen in the market being used to value goods.[72] In light of that argument, it might make more sense to use

MCDA methods to elicit weights from the stakeholders involved, because those are not solely determined by market signals, and give the stakeholder an opportunity to explicitly recognize tradeoffs with his/her decision.

It has been proposed that the monetary equivalent should be determined for all the 'commodities' for which it is relatively straightforward, and that analysis should be complemented with an MCDA for valuing impacts that cannot be readily monetized.[73] Again, an MCDA is able to take into account not just the quantified value of each attribute, but also the context of the decision being made. Instead of a single optimum solution universally, an MCDA would allow for changing optima by using weights to reflect stakeholder priorities in a given situation, as well as the changing resource constraints by altering the weights- a flexibility absent if single dollar values are attached to each technology.

5. CONCLUSIONS

Based on the results from the weighted scoring, it can be seen that different technologies emerge superior when certain objectives are prioritized over others. If the emphasis is on minimization of the life cycle water consumption and carbon dioxide footprint, wind power emerges superior compared to the other options. If we are to optimize solely for minimization of land intensity, nuclear power would be our best bet. Similarly, for costs, geothermal power is most superior. However, it should be noted that increasing the weight allocated to a particular objective comes at the expense of the other objectives, and there are tradeoffs associated with each of the options that show up as optimal under the weighting schemes.

If geothermal is eliminated from the analysis because of its relative location specificity, generation from natural gas is the lowest in terms of costs, and it forms one of the extremes of the Pareto frontier, along with wind energy and nuclear energy.

However, it is important to note that the different technologies vary considerably in terms of reliability, dispatchability, and other ancillary services offered to the grid. If the new generation coming online is to replace retiring coal fired power plants, building a wind power plant for water and carbon dioxide optimization may not serve the purpose of base load generation, and create issues associated with the intermittency of wind. It is also important to note that the optimization is carried out for a ‘snapshot’ period, and is likely to change over time in terms of optimal recommendations. This is especially true if we consider the case of variable renewable energy generation, whose marginal benefit to the system is likely to decrease with increasing penetration. To account for such changes, additional complexity can be added to the model which instead of using constant LCOE and LACE values, uses a decreasing value for both over time.

The results and their robustness across the two scoring rubrics help highlight the suitability of MCDA methods as a decision framework for energy planning, along with its advantages over a traditional benefit-cost analysis. It also shows how MCDA methods could be used to incorporate objectives other than costs into decision making.

An important characteristic of the two schemes used in this analysis is the fact that even after weighting, at no point do suboptimal solutions come up as optimal. This ensures that the recommendation after accounting for subjective preferences is still among the objectively optimal solutions.

Further research is needed to study the optimality of different generation technologies when a specific region is under consideration. As seen, there is significant variation in values for land impacts based on the location (generation weighted land use of solar PV and CSP is likely to be lower if the region has an exceptional solar resource), as well as in water consumption values based on cooling technology type used. The costs, too, are expected to be different in different regions not just because of the geography, but also the system into which the resource is being added. The same is expected from emissions. Consequential Life-Cycle Analysis values specific to the particular system being studied will help in giving the optimal solutions specific to the system. Similarly, instead of hypothetical weights, weights that accurately reflect the geography as well as preferences of the region being considered could be formulated by attaching appropriate priority weights to capture the same.

The comparison between an MCDA and BCA can also be studied further by comparing MCDA results to a BCA when land degradation penalties, and water consumption penalties in terms of $ value are attached to the latter.

6. APPENDICES

Appendix A:

Point Estimates Derived from Data Ranges:

1) Life Cycle Carbon Dioxide eq. Emissions

Generation Technology	CO_2 emissions in kg CO_2/MWh (Data from IPCC Report[74 75]		
	Low	Median	High
Coal (Tower cooling)	740	820	910
NG (Tower cooling, Combined cycle)	410	490	650
Solar (PV) (Utility)	18	48	180
Solar (CSP, Tower cooling, Trough technology)	8.8	27	63
Wind (onshore)	7	11	56
Hydro (In stream and reservoir technology)	1	24	2200
Nuclear (tower cooling)	3.7	12	110
Geothermal	6	38	79
Biomass	130	230	420
Wind-Offshore	8	12	35

2) Life Cycle Water Consumption

(For derivation of water use in various life cycle stages, refer to "Supplemental Dataset".[76]

Generation Technology	Water consumption in gallons/MWh (Data from Table A-35,[iii] and NREL Report.[iv])[77 78]				
	Power Plant	Fuel Cycle	Fixed O&M	Variable O&M	Baseline (total)
Coal (Tower cooling)	1	22	90	440	553
NG (Tower cooling, Combined cycle)	1	4	2	208	215
Solar (PV) (Utility)	94		2.5	3.5	100
Solar (CSP, Tower cooling, Trough technology)	160		50	840	1050
Wind (onshore)	1		0	1	2

Hydro (In stream and reservoir technology)*					4491
Nuclear (tower cooling)	1	56	30	690	777
Geothermal	2		0	290	292
Biomass*					553
Wind-Offshore**	1		0	1	2

*Operational water consumption data used, due to lack of availability for full cycle.[79]

**Assumed to be the same as onshore wind, due to lack of distinction made in the dataset.[80]

3) Costs data.

Generation Technology	LCOE in 2012 $/MWh (EIA Dataset for LCOE)[81]					
	Low	Average	High	With subsidies low	With subsidies average	With subsidies high
Coal (Tower cooling)	87	95.6	114.4			
NG (Tower cooling, Combined cycle)	59.6	64.4	73.6			
Solar (PV) (Utility)	101.4	130	200.9			
Solar (CSP, Tower cooling, Trough technology)	176.8	243.1	388			
Wind (onshore)	71.3	80.3	90.3			
Hydro (In stream and reservoir technology)	61.6	84.5	137.7			
Nuclear (tower cooling)	92.6	96.1	102	82.6	86.1	92
Geothermal	46.2	47.9	50.3			
Biomass	92.3	102.6	122.9			
Wind-Offshore	168.7	204.1	271			

Generation Technology	LACE in 2012 $/MWh (EIA Dataset for LACE)[82]		
	Minimum	Average	Maximum
Coal (Tower cooling)	54.6	62.2	70.6
NG (Tower cooling, Combined cycle)	54.5	62.9	74.2
Solar (PV) (Utility)	50.8	73.4	89.6
Solar (CSP, Tower cooling, Trough technology)	48.2	73.3	82.3
Wind (onshore)	51.7	55.7	66.4

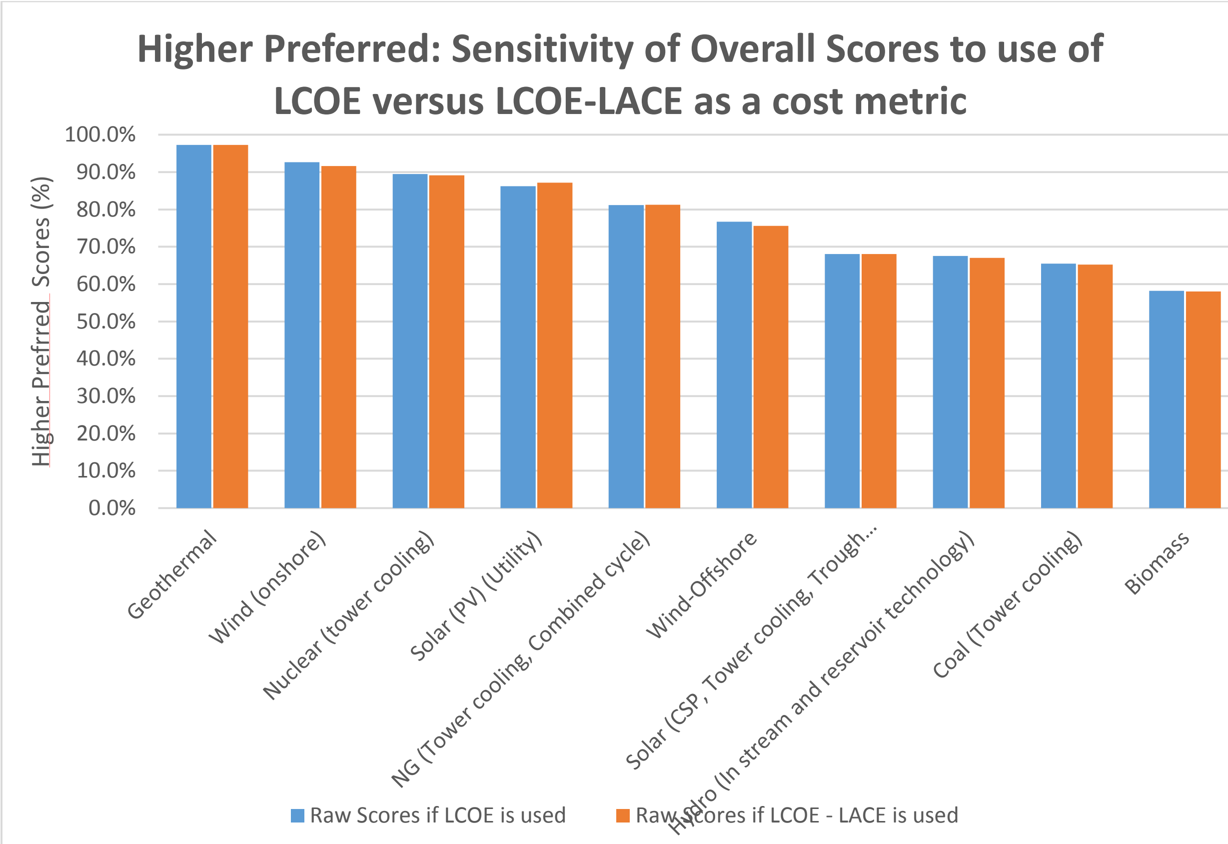
Hydro (In stream and reservoir technology)	54.1	59.9	69.5
Nuclear (tower cooling)	54.6	61.7	70.5
Geothermal	58.3	60.9	62.4
Biomass	54.5	63.3	74.5
Wind-Offshore	55.1	62.3	73.7

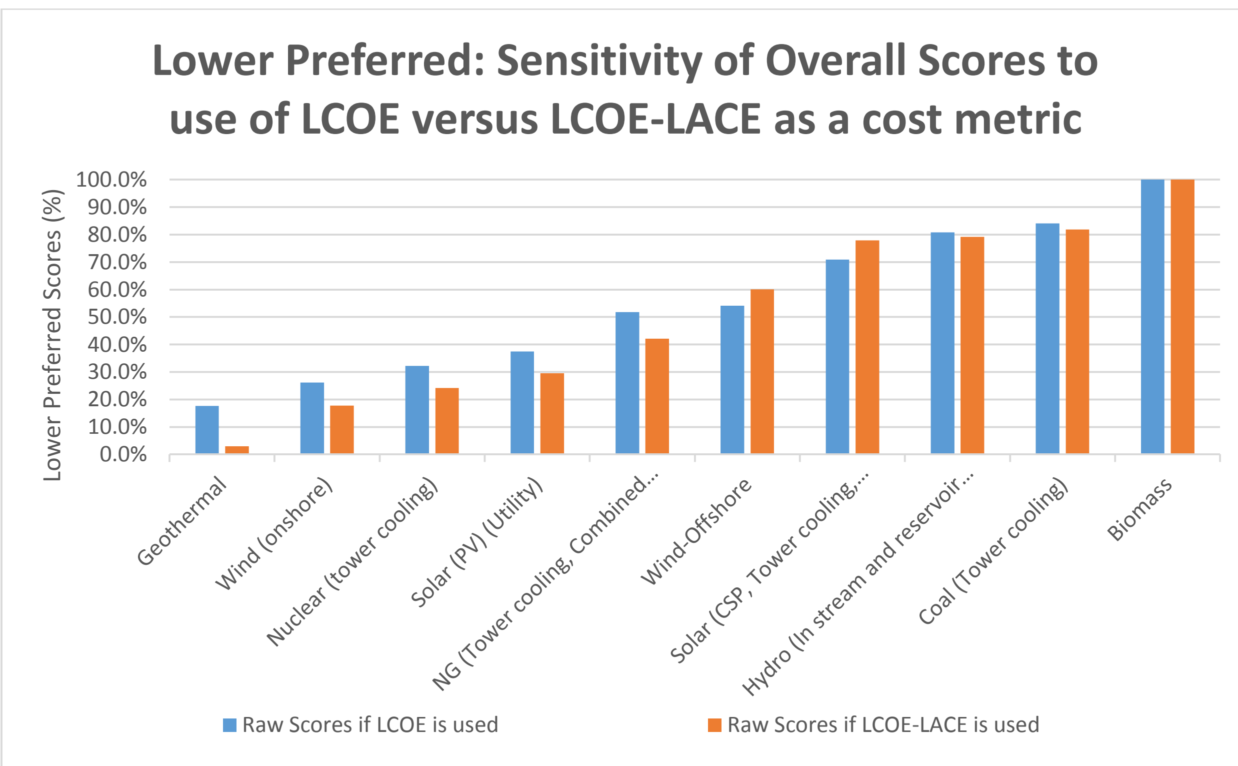
4) Life-cycle Land use data:

Generation Technology	Life-cycle Land Use (kilometer square/TWh/yr)[83]		
	Minimum	Midpoint	Maximum
Coal (Tower cooling)	2.5	9.7	17
NG (Tower cooling, Combined cycle)*		18.6	
Solar (PV) (Utility)*		36.9	
Solar (CSP, Tower cooling, Trough technology)*		15.3	
Wind (onshore)*		72.1	
Hydro (In stream and reservoir technology)*		54	
Nuclear (tower cooling)	1.9	2.4	2.8
Geothermal	1	7.5	13.9
Biomass	433	543.4	654
Wind-Offshore		72.1	

*Ranges not explicitly mentioned in the source.

Appendix B:


Higher Preferred: Sensitivity of Overall Scores to use of LCOE versus LCOE-LACE as a cost metric
Higher Prefrred Scores (%)
100.0%
90.0%
80.0%
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
Geothermal
Wind (onshore)
Nuclear (tower cooling)
Solar (PV) (Utility)
NG (Tower cooling, Combined cycle)
Wind-Offshore
Solar (CSP, Tower cooling, Trough...
Hydro (In stream and reservoir technology)
Coal (Tower cooling)
Biomass
Raw Scores if LCOE is used
Raw Scores if LCOE - LACE is used


Lower Preferred: Sensitivity of Overall Scores to use of LCOE versus LCOE-LACE as a cost metric
Lower Preferred Scores (%)
100.0%
90.0%
80.0%
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
Geothermal
Wind (onshore)
Nuclear (tower cooling)
Solar (PV) (Utility)
NG (Tower cooling, Combined...
Wind-Offshore
Solar (CSP, Tower cooling,...
Hydro (In stream and reservoir...
Coal (Tower cooling)
Biomass
Raw Scores if LCOE is used
Raw Scores if LCOE-LACE is used

Appendix C (Highlighted text indicates inconsistency in recommendation between methods):

LCOE/LCOE -LACE = 0.1			Higher Preferred, LCOE used	Higher Preferred, LCOE-LACE used	Lower Preferred, LCOE used	Lower Preferred, LCOE-LACE used
Water Weight	Emissions Weight	Land Intensity Weight	Optimal Solution	Optimal Solution		
0	0	0.9	Geothermal	Geothermal	Geothermal	Geothermal
0	0.1	0.8	Geothermal	Geothermal	Geothermal	Geothermal
0	0.2	0.7	Geothermal	Geothermal	Geothermal	Geothermal
0	0.3	0.6	Geothermal	Geothermal	Geothermal	Geothermal
0	0.4	0.5	Geothermal	Geothermal	Geothermal	Geothermal
0	0.5	0.4	Geothermal	Geothermal	Geothermal	Geothermal
0	0.6	0.3	Geothermal	Geothermal	Nuclear	Geothermal
0	0.7	0.2	Geothermal	Geothermal	Nuclear	Geothermal
0	0.8	0.1	Nuclear	Nuclear	Nuclear	Geothermal
0	0.9	0	Wind	Wind	Wind	Geothermal
0.1	0	0.8	Geothermal	Geothermal	Geothermal	Geothermal
0.1	0.1	0.7	Geothermal	Geothermal	Geothermal	Geothermal
0.1	0.2	0.6	Geothermal	Geothermal	Geothermal	Geothermal
0.1	0.3	0.5	Geothermal	Geothermal	Geothermal	Geothermal
0.1	0.4	0.4	Geothermal	Geothermal	Geothermal	Geothermal
0.1	0.5	0.3	Geothermal	Geothermal	Geothermal	Geothermal
0.1	0.6	0.2	Geothermal	Geothermal	Geothermal	Geothermal
0.1	0.7	0.1	Wind	Geothermal	Wind	Geothermal
0.1	0.8	0	Wind	Wind	Wind	Geothermal

0.2	0	0.7	Geothermal	Geothermal	Geothermal	Geothermal
0.2	0.1	0.6	Geothermal	Geothermal	Geothermal	Geothermal
0.2	0.2	0.5	Geothermal	Geothermal	Geothermal	Geothermal
0.2	0.3	0.4	Geothermal	Geothermal	Geothermal	Geothermal
0.2	0.4	0.3	Geothermal	Geothermal	Geothermal	Geothermal
0.2	0.5	0.2	Geothermal	Geothermal	Geothermal	Geothermal
0.2	0.6	0.1	Wind	Wind	Wind	Geothermal
0.2	0.7	0	Wind	Wind	Wind	Geothermal
0.3	0	0.6	Geothermal	Geothermal	Geothermal	Geothermal
0.3	0.1	0.5	Geothermal	Geothermal	Geothermal	Geothermal
0.3	0.2	0.4	Geothermal	Geothermal	Geothermal	Geothermal
0.3	0.3	0.3	Geothermal	Geothermal	Geothermal	Geothermal
0.3	0.4	0.2	Geothermal	Geothermal	Geothermal	Geothermal
0.3	0.5	0.1	Wind	Wind	Wind	Geothermal
0.3	0.6	0	Wind	Wind	Wind	Geothermal
0.4	0	0.5	Geothermal	Geothermal	Geothermal	Geothermal
0.4	0.1	0.4	Geothermal	Geothermal	Geothermal	Geothermal
0.4	0.2	0.3	Geothermal	Geothermal	Geothermal	Geothermal
0.4	0.3	0.2	Geothermal	Geothermal	Geothermal	Geothermal
0.4	0.4	0.1	Wind	Wind	Wind	Geothermal
0.4	0.5	0	Wind	Wind	Wind	Geothermal
0.5	0	0.4	Geothermal	Geothermal	Geothermal	Geothermal
0.5	0.1	0.3	Geothermal	Geothermal	Geothermal	Geothermal
0.5	0.2	0.2	Geothermal	Geothermal	Wind	Geothermal
0.5	0.3	0.1	Wind	Wind	Wind	Geothermal
0.5	0.4	0	Wind	Wind	Wind	Geothermal

0.6	0	0.3	Geotherma l	Geotherma l	Geotherma l	Geothermal
0.6	0.1	0.2	Wind	Geotherma l	Wind	Geothermal
0.6	0.2	0.1	Wind	Wind	Wind	Geothermal
0.6	0.3	0	Wind	Wind	Wind	Geothermal
0.7	0	0.2	Wind	Wind	Wind	Geothermal
0.7	0.1	0.1	Wind	Wind	Wind	Geothermal
0.7	0.2	0	Wind	Wind	Wind	Geothermal
0.8	0	0.1	Wind	Wind	Wind	Geothermal
0.8	0.1	0	Wind	Wind	Wind	Geothermal
0.9	0	0	Wind	Wind	Wind	Geothermal

Appendix D (Highlighted text indicates inconsistency in recommendation between methods):

LCOE/LCOE -LACE = 0.1			Higher Preferred , LCOE used	Higher Preferred, LCOE-LACE used	Lower Preferred, LCOE used	Lower Preferred, LCOE-LACE used
Water Weight	Emissions Weight	Land Intensity Weight	Optimal Solution	Optimal Solution	Optimal Solution	Optimal Solution
0	0	0.9	Nuclear	Nuclear	Nuclear	Nuclear
0	0.1	0.8	Nuclear	Nuclear	Nuclear	Nuclear
0	0.2	0.7	Nuclear	Nuclear	Nuclear	Nuclear
0	0.3	0.6	Nuclear	Nuclear	Nuclear	Nuclear
0	0.4	0.5	Nuclear	Nuclear	Nuclear	Nuclear
0	0.5	0.4	Nuclear	Nuclear	Nuclear	Nuclear
0	0.6	0.3	Nuclear	Nuclear	Nuclear	Nuclear
0	0.7	0.2	Nuclear	Nuclear	Nuclear	Nuclear
0	0.8	0.1	Nuclear	Nuclear	Nuclear	Nuclear
0	0.9	0	Wind	Wind	Wind	Wind
0.1	0	0.8	NG	NG	NG	NG
0.1	0.1	0.7	Nuclear	Nuclear	Nuclear	Nuclear
0.1	0.2	0.6	Nuclear	Nuclear	Nuclear	Nuclear
0.1	0.3	0.5	Nuclear	Nuclear	Nuclear	Nuclear
0.1	0.4	0.4	Nuclear	Nuclear	Nuclear	Nuclear
0.1	0.5	0.3	Nuclear	Nuclear	Nuclear	Nuclear
0.1	0.6	0.2	Wind	Nuclear	Nuclear	Nuclear
0.1	0.7	0.1	Wind	Wind	Wind	Wind
0.1	0.8	0	Wind	Wind	Wind	Wind
0.2	0	0.7	NG	NG	NG	NG
0.2	0.1	0.6	Nuclear	Nuclear	Nuclear	Nuclear
0.2	0.2	0.5	Nuclear	Nuclear	Nuclear	Nuclear
0.2	0.3	0.4	Nuclear	Nuclear	Nuclear	Nuclear
0.2	0.4	0.3	Wind	Wind	Wind	Wind
0.2	0.5	0.2	Wind	Wind	Wind	Wind
0.2	0.6	0.1	Wind	Wind	Wind	Wind
0.2	0.7	0	Wind	Wind	Wind	Wind
0.3	0	0.6	NG	NG	NG	NG
0.3	0.1	0.5	Nuclear	Nuclear	Nuclear	Nuclear
0.3	0.2	0.4	Wind	Wind	Wind	Wind
0.3	0.3	0.3	Wind	Wind	Wind	Wind
0.3	0.4	0.2	Wind	Wind	Wind	Wind
0.3	0.5	0.1	Wind	Wind	Wind	Wind

0.3	0.6	0	Wind	Wind	Wind	Wind
0.4	0	0.5	NG	NG	NG	NG
0.4	0.1	0.4	Wind	Wind	Wind	Wind
0.4	0.2	0.3	Wind	Wind	Wind	Wind
0.4	0.3	0.2	Wind	Wind	Wind	Wind
0.4	0.4	0.1	Wind	Wind	Wind	Wind
0.4	0.5	0	Wind	Wind	Wind	Wind
0.5	0	0.4	NG	NG	NG	NG
0.5	0.1	0.3	Wind	Wind	Wind	Wind
0.5	0.2	0.2	Wind	Wind	Wind	Wind
0.5	0.3	0.1	Wind	Wind	Wind	Wind
0.5	0.4	0	Wind	Wind	Wind	Wind
0.6	0	0.3	NG	NG	NG	NG
0.6	0.1	0.2	Wind	Wind	Wind	Wind
0.6	0.2	0.1	Wind	Wind	Wind	Wind
0.6	0.3	0	Wind	Wind	Wind	Wind
0.7	0	0.2	Wind	NG	Wind	NG
0.7	0.1	0.1	Wind	Wind	Wind	Wind
0.7	0.2	0	Wind	Wind	Wind	Wind
0.8	0	0.1	Wind	Wind	Wind	Wind
0.8	0.1	0	Wind	Wind	Wind	Wind
0.9	0	0	Wind	Wind	Wind	Wind

Appendix E (Highlighted text indicates inconsistency in recommendation between methods):

LCOE/LCOE-LACE = 0.1			Lower Preferred, LCOE used	Lower Preferred, LCOE-LACE used, Artificially Positive Value for Geothermal
Water Weight	Emissions Weight	Land Intensity Weight		
0	0	0.9	Geothermal	Geothermal
0	0.1	0.8	Geothermal	Geothermal
0	0.2	0.7	Geothermal	Geothermal
0	0.3	0.6	Geothermal	Geothermal
0	0.4	0.5	Geothermal	Geothermal
0	0.5	0.4	Geothermal	Geothermal
0	0.6	0.3	Nuclear	Nuclear
0	0.7	0.2	Nuclear	Nuclear
0	0.8	0.1	Nuclear	Nuclear
0	0.9	0	Wind	Wind
0.1	0	0.8	Geothermal	Geothermal

0.1	0.1	0.7	Geothermal	Geothermal
0.1	0.2	0.6	Geothermal	Geothermal
0.1	0.3	0.5	Geothermal	Geothermal
0.1	0.4	0.4	Geothermal	Geothermal
0.1	0.5	0.3	Geothermal	Geothermal
0.1	0.6	0.2	Geothermal	Geothermal
0.1	0.7	0.1	Wind	Wind
0.1	0.8	0	Wind	Wind
0.2	0	0.7	Geothermal	Geothermal
0.2	0.1	0.6	Geothermal	Geothermal
0.2	0.2	0.5	Geothermal	Geothermal
0.2	0.3	0.4	Geothermal	Geothermal
0.2	0.4	0.3	Geothermal	Geothermal
0.2	0.5	0.2	Geothermal	Geothermal
0.2	0.6	0.1	Wind	Wind
0.2	0.7	0	Wind	Wind
0.3	0	0.6	Geothermal	Geothermal
0.3	0.1	0.5	Geothermal	Geothermal
0.3	0.2	0.4	Geothermal	Geothermal
0.3	0.3	0.3	Geothermal	Geothermal
0.3	0.4	0.2	Geothermal	Geothermal
0.3	0.5	0.1	Wind	Wind
0.3	0.6	0	Wind	Wind
0.4	0	0.5	Geothermal	Geothermal
0.4	0.1	0.4	Geothermal	Geothermal
0.4	0.2	0.3	Geothermal	Geothermal
0.4	0.3	0.2	Geothermal	Geothermal
0.4	0.4	0.1	Wind	Wind
0.4	0.5	0	Wind	Wind
0.5	0	0.4	Geothermal	Geothermal
0.5	0.1	0.3	Geothermal	Geothermal
0.5	0.2	0.2	Wind	Wind
0.5	0.3	0.1	Wind	Wind
0.5	0.4	0	Wind	Wind
0.6	0	0.3	Geothermal	NG
0.6	0.1	0.2	Wind	Wind
0.6	0.2	0.1	Wind	Wind
0.6	0.3	0	Wind	Wind
0.7	0	0.2	Wind	NG
0.7	0.1	0.1	Wind	Wind
0.7	0.2	0	Wind	Wind
0.8	0	0.1	Wind	Wind
0.8	0.1	0	Wind	Wind
0.9	0	0	Wind	Wind

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