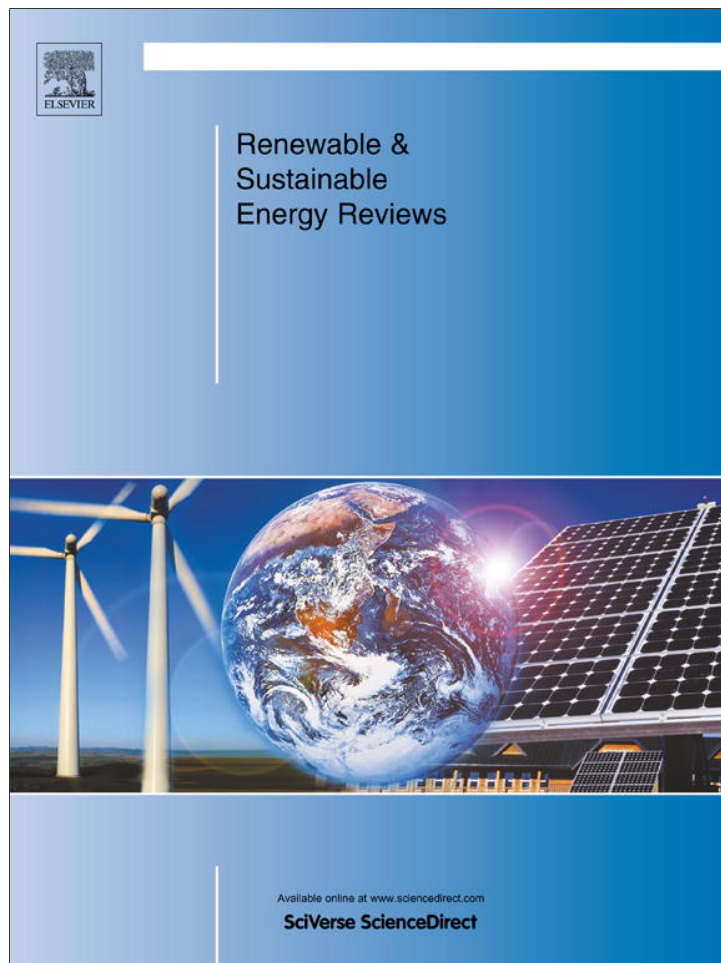


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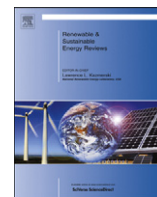
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A comprehensive multi-criteria model to rank electric energy production technologies

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ABSTRACT

The purpose of this research was to develop a model for decision-makers to rank various renewable and non-renewable electricity production technologies according to multiple criteria. The model ranks electric power plants using wind, solar, geothermal, biomass, hydropower (i.e., renewable sources), nuclear, oil, natural gas and coal in terms of four comprehensive criteria clusters: financial, technical, environmental and socio-economic-political. The model was built using the Analytic Hierarchy Process (AHP) with empirical data from government and academic sources. The results indicate that wind, solar, hydropower and geothermal provide significantly more overall benefits than the rest even when the weights of the primary criteria clusters are adjusted during sensitivity analysis. The only non-renewable sources that appear in three of the 20 top rank positions are gas and oil, while the rest are populated with renewable energy technologies. These results have implications for policy development and for decision makers in the public and private sectors. One conclusion is that financial incentives for solar, wind, hydropower and geothermal are sound and should be expanded. Conversely, subsidies for non-renewable sources could be diminished. The work concludes with ideas for future research such as exploring a full range of sensitivity analyses to help determine an optimal mix of renewable and non-renewable technologies for an overall energy system. The scope of the model could also be expanded to include demand as well supply side factors.

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1. Introduction and justification

The primary criticism of electricity-producing technologies that rely on non-renewable fuels (e.g., coal, oil, natural gas and uranium) is that most of these fuels will be depleted within about 100 years [27,51]. Another concern is that the cost of these fuels continues to rise. For example, the average retail price of gasoline for all formulations in the U.S.A. increased from \$1.07 to nearly \$4.00 per gallon between April 1993 and April 2012 (EIA 2013). Furthermore, the collapse of several tightly controlled political states has heightened the fragility of the geo-political world order. This turbulence and instability threaten global supply chains associated with most non-renewable sources of energy and especially oil. Technological disasters such as the Fukushima Daiichi meltdown have prompted Japan and other countries to abandon nuclear and seek alternatives.

In the long-term, power plants based on renewable fuels offer the most comprehensive solution to these problems. Consequently, decision makers throughout the world have established policies that encourage the transition to renewable fuels, which include solar, wind, hydropower, geo-thermal and biomass. Germany's commitment to solar began decades ago and is an exemplar for how subsidies can spur an industry. It reached a milestone recently when half of the country's daytime demand was met by solar power this past summer (Lobel, [33]). In the U.S.A., the Renewable Portfolio Standards (RPS) were first implemented in the 1990s as a similar means to accelerate the adoption of renewable technologies. As of 2012, 29 states plus Puerto Rico and Washington, DC require that a percentage of electricity generated by power plants come from renewable sources. According to Wiser et al. [65], p. 1, "RPS requires electricity suppliers (or, alternatively, electricity generators or consumers) to source a certain quantity (in percentage, megawatt-hour, or megawatt terms) of renewable energy." Each state sets its own standards and timetables, which can be adjusted by policy makers over time. For instance, in Arizona, the targeted RPS is 10.5% by the year 2025 whereas the target for Massachusetts is 25% by 2030 (see Table 1).

Increasingly, states are specifying which renewable technologies are preferred over others through the provision of *tiers*, which target specific resources or technologies such as solar (North Carolina State University, RPS Data 2013). Because there is considerable variance between states on target production levels and technologies, the markets for renewable energy credits also vary significantly. For example, the average price per solar energy credit in Massachusetts is about \$210/MWh whereas in Pennsylvania it is \$15/MWh as of this writing (SRECTrade, 2013). These differences challenge investors and long-term planners.

Utilities must comply with these laws or risk significant fines. For example, in California, the cost of non-compliance for total RPS targets is priced at \$50/MWh, which can be substantial for large power generators. States can also define stiffer penalties for specific technologies. For example in Ohio, the penalty for failure to meet RPS targets for solar energy is \$350/MWh. The RPS standards apply to investor-owned utilities (IOUs) as well as electric cooperatives and municipal producers.

While renewable fuels offer many benefits such as being "free" and plentiful, power plants based on these fuels suffer from production and capacity limitations due to the variability of solar radiation and thermal currents throughout the day and year. These and other financial, technical and socio-economic trade-offs pose immense problems for policy makers and investors as they

struggle to assess which renewable technological options are "best" in both the short-term and the long term, prompting some to ask:

- What criteria should be used to evaluate energy alternatives?
- How much "better" are renewable sources than non-renewable sources of energy?
- What is the best mix of renewable and non-renewable energy sources?
- Which renewable energy sources are preferred over others and should be offered incentives? For instance, is it appropriate to offer special incentives for solar?

The purpose of the study was to develop a method to help answer these questions. Toward that end, a comprehensive multi-criteria decision making (MCDM) model was implemented to evaluate nine different types of electricity-producing power plants (using both renewable and non-renewable energy sources) according to 11 key metrics. It is believed that this method and these results are of value to policy experts, investors and utility company executives responsible for making policy and investment decisions.

2. Background and review of the literature

Multi-criteria decision making (MCDM) methods have been applied to several different types of energy problems over the past three decades. The advantage of these models is that they allow for the evaluation of multiple, sometimes conflicting, criteria. Unlike simple cost-benefit models that are uni-dimensional, multi-criteria models allow stakeholders to compare options across several dimensions. Criteria may include factors of financial performance in addition to technical, social, or even esthetic dimensions. Evaluations may be based on historical data or preference rankings by domain experts.

Multi-criteria decision making methods and tools include Data Envelop Analysis (DEA), the Analytic Hierarchy Process (AHP), Multi-Attribute Utility Theory (MAUT), Multi-Attribute Value Theory (MAVT), PROMETHEE, ELECTRE and several others. Each has its strengths, weaknesses and areas of application. Advice on which method is best suited for a particular application is provided by Guitoni and Martel [22] and Polatidis and Munda [42]. Some methods (e.g., AHP) allow for the combination of both quantitative and qualitative data (e.g., [26,30,66]). Once the model has been built, sensitivity analysis can be performed by adjusting the weights of the criteria. This is particularly useful for policy analysis.

A review of the literature identifies several studies that have employed MCDM methods to site energy production facilities (e.g., [4,10,13,16,62]). For example, Al-Yahyai et al. [4] use AHP and GIS to site wind farms according to economic, technical, environmental, and social selection criteria. van Haaren and Fthenakis [62] also focus on site selection of wind farms using spatial data and multiple criteria in the U.S. state of New York. Charabi and Gastli [10] employed MCDM to site solar-PV farms in Oman using multiple criteria and GIS data. Defne et al. [16] assess tidal stream power potential using physical, environmental and socioeconomic constraints and GIS data in the U.S. state of

Table 1
RPS U.S. State Policies^{ab}.

State	RPS type (IOU's, etc.)	Tier (Tech)	Load covered (%)	Penalty or ACP (\$/MWh)	Duration (years)	Starting RPS (%) or (MW)	Start year (yyyy)	Target RPS (%) or (MW)	Target year (yyyy)
Arizona	1	1	58.8		100	1.25%	2006	10.5%	2025
	1	2	58.8		100	0.08%	2007	4.5%	2025
California	1	1	98.2	50	100	14.00%	2004	33.0%	2020
Colorado	1	1	58.7		100	2.88%	2007	27.0%	2020
	1	2	58.7		100	0.12%	2007	3.0%	2020
	2	1	35.6		100	1.00%	2008	10.0%	2020
Connecticut	1	1	93.4	55	100	2.00%	2006	20.0%	2020
	1	2	93.4	55	100	3.00%	2006	3.0%	2020
	1	3	93.4	55	100	1.00%	2007	4.0%	2020
Delaware	1	1	70		100	1.00%	2008	21.5%	2027
	1	2	70		100	0.01%	2009	3.5%	2027
	1	3	70		18	1.00%	2008	0.0%	2027
District of Columbia	1	1	100	50	100	1.50%	2007	17.5%	2023
	1	2	100	10	12	2.50%	2007	0.0%	2020
	1	3	100	500	100	0.01%	2007	2.5%	2023
Hawaii	1	1	100		100	10.00%	2010	40.0%	2030
Illinois	1	1	43.2		100	1.50%	2008	18.8%	2025
	1	2	43.2		100	0.50%	2008	4.8%	2025
	1	3	43.2		100	0.60%	2015	1.5%	2025
	2	1	45.7	5.12	100	3.00%	2010	15.0%	2025
	2	2	45.7	5.12	100	2.00%	2010	8.5%	2025
	2	3	45.7	5.12	100	0.60%	2015	1.5%	2025
Iowa	1	1	75.7		100	105 MW		105 MW	2000
Kansas	1	1	81.5		100	10.00%	2011	20.0%	2020
Maine	1	1	98.3	64.03	100	1.00%	2008	10.0%	2017
	1	2	98.3	64.03	100	30.00%	2000	30.0%	2017
Maryland	1	1	93.4	40	100	1.00%	2006	18.0%	2022
	1	2	93.4	15	12	2.50%	2006	0.0%	2022
	1	3	93.4	400	100	0.01%	2008	2.0%	2022
Massachusetts	1	1	86	64.02	100	1.00%	2004	25.0%	2030
	1	2	86	26.68	100	3.60%	2009	3.6%	2020
	1	3	86	10.51	100	3.50%	2009	3.5%	2020
	1	4	86	550	10	6.7% or 30	2010	0% or 400	2017
Michigan	1	1	100			4.8% or 500	2012	10% or 1100	2015
Minnesota	1	1	47.8		100	2.50%	2010	5.0%	2020
	1	2	47.8		100	12.50%	2010	25.0%	2020
	2	1	52.2		100	12.00%	2012	25.0%	2025
Missouri	1	1	70		100	1.96%	2011	14.7%	2021
	1	2	70		100	0.04%	2011	0.3%	2021
Montana	1	1	66.6	10	100	5.00%	2008	15.0%	2015
Nevada	1	1	88.2		100	5.70%	2005	23.5%	2025
	1	2	88.2		100	0.30%	2005	1.5%	2025
New Hampshire	1	1	98.2	55	0	0.50%	2009	12.4%	2025
	1	2	98.2	25	0	0.20%	2013	2.6%	2025
	1	3	98.2	55	11	0.04%	2010	0.3%	2025
	1	4	98.2	31.5	10	3.50%	2008	8.0%	2025
	1	5	98.2	26.5	10	0.50%	2008	1.5%	2025
New Jersey	1	1	98.3	50	100	0.74%	2005	17.9%	2021
	1	2	98.3	50	100	2.50%	2005	2.5%	2021
	1	3	98.3	641	100	0.01%	2005	4.1%	2028
New Mexico	1	1	67.7		100	5.00%	2006	9.4%	2020
	1	2	67.7		100	2.00%	2011	4.0%	2020
	1	3	67.7		100	2.00%	2011	4.0%	2020
	1	4	67.7		100	1.00%	2011	2.0%	2020
	1	5	67.7		100	0.15%	2011	0.6%	2020
	2	1	20.8		100	5.00%	2015	10.0%	2020
New York	1	1	84.7		100	0.43%	2006	7.6%	2015
	1	2	84.7		100	0.02%	2007	0.5%	2015

Table 1 (continued)

State	RPS type (IOU's, etc.)	Tier (Tech)	Load covered (%)	Penalty or ACP (\$/MWh)	Duration (years)	Starting RPS (%) or (MW)	Start year (yyyy)	Target RPS (%) or (MW)	Target year (yyyy)
North Carolina	1	3	84.7		100	19.75%	2003	20.7%	2015
	1	1	75.2		100	2.74%	2012	11.5%	2021
	1	2	75.2		100	0.02%	2010	0.2%	2021
	1	3	75.2		100	0.07%	2012	0.2%	2021
	1	4	75.2		100	0.12%	2012	0.6%	2021
	2	1	24.8		100	2.74%	2012	9.0%	2021
	2	2	24.8		100	0.02%	2010	0.2%	2021
	2	3	24.8		100	0.07%	2013	0.2%	2021
	2	4	24.8		100	0.12%	2013	0.6%	2021
	Ohio	1	1	88.6	47.56	100	0.25%	2009	12.0%
1		2	88.6	350	100	0.00%	2009	0.5%	2024
Oregon	1	1	74.6	50	100	5.00%	2011	25.0%	2025
	2	1	10.2	0	100	10.00%	2025	10.0%	2025
	3	1	15.2	50	100	5.00%	2025	5.0%	2025
Pennsylvania	1	1	97.3	45	100	1.50%	2007	7.5%	2021
	1	2	97.3	45	100	4.20%	2007	10.0%	2021
	1	3	97.3	550.15	100	0.00%	2007	0.5%	2021
Rhode Island	1	1	99.3	64.02	100	1.00%	2007	14.0%	2019
	1	2	99.3	64.02	100	2.00%	2007	2.0%	2019
Texas	1	1	75.9	50	100	1400 MW	2006	5000 MW	2014
	1	2	75.9	50	100	880 MW	2006	880 MW	2014
Washington	1	1	84.7	50	100	3.00%	2012	15.0%	2020
Wisconsin	1	1	100		100	3.55%	2006	9.6%	2015

^a Table synthesized from data compiled by the DSIRE Quantitative RPS Data Project (North Carolina State University, 2013).

^b The following states have voluntary goals: Indiana, North Dakota, Oklahoma, South Dakota, Utah, Vermont, Virginia, West Virginia and are not represented here.

Georgia. Choudhary and Shankar [13] use fuzzy AHP to identify sites for thermal power plants in India based on social, technical, economical, environmental, and political (i.e., STEEP) factors.

Another area of application has been in project selection (e.g., [5,24,32,49]). For instance, San Cristobal [49] illustrates how to rank renewable energy production alternatives (wind, solar-PV, solar-thermal, biofuel, and hydro) using AHP based on seven financial, technical and environmental criteria. Lee et al. focus on selecting a suitable wind farm project for various stakeholders using AHP. Haralambopoulos and Polatidis [24] developed a framework for achieving group consensus on renewable energy projects using PROMETHEE, which is then applied to a geothermal reservoir project on the island of Chios. Aragonés-Beltrán et al. [5] evaluate the financial suitability of solar-PV projects using the Analytical Hierarchy Network (AHN).

More general and methodological oriented studies have shown how the methods can be vital to planning and decision making (e.g., [41,44,46,63]) as well as analysis and assessment (e.g., [8,9,34,55]). For example, Pohekar and Ramachandran [41] review the application of various methods to RE planning, site selection, and project evaluation.

Finally, MCDM has been used to evaluate, rank and prioritize energy production technologies (e.g., [11,12,17,21,23,26,30,39,40,54,57,61,66]). Table 2 summarizes the criteria used in previous studies specifically designed to evaluate, prioritize or rank various electricity generation options. The evaluation measures used in previous research studies have been grouped into the following primary categories:

- financial factors
- technological factors

- environmental factors
- social/economic/political factors

Financial factors include capital investment and the fixed and variable operating costs of the production facility. Technical factors focus on the production efficiency of the generation source. Environmental factors include air quality, emissions, noise, etc., and impacts on human health as well as the natural environment. Social/Economic/Political criteria include the creation of employment opportunities, national security and other factors. Previous studies have used a variety of government, academic and industry sources of data from the U.S.A., Asia and Europe.

Energy options include both renewable sources such as wind, solar and hydropower as well as plants powered by non-renewable sources such as coal and oil. For example, Hamalainen [23] looked at coal and nuclear energy. More recent studies by Chatzimouratidis and Pilavachi [11,12] and Streimikiene et al. [54] examine the relative benefits of both non-renewable production technologies (e.g., coal, oil, natural gas, nuclear) and renewable technologies (e.g., hydro, wind, solar, biomass, and geothermal).

3. Current study design and objectives

Several objectives served to constrain the design choices for the current research. First, both renewable and non-renewable sources were selected for evaluation. Only a few of the previous studies have examined both renewable and non-renewable power plants. Renewable energy sources selected included solar, hydro, wind, biomass, and geo-thermal. Non-renewable (i.e., conventional) means of power

Table 2
Review of studies using multi-criteria decision analysis to evaluate electricity generation options.

Author/Method	Energy options	Financial criteria	Technological criteria	Environmental criteria	Social/Economic/Political criteria
Streimikiene et al. [54]	Nuclear	Private costs		GHG emissions	Tech-specific job opportunities
MULTIMOORA	Fuel cells	Average load factor		Environmental external costs	Food safety risk
TOPSIS	Hard coal Lignite Oil Natural gas	Security of supply costs of grid connection peak load response		Radionuclide costs Human health impact	Fatal accidents from past experience Severe accidents perceived in future
Yi et al. [66]	Hydro Biomass Solar-PV Solar-thermal Wind				
AHP	Wind Solar-PV	Facility construction cost Facility maintenance cost	Technology transfer Technological availability and readiness		Availability of resources Area development
	Solar-thermal	Infrastructure cost			Improvement of relations with neighboring countries Development of industry appropriateness
	Small hydropower Geothermal Waste Biogas				
Heo et al. [26]	New and existing renewable energy sources	Supply capability	Superiority	Reduction in greenhouse gases	Domestic market size
Fuzzy AHP		Economic feasibility Supply durability	Completeness Reliability acquisition rights	Resource requirements Resident acceptance	Global market size Competitiveness Alignment with dissemination goals Spillover effect Linkage with R&D programs Influence of existing social system
Chatzimouratidis and Pilavachi [11,12]	Coal	Capital costs	Efficiency coefficient	External costs	
AHP	Oil Natural gas Nuclear Hydro Wind PV Biomass Geothermal	O & M costs fuel costs	Availability Capacity Reserves/ Production ratio		
Tsoutsos et al. [57]	Wind	Investment	Maturity of Technology	CO ₂ emissions avoided	Local development/welfare
PROMETHEE	Wind and PV Wind, PV and olive Wind, PV, biomass	O & M costs Conventional fuel savings	Safety of supply		
Papadopoulos and Karagiannidis [40]	Wind	NPV	Blackout cost	CO ₂ emissions	
ELECTRE	Solar Geothermal Biomass	DPB LCC	(Network stability)		
Diakoulaki and Karangelis [17]	Lignite	Capital costs	Availability	CO ₂ emissions	
PROMETHEE	Oil Natural gas Hydro Wind and other RES	Operational costs	Response to peak load Supply security	SO ₂ NO _x	
van Alphen et al. [61]	Wind Solar-PV Wind hybrid Solar hybrid	NPV Levelized costs of energy O&M costs	Compatibility Triability	CO ₂	Fuel dependency
DEFINITE					
Kim and Min [30]		NPV IRR VCF		SO ₂ emissions NO ₂ CO ₂	
AHP					
Nigim et al. [39]	Solar-PV Wind Geothermal Hydro Solar thermal	Financial viability Resource availability	Technical feasibility	Ecological impact	Educational potential Social and economic impacts
AHP					
SIMUS					
Georgopoulou et al. [21]	S1-no facilities	Capital cost	Peak load coverage	Air quality	Cohesion to local area

Table 2 (continued)

Author/Method	Energy options	Financial criteria	Technological criteria	Environmental criteria	Social/Economic/Political criteria
ELECTRE III	S2-coal/oil plant	O & M cost	Operability Stability of the network	Noise Visual amenity Depletion of resources Risk of climate change Ecosystem protection Land use	Regional employment
	S3-conservation				
	S4-coal/oil+wind				
	S5-wind+conservation				
	S6-biomass+wind				
Hamalainen [23]	S7-biomass+wind+cons	Cost of electricity Capital costs	Pollution Natural resources accidents/LT risks	Foreign trade balance Centralization of power Political cooperation	
	S8-solar+biomass+cons				
	Nuclear power Coal-fired power				

generation included coal, oil, natural gas and nuclear energy. More information on these energy sources is given in a subsequent section.

Second, it was important to evaluate each energy option according to all four of the primary categories of evaluation, thus adding to the comprehensiveness of the evaluation. Earlier studies tended to omit one or more of the key categories. The most current data available was selected from trusted government and academic web sites and databases. More information on these data sources is provided in a subsequent section.

Third, the Analytic Hierarchy Process (AHP) was chosen as the method for evaluation. AHP allows for the evaluation of qualitative (i.e., based on preferences) and quantitative data types. It also allows the user to easily conduct sensitivity analysis to gauge the effects of different assumptions on the outcome, which is expected for stakeholders representing different interests. It has been used in numerous energy studies as indicated in literature review section of this paper (e.g., [4,5,11–13,26,30,66]). Full elaboration of the AHP method is given in the next section.

4. Requirements of the AHP method

AHP addresses subjective issues by using “fuzzy set” theory based on the idea that decisions are usually not absolute but are often made up of concepts that are defined only in “fuzzy” or relative terms. Developed by Saaty [48], AHP has been used as a method for evaluating complex multi-criteria decision making problems ranging from site selection to national security concerns. The method allows users to analyze both qualitative and quantitative criteria for purposes of generating weights of importance of the decision criteria and measuring the relative performance of alternatives in terms of each individual decision criterion. AHP simplifies the decision making process by breaking the problem into three basic steps: (1) problem decomposition; (2) pair-wise comparisons; and (3) synthesizing the result [3].

4.1. Step 1: Decomposing the problem

In the first step, the problem is decomposed into a hierarchical (or network) structure that consists of an objective (i.e., overall goal), criteria, sub-criteria, sub-sub-criteria, etc. and decision alternatives. The objective of the decision is represented at the top level of the hierarchy. The criteria and sub-criteria are represented at the intermediate levels. The decision alternatives

Table 3

Saaty [48] Nine-point Evaluation Scale.

Weight	Interpretation
1	Equally preferred
2	Equally to moderately preferred
3	Moderately preferred
4	Moderately to strongly preferred
5	Strongly preferred
6	Strongly to very strongly preferred
7	Very strongly preferred
8	Very to extremely strongly preferred
9	Extremely preferred

or selection choices are represented at the last level of the hierarchy.

4.2. Step 2: Pair-wise comparisons

The second step involves the comparison of pairs of criteria, pairs of sub-criteria (pairs of sub-sub-criteria, etc.) and pairs of alternatives. Comparisons may be based on historical data (e.g., the average output of each power plant) or estimates by domain experts (e.g., “In my experience, this outcome is roughly 5 times as likely as this one.”). In the first case, the data itself is the basis for the pair-wise comparison. For example, if Power Plant A has a mean efficiency of 0.15 and Power Plant B has an efficiency of 0.45, then in the comparison matrix, a value of “3” would be entered; i.e., “Plant B is 3 times as efficient as Plant A.” In the absence of historical data, domain experts can be asked to provide such estimates; e.g., “In my experience, Plant B is about 2–3 times as efficient as Plant A.” Saaty [48] recommends using a linear nine-point scale as shown in Table 3 in instances where the opinions of experts are the basis for comparisons.

The pair-wise comparisons are given in terms of how much element A is more important (or greater than or preferred) than element B. For example, for a given criteria, if alternative A is “Very strongly preferred” over alternative B, then a value of 7 is entered. If alternative A is “Strongly preferred” over alternative C, then a value of 5 is entered. Consequently, the relative importance of alternative B and C to alternative A is the reverse value, which is 1/7 and 1/5 respectively.

These data (historical or preference rankings) are then entered into matrices as shown in Table 4.

Table 4
Comparison matrix illustration.

Criteria 1	Alternative A	Alternative B	Alternative C
Alternative A	1	7	5
Alternative B	1/7	1	V_C
Alternative C	1/5	1/ V_C	1

A matrix is constructed for each evaluation criteria. For example, financial criteria may include four specific metrics so a 4×4 matrix would be constructed representing all possible comparisons. The weight of a matrix at any level depends on the number of elements at the lower levels to which it is linked.

4.3. Step 3: Synthesis

The third step involves using the values entered in the second step to perform computations to determine the best alternative for a particular goal. Once a pair-wise comparison matrix is constructed, the table is normalized by dividing each value in a column by its column sum. Next, the priority vector, which is a set of eigenvalues of the matrix, is developed by taking the row average of the normalized matrix. These row averages form the priority vector of alternative preferences with respect to a particular criterion. The values in this vector sum to 1. In this step, we also have the capability to measure the consistency of the comparisons, which is necessary when the opinions of experts are used instead of historical data. The consistency of the subjective input in the pair-wise comparison matrix (Step 2) can be determined by calculating a consistency ratio (CR). In general, a consistency ratio of less than 0.1 is considered good [48]. In the next section, we show how the AHP method was used to rank energy technology alternatives.

5. Setting up the method to rank energy production technologies

The first step in AHP is to set up the hierarchy of criteria and alternatives. The hierarchy is illustrated in Fig. 1.

General Model

$$\text{Energy Score (Ai)} = \text{FCscore (FC weight)} + \text{TCscore (TC wght)} + \text{ENscore (EN wght)} + \text{SEPscore (SEP wght)}$$

Notes:

- Score=scores of alternative *i* by criteria
- Weight=weight of each criteria
- FC=weight for Financial criteria
- TC=weight for Technical criteria
- EN=weight for Environmental criteria
- SP=weight for Socio-Economic-Political criteria

Technology options: this study examined two types of utility-scale (i.e., greater than 5 MW) electricity generating technologies: conventional (e.g., non-renewable) and those based on renewable sources. Non-renewable energy sources included oil, natural gas, coal and nuclear. Characteristics of these well-known sources are that there is a finite amount of fuel available, the fuel is “dirty” and “cheap,” and has a high carbon content (except nuclear). Although, several technologies burn oil, gas and coal, the ones profiled in this study included scrubbed coal, oil combined cycle, and conventional combustion gas turbines as defined by the EIA [60]. These systems tend to be of larger generating capacity and can

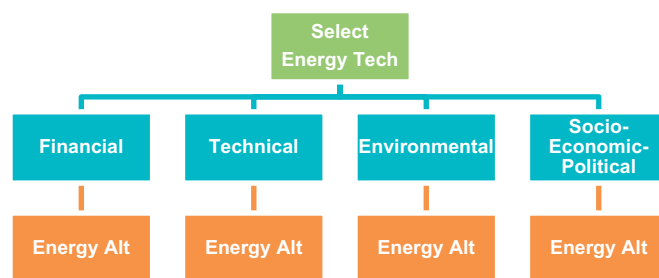


Fig. 1. Hierarchy for energy technology evaluation.

range from 500 MW for conventional gas fired plants to as high as 2 GW for nuclear.

Renewable energy power plant technologies profiled in the study included solar (photovoltaic), wind, hydropower, geo-thermal, and biomass. Characteristics of renewable sources include almost unlimited amounts of “fuel” and having a low or zero carbon foot-print (except biomass). Despite these advantages, they pose certain challenges with regard to production and storage. These systems tend to be of smaller generating capacity and range from 50 MW for bio-fuel and geo-thermal to 100–150 MW for solar-pv and wind. Hydropower systems at the utility level are often larger and in the range of 500 MW.

These renewable technologies were chosen based on the availability of reliable data. For example, while Solar-Thermal is an important emerging technology, it was not included in the initial analysis because of gaps in the data set. Table 5 provides a brief summary of the characteristics of each renewable technology included in the study.

Evaluation criteria: evaluation of each technology was based on the application of four primary criteria:

- Financial (FC): financial value of the technology and return on investment.
- Technical (TC): characteristics of the technology as a power source and its production capabilities.
- Environmental (EN): impact of power plant on local and regional environment, as well as human health.
- Social/Economic/Political (SEP): impact on local economy and communities, as well as congruence with overall national policies.

Historical data on the financial, technical, environmental and socio/economic/political characteristics associated with each of the energy technologies was used. Table 6 shows the various metrics used and their sources. Data sources were selected for trustworthiness and overall validity; i.e., government sponsored studies or appearing in peer-reviewed journals.

5.1. Financial criteria

Four financial criteria pertaining to the cost to build, operate and maintain each power technology were selected for input to the model. Total overnight cost (\$/kW) is the cost to build the power plant without accounting for the interest charges on loans and bonds. In this case, nuclear power plants are the most expensive and natural gas plants are the least expensive. Variable O&M and Fixed O&M indicate the variable and fixed costs to operate and maintain a power plant. In this case, geothermal has the highest variable O&M cost while solar and wind power are zero. Geothermal has the highest fixed O&M costs, while gas-fired plants have the lowest fixed costs. Finally, we looked at the cost of the fuels themselves. To facilitate comparison, all fuels were

Table 5
Characteristics of renewable energy technologies evaluated in the study^a.

Tech	Description
Solar (PV) ^b	Method: panels convert sunlight directly into electricity Efficiency: 20% (upper-tier commercial panels) Cost: small to large capital investment. Cost per panel now under \$1/watt Size: ranges from a few kW to 250 MW and larger Notes: CA is a leader in the USA
Wind	Method: electricity generated by large aerodynamic blades that power turbine Efficiency: 35% (average) Cost: modest to large capital investment Size: ranges from a few kW to 1000 MW and larger Notes: fastest growing energy source. Texas, CA, and PA among largest producers of wind energy in the USA
Hydro	Method: water descends on to in-water turbines that generate electricity Efficiency: as high as 95% Cost: modest to large capital investment Size: is a function of the height and volume of the water column. Ranges from a few kW to 20,000 MW and larger Notes: oldest clean energy source and one of the largest plant types
Biomass	Method: electricity generated by burning waste products derived from living or recently living organisms such as wood, waste, and alcohol fuels Efficiency: 25% (average) Cost: requires modest to large capital investment Size: ranges from 100 kW to 100 MW and larger Notes: biomass may be converted to another fuel such as liquid biofuel or biogas and burned. Higher carbon footprint than other renewable sources
Geo-Thermal	Method: electricity is produced from the latent heat in the earth contained in super-heated steam Efficiency: 10–12% range Cost: medium to large capital investment Size: ranges from 100 kW to 100 MW and larger Notes: not to be confused with residential geothermal also known as geexchange or ground water assisted HVAC, which are passive, not generative systems

^a Data for this study were based on larger, utility-scale systems; i.e., 5 MW or greater.

^b This study did not review solar thermal generators because there was insufficient data across all evaluation criteria required for the AHP model. Concentrating solar thermal power plants produce electric power by converting the sun's energy into high temperature heat using various mirror or lens configurations. Solar thermal systems (trough, dish-Stirling, power tower), transfer heat to a turbine or engine for power generation. Concentrating photovoltaic (CPV) plants provide power by focusing solar radiation onto a photovoltaic (PV) module, which converts the radiation directly to electricity.

Table 6
Sources of data for AHP model.

Type	Variables	Source
FC	Total overnight cost (\$/kW)	EIA 2011 Assumptions to the Annual Energy Outlook, p. 97.
	Variable O&M (\$2009 mills/kWh)	EIA 2011 Assumptions to the Annual Energy Outlook, p. 97.
	Fixed O&M (\$2009/kW)	EIA 2011 Assumptions to the Annual Energy Outlook, p. 97.
	Fuel costs (\$/MBtu)	Fossil fuels—EIA-Electric Power Monthly, May 2012, p. 73 Nuclear http://www.world-nuclear.org/info/inf02.html
TC	Average efficiency coefficient ^a %	Oil, Coal Gas, Nuclear, and Biomass—EIA 2011 Assumptions to the Annual Energy Outlook, p. 97.
	Average capacity factor %	Solar, Wind, and Hydropower—see text Tidball et al. [56], NREL Report, p. 10 EIA—Annual Energy Outlook 2009
EN	Average external \$ costs	www.ExternE.info
	Loss of life expectancy (LLE)	Nathwani, Siddall, Lind, "Energy for 300 years," 1992, Table A
SEP	Job creation	Wei, Patadia, Kammen, "Putting renewables and energy efficiency to work," Energy Policy (2010)
	Net import % of energy	Energy Information Agency (http://www.eia.gov/totalenergy/data/monthly/)
	Fuel reserve years	Fossil fuels—Shafiee and Topal, "When will fossil fuel reserves be diminished?" Energy Policy 37 (2009) 181–189 Nuclear—Uranium 2009: Resources, Production and Demand http://www.iaea.org/newscenter/news/2010/uraniumfuels.html

^a Based on Heat Rate in 2010 (BTU/kWh) from the EIA 2011 Assumptions to the Annual Energy Outlook, p. 97.

converted to \$ per million Btu (British thermal units), which is a standard measurement of energy content. As is clear from Table 7, all renewable sources are zero in this regard, while oil is the most expensive.

5.2. Technical criteria

Two technical criteria pertaining to the production characteristics of each technology were selected for input to the model. The

first criterion in this category is the efficiency of the technology. Plant efficiencies vary widely from as high as 95% for hydropower to the mid-range values (e.g., 35–45%) for gas and oil-fired turbines to 10–15% for geothermal.

To determine non-renewable plant efficiencies, the most up to date data on heat rates for fossil fuels and geothermal were used (see Table 8). Heat rate is a measure of the energy conversion efficiency of a plant, which can be written as: $\phi_{hr} = H/E$ where ϕ_{hr} = heat rate (Btu/kWh) and H = heat supplied to the power

Table 7
Financial (FC) criteria data.

Technology	Size MW ^a	Total overnight cost in 2010 (2009 \$/kW)	Variable O&M in 2010 (2009 \$/MWh)	Fixed O&M in 2010 (2009 \$/Moh)	Fuel costs \$/MMBtu
Solar-PV	150	4697	0	25.73	0
Wind	100	2409	0	27.73	0
Hydropower ^b	500	2221	2.42	13.55	0
Geothermal	50	2482	9.52	107.27	0
Biomass	50	3724	6.94	99.3	12.63
Nuclear ^c	2200	5275	2	87.69	2.26
Coal ^d	1300	2809	4.2	29.31	10.67
Oil ^e	500	967	3.37	14.22	36.02
Gas ^f	85	961	8.15	9.75	13.24

^a Approximate size of plant. All plants in this study are utility scale and greater than 5 MW.

^b Conventional hydropower.

^c Advanced nuclear.

^d Scrubbed coal.

^e Conventional oil combined cycle (also runs on gas).

^f Conventional gas turbine.

Table 8
Technical (TC) criteria data.

Technology ^a	Heat rate in 2010 (BTU/kWh) ^b	Production efficiency (%)	Capacity factor %
Solar-PV	** ^c	20.0	22
Wind	**	35.0	44
Hydropower	**	90.0	57
Geothermal	30,000	11.4	90
Biomass	13,500	25.3	83
Nuclear	10,453	32.6	90
Coal	8800	38.8	85
Oil	7050	48.4	87
Gas	10,745	31.8	92

^a All plants in this study are utility scale and greater than 5 MW.

^b Heat rate values listed in table are for informational purposes and are not used in the model. Only the efficiency figures are used for input to the AHP model.

^c The heat rates provided by the EIA for solar, wind and hydropower (e.g., 9854) are proxies. The EIA does not specify actual rates for renewable technologies but assigns the average of all heat producing technologies in its tables.

plant for a period (Btu) and E =energy output from the power plant in the period (kWh) [43]. “It accounts for all the electricity that the plant itself consumes to operate the generator(s) and other equipment, such as fuel feeding systems, boiler water pumps, cooling equipment, pollution control devices, etc.” [58,59]. Oil is the most efficient while geothermal has the lowest efficiency. To calculate the efficiency of a generator or power plant as a percentage, we divide the equivalent Btu content of a kWh of electricity (which is 3412 Btu/kWh) by the heat rate [58,59]. These calculated values are listed in Table 8.

The efficiency values for most renewable sources, because they do not require heat to produce electricity (e.g., direct conversion of sunlight to electricity for solar) cannot be calculated using heat rates [58,59]. Consequently, the ‘heat rates’ provided by the EIA for solar, wind and hydropower (e.g., 9854) are proxies and should not be used because the EIA arbitrarily assigns the average of all heat producing technologies in its tables to the renewable sector. As a consequence, the average efficiency rates for solar, wind and hydropower were obtained elsewhere. Solar efficiencies range from 14% to 22% with a theoretical limit of 33.7% [52]. A value of 20% nominal efficiency conversion rate was used for this study, which is typical for many commercially produced panels (e.g., www.sunpower.com). Wind turbines have a theoretical limit

of 59.3% according to Betz’s law but have more practical efficiencies in the range of 35–45% [28]. As a total system (including rotor, transmission, generator, etc.) the actual value may be less. Consequently, a value of 35% was used. The efficiency of hydroelectric plants is well known, with efficiencies of over 95% [20]. A value of 90% was used for the AHP model. Based on these data, hydropower has the highest overall plant efficiency and geothermal has the lowest.

The Capacity Factor of a power plant is the ratio of the electrical energy produced by a generating unit for the period of time considered to the electrical energy that could have been produced at continuous full power operation during the same period [58,59]. In their review of energy-economic models, Tidball et al. [56] find relatively small variations in capacity factors among the five data sets profiled in their study. For the purposes of this study, data from the EIA’s Annual Energy Outlook were used to populate the AHP model. Table 8 indicates that natural gas has the highest overall capacity rating while solar has the lowest because of the daily variability in weather conditions that affect solar energy incident on the earth (this is of course also a function of local geography).

5.3. Environmental (EN) criteria

Two criteria pertaining to the environmental impacts of each technology on human populations and natural systems were selected for input to the model. Externalities can be measured in a variety of ways such as emissions (e.g., SO₂, CO₂, NO_x, etc), the impact on human health, injuries, or damage to ecosystems. These represent the “hidden” costs of energy production and use, which are not reflected in market prices of coal, oil, and other energy sources. A study by the National Research Council [37,38] estimated these external costs at \$120 BB. To simplify the task of assessing the impacts of energy production technologies, data from the ExternE project were used for comparisons. The ExternE Project ([2]) ranks all major energy production technologies according to external costs. These data are presented in Table 9. According to these data, wind has the lowest external costs whereas coal has the highest external costs.

The second criterion is the Loss of Life Expectancy (LLE) associated with each technology. LLE is a measure of the degree to which the technology results in a loss of human life based on “...the comprehensive assessment of all the activities that comprise the total life cycle of each major supply option.” ([36], p. ix). According to Table 9, the risks posed by solar and wind power are negligible, while coal poses the most risk to human life. However,

Table 9
Environmental (EN) criteria data.

Technology	External costs (EU cent/kWh)	LLE (days)
Solar-PV	0.60	0.1 ^a
Wind	0.19	0.1 ^b
Hydro	0.54	2.3
Geothermal	0.20 ^c	2.3 ^d
Biomass	2.01	3.5
Nuclear	0.39	0.8
Coal	5.71	8.4
Oil	5.70	4.5
Gas	1.85	0.8

^a Listed in source as “negligible” (i.e., < 1.0). An estimate of 0.1 was therefore used.

^b Listed in source as “negligible” (i.e., < 1.0). An estimate of 0.1 was therefore used.

^c This value reported by Chatzimouratidis and Pilavachi [12] and not available in the ExternE study.

^d Estimated as the same as hydroelectric.

all is relative and these numbers should be put into perspective. The LLE is significantly less than the gain in life expectancy (GLE=62) as a result of the provision of energy for human populations [36].

5.4. Social/economic/political (SEP) criteria

Three criteria pertaining to the socio-economic-political characteristics of each technology were selected for input to the model. The first factor in this category is Fuel Reserve Years. Fuel Reserve Years are defined as the number of years until full depletion on the earth of a given non-renewable resource; i.e., oil, coal, uranium, and gas. A recent study by Shafiee and Topal [51] found that earlier estimates of resource depletion were significantly lower than actual because they did not account for consumption. Revised estimates for oil, coal, and gas are 40 years, 200 years, and 70 years respectively based on 2006 rates of consumption (p. 187). These estimates assume that no new large reserves are identified over the time period or that consumption levels change dramatically. The estimate for nuclear fuel reserves is based on the International Atomic energy Agency's bi-annual report, which concludes that at 2008 rates of consumption, total worldwide uranium resources are predicted to last about 100 years [27]. Solar, wind, hydro and geothermal are considered "unlimited" and have been assigned 2BB years (e.g., the life expectancy of the earth in its current form based on the sun's life cycle [7] for comparison purposes. Biomass includes all non-fossil organic materials such as vegetation, trees, municipal solid waste, sewage, and other organic wastes [6]. It is renewable and

unlimited in the sense that it can be grown or is available as a by-product of human activity. For comparison purposes, the fuel reserve years for biomass was estimated at 5000 years.

Job creation by production technology is the second factor in this category; i.e., how many jobs are created throughout the life-cycle of a power plant including design, construction, operation, maintenance, etc. A recent study by Wei et al. [64] compares several power plant technologies in their ability to generate jobs in the U.S.A. The study normalizes jobs data to average employment (e.g., job-years) per unit of energy (GWh) produced over the lifetime of a plant. Based on these data, coal has the lowest job producing value while solar-pv has the highest.

The last SEP criterion used in the model was the degree to which a nation (e.g., the United States) imported (or exported) the fuel required for the plant. The reliance on fuel through global supply chains poses many geo-political and security issues and accompanies most discussions of energy policy. In this regard, all renewables pose many significant advantages because net imports are zero (see Table 10). In the case of the U.S.A., it has sizable reserves in uranium [27], so it does not have to import this fuel source either. On the other hand, for the U.S.A. oil is the most problematic fuel source in this regard since it imports about 45% of its needs, although this number has diminished in recent years [60]. Coal on the hand is the only energy source of which the U.S.A. is a net exporter.

In the next section, the results of the analysis are presented.

Table 10 Socio-economic-political (SEP) criteria data.

Tech	Fuel reserve years	Job creation (job-years/GHz)	Net import as % of consumption (2011)
Solar-PV	2,000,000,000	0.87	0
Wind	2,000,000,000	0.17	0
Hydro	2,000,000,000	0.27	0
Geothermal	2,000,000,000	0.25	0
Biomass	5000	0.21	0
Nuclear	100	0.14	0
Coal	200	0.11	-9.4 ^a
Oil	40	0.11 ^b	44.8
Gas	70	0.11	8.0

^a The USA exports more coal than it imports.

^b Estimated to be the same as the natural gas industry since many employment studies group them together.

6. Results of the analysis

The software used for this analysis was Super Decisions™. Super Decisions implements a generalization of AHP identified as the Analytic Network Process developed by Saaty (www.superdecisions.com) [1]. It allows the user to quickly set up nodes of choices and alternatives in a hierarchy or a network. The software then calculates ratio scale priorities for elements and clusters of elements by making paired comparisons of elements on a common property or criterion using the input data. The system can accept preference data or historical data as input. The data may be inverted for variables that are "less good" as they increase; e.g., costs. The model was set up using a model template in Super Decisions and the data was entered directly.

The results of the analysis are found in Fig. 2. These results represent the normalized scores of power production technologies according to the four criteria clusters (e.g., financial, technical, etc.) while assuming that each cluster and its components

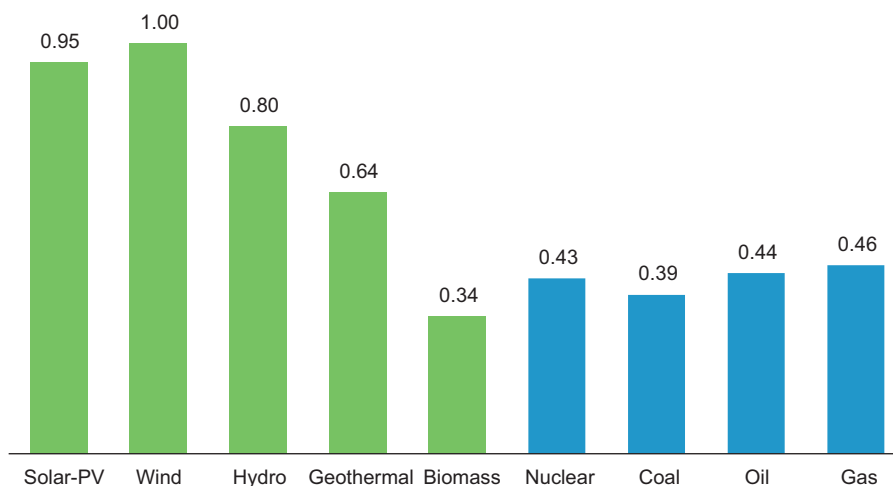


Fig. 2. Ranking of power technologies assuming equal weights to all criteria.

have equal weight (*Note: in the next section we will explore the impact of changing the weights using sensitivity analysis*).

The results show that wind and solar-pv provide the most overall benefits across multiple dimensions, thus lending support for policies that encourage accelerated investment in wind and solar power through government tax incentives, energy credits, and the RPS standards (more on this issue in a later section). They are both significantly better (2–3 times) than conventional plants powered by coal, oil and gas, as well as nuclear. Hydropower provides about 80% as much utility as wind, while geothermal scores about 63%. These results show that four out of five renewable energy sources are considerably better than non-renewable sources based on a balanced multi-criteria assessment. This outcome is consistent with the results of previous studies (e.g., [11,12]) although the exact order of the rankings within technology categories (e.g., renewables, non-renewables) is somewhat different.

The next cluster of technologies by score includes natural gas, oil and nuclear, which all provide about the same utility (e.g., 42–46% as good as wind). This result lends credence to efforts to position natural gas and nuclear as “transition” energy sources, although they score less than half as well as wind and solar. Oil continues to be short-term fix but one that is not sustainable. It should also be noted that the score for nuclear does not include upward revisions to risk estimates associated with this power source as a consequence of the Japanese Fukushima reactor meltdown in 2011 and scores may drop as a consequence. Coal scores less than 40% as well as wind. Coal has the second lowest utility of all technologies across all dimensions and is not likely to be a good future source of energy according to these results. Biomass is the only renewable source that scores poorly, partly because of its high carbon content, and may have only a limited role in the future energy picture.

Interestingly, if we run an exploratory analysis of the ranking of Solar-Thermal technology using available data (and substituting some data used for Solar-PV), the results show that Solar-Thermal scores just above hydropower in terms of overall utility assuming equal weights. One of Solar-Thermal’s advantages is its higher efficiency rate over PV. On the other hand, these types of plants tend to be more capital intensive. Future studies should expand the scope of the current model to rank Solar-Thermal and other promising renewable technologies in terms of overall utility as data becomes available.

As was stated at the outset, it was assumed that all criteria have equal weight in the evaluation. In the next section, we examine the impact that modifying the weights of each of the criteria clusters has on the overall rankings.

7. Sensitivity analysis and use of the model by various stakeholders

One of the challenges of multi-criteria decision problems is that the set of solutions that are deemed “acceptable” depends on the values and interests of the stakeholders. In this case, there are numerous stakeholders and each brings a unique perspective and set of values regarding energy generation (see Fig. 3); i.e., what is preferred for one stakeholder may not be for another.

For example, a utility company may be more concerned with plant performance and return on capital (e.g., a higher weighting on technical and financial factors) whereas a community group might be more concerned with social, economic and environmental impacts. These assumptions would be reflected in the weights assigned to the major criteria groups (or even to individual measures). Having the ability to adjust the weights to run a sensitivity analysis is therefore a critical aspect of any

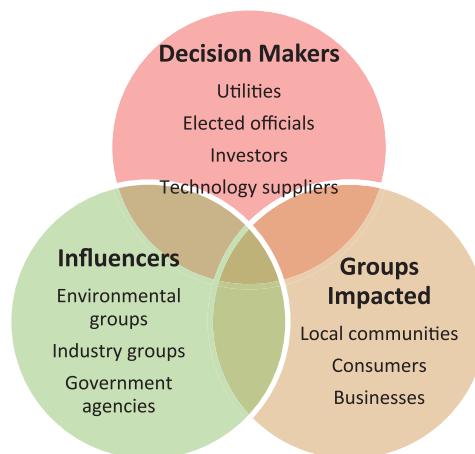


Fig. 3. Stakeholders impacting or impacted by energy production technology decisions.

Table 11
Weights of criteria clusters according to various scenarios.

Criteria cluster/ scenario	Financial return (%)	Operational efficiency (%)	Community interest (%)	National priorities (%)
Financial	60	25	5	5
Technical	25	60	10	10
Environmental	10	10	60	25
Socio/economic/ political	5	5	25	60

analysis such as this. This is easily accomplished in AHP by adjusting the weights of individual factors or criteria clusters of the model. We can examine four scenarios that reflect the values of different stakeholder groups. Table 11 provides a summary of the scenarios and the weights that might be assigned in each case.

7.1. Scenario 1: Financial return scenario

In this scenario, the stakeholder considers financial criteria (FC weight=60%) to be most important. The emphasis here is return on investment and minimizing operating costs. The results using these weights are illustrated in Fig. 4. From an investment perspective, wind, solar, hydropower and gas are the most attractive. Biomass and nuclear power are the least attractive.

7.2. Scenario 2: Operational efficiency scenario

In this scenario, the stakeholder considers technical criteria (TC weight=60%) to be most important; i.e., operational efficiency. The emphasis here is plant performance, production and output. The results using these weights are illustrated in Fig. 5. From an operational perspective, hydropower, wind, oil and gas provide the greatest utility. Biomass has the least utility from this perspective.

7.3. Scenario 3: Community interest scenario

In this scenario, the stakeholder considers environmental criteria (EN weight=60%) to be the most important. The emphasis here is on minimizing environmental impact and human health risks. The model results using these weights are illustrated in Fig. 6. Wind, solar, geothermal, and hydropower are the best choices in this scenario. Oil is the least desirable choice from this perspective.

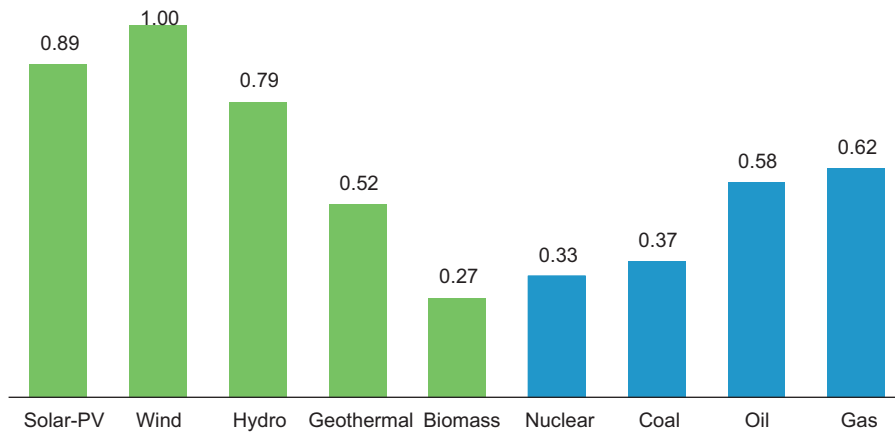


Fig. 4. Ranking of power technologies weighted for financial return scenario.

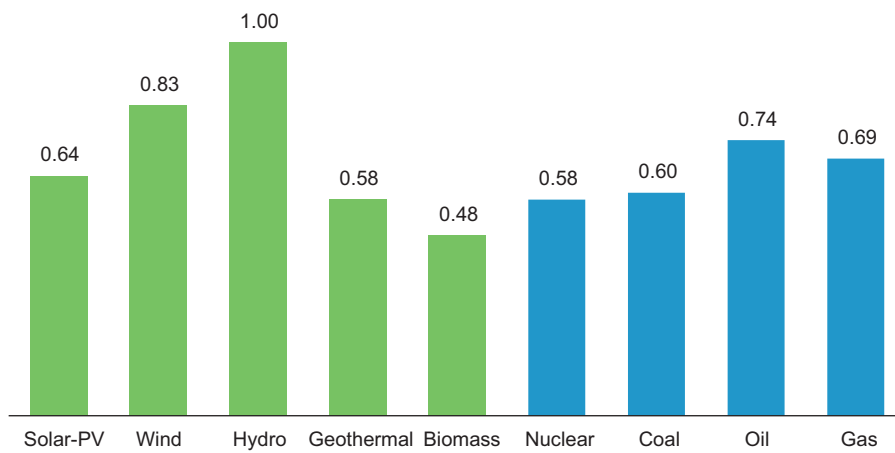


Fig. 5. Ranking of power technologies weighted for production efficiency scenario.

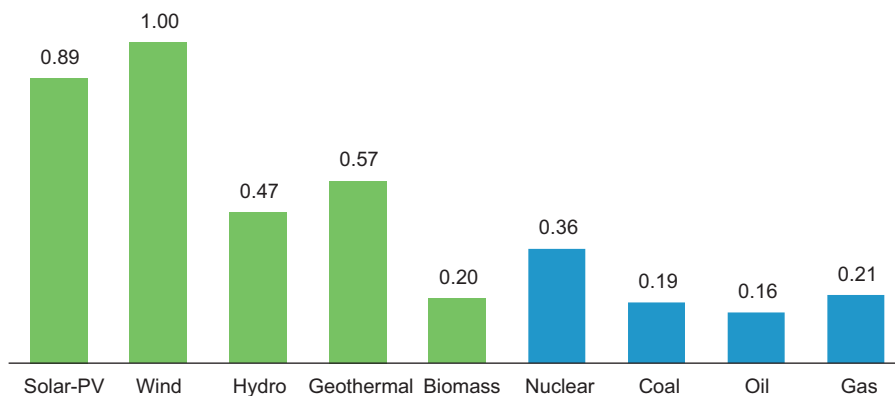


Fig. 6. Ranking of power technologies weighted for community interest scenario.

7.4. Scenario 4: National priorities scenario

In this scenario, the stakeholder considers socio-economic-political criteria (SEP weight=60%) to be the most important. The emphasis here is a commitment to national priorities such as energy independence, job creation, and security. The model results using these weights are illustrated in Fig. 7. Solar, wind, hydropower, and geothermal are the best choices in this scenario. Oil is the least desirable choice from this perspective.

8. Policy implications and applications of the model

We began this study with several questions:

- What criteria should be used to evaluate energy alternatives?
- How much “better” are renewable sources than non-renewable sources of energy?
- What is the optimal mix of renewable and non-renewable energy sources?

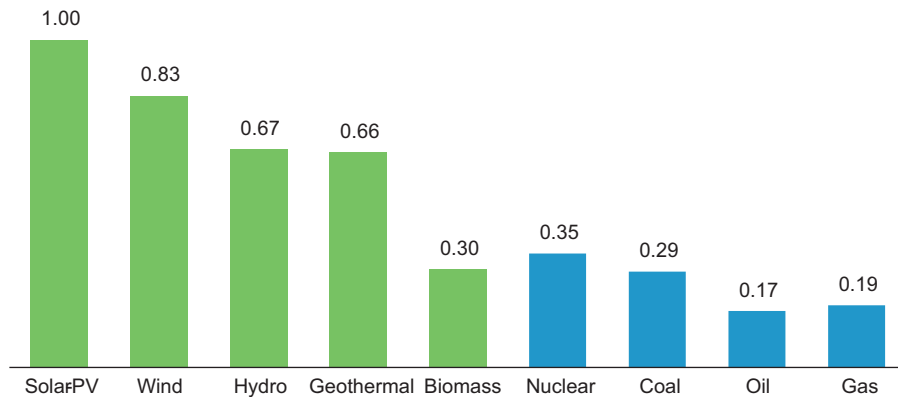


Fig. 7. Ranking of power technologies weighted for national priorities scenario.

Table 12
Top four technologies for all scenarios.

Rank	Balanced scenario (equal weights)	Scenario 1 Financial return	Scenario 2 Operational efficiency	Scenario 3 Community interest	Scenario 4 National priorities
1	Wind	Wind	Hydro	Wind	Solar
2	Solar	Solar	Wind	Solar	Wind
3	Hydro	Hydro	Oil	Geothermal	Hydro
4	Geothermal	Gas	Gas	Hydro	Geothermal

- Which renewable energy sources are preferred over others and should be offered incentives? For instance, is it appropriate to offer special incentives for solar?

A careful review of the literature reveals that studies of the comparative benefits of various electricity producing technologies using multi-criteria methods utilized criteria that fall into four primary categories: financial, technical, environmental, and socio-economic-political. These results suggest that any ranking of energy technologies must be comprehensive. Evaluations using MCDM are thus similar in breadth and scope to the balanced scorecard approach as suggested by Kaplan and Norton [29] and widely implemented as a planning method to align business activities with strategy. Consistent with these findings, this analysis was based on an evaluation of 11 factors representing four distinct clusters of criteria.

The second question was: “How much ‘better’ are renewable sources than non-renewable sources of energy?” Table 2 (e.g., the balanced equal-weight scenario) indicates that technologies such as wind and solar are significantly better overall and in some cases by a factor of 2–3 times. Table 12 identifies energy technologies that perform well across multiple scenarios with differing goals (i.e., weights) imposed by the decision makers. Renewable energy technologies consistently score at the top across all scenarios, as well as in the balanced scenario. According to this analysis, renewable technologies populate 17 out of 20 top rank positions. Gas and oil are the only non-renewable technologies that appear in at least one scenario where they were ranked either third or fourth. Nuclear energy does not appear in any of the top four positions in any scenario. In sum, renewable technologies are much better than non-renewable ones across a variety of scenarios that reflect differing goals of the decision makers.

The results also lend support for policies that encourage investment in renewable production technologies, especially wind and solar. Conversely, it suggests that subsidies for fossil-

fuel based technologies be diminished or eliminated. Some free market economists argue that subsidies for renewable energy sources are “bad” and distort the market, yet fail to acknowledge existing subsidies for non-renewable sources. Research by the Environmental Law Institute [19] found that subsidies to fossil-fuel based technologies amounted to \$72 billion in the U.S.A. between 2002 and 2008 while subsidies for renewable fuel sources totaled \$29 billion. The results of this study lend support for increased and continued subsidies for renewable sources and decreased spending on non-renewable sources of energy including nuclear.

The third question was: “what is the optimal mix of renewable and non-renewable energy sources?” The optimal design of an electric power system that employs both renewable and non-renewable technologies is complex and variable because one or more objectives need to be achieved; i.e., capital costs, technical performance, minimizing externalities such as CO₂ production, job creation, etc. Consequently, the answer to this question is a function of the decision maker's goals. The scenarios discussed in this paper illustrate how weighting various clusters can modify the positions of the technologies in the rank order. For example, oil and gas are much more attractive if the weighting is skewed to technical performance. We could also run the model by maximizing (or minimizing) a selection of factors within clusters such as capacity, capital costs, or environmental impact and using the resulting ranks to establish a mix of technologies for a region or country.

Another way the results can be used to answer this question is to rule out technologies that consistently under-perform or target those that provide maximum benefits. For example, coal, nuclear and biomass in their current forms score near the bottom of all scenarios. On the other hand, wind and solar are clearly advantageous overall and could merit higher concentrations in the mix. This conclusion lends support for a recent study by Heide et al. [25] who developed a plan for the optimal mix of wind and solar for the European continent. Their work is based on the observation that wind and solar generation complement one another throughout the year; i.e., wind generation improves in the winter when solar falls off and vice-versa. They show how Europe could transition to a power structure based almost entirely on a mix of solar and wind. One of the chief concerns of any allocation is the ability to meet base load. They address this condition by running scenarios with energy supplements from fossil and nuclear plants until sufficient storage can be developed.

Another way to approach the issue of optimal mix is to explore outcomes under specific constraints such as base load requirements, storage capabilities, available fuel, etc. using complementary analyses. For example, Muis et al. [35] illustrate how mixed integer linear programming (MILP) can be used to generate a solution to the

problem of reducing CO₂ emissions by 50% in Malaysia while matching demand curves and minimizing capital costs. The model specifies the percentages of electricity that should be generated by each technology, which included coal (IGCC), natural gas (NGCC), nuclear, and biomass in the preferred solution. Solar–PV was ruled out because of its high capital costs. In another study, De Jonghe et al. [15] explore the integration of high levels of wind energy into the generation system using linear programming. One of the conclusions is that storage and interconnection capabilities can increase flexibility to help accommodate the load fluctuations presented by wind. To summarize, a complete answer to the question of optimal mix is outside the scope of the current paper and will require further study by running the model with various constraints and weights, while taking into account the evolution of the technologies themselves along with ancillary improvements in system storage and distribution.

The final question was: “which renewable energy sources are preferred over others and should be offered incentives?” The answer to that is now clear. Wind and solar are the top performers across all scenarios. U.S. states that have set RPS standards are justified in doing so. Policies that favor wind and solar technologies are therefore justified according to these results. One issue is the degree to which each are supported with incentives. Both wind and solar should garner incentives that are roughly equivalent, although that is not always the case. Furthermore, those that wish to accelerate investment in these key technologies should ensure that power generation capacity targets are set high enough to create ample markets. Unfortunately, there is considerable variation among the states that have RPS standards. As mentioned earlier, Solar Renewable Energy Credits (SRECs) are worth about \$210 in Massachusetts while in Pennsylvania they are only worth about \$15 as of this writing. This disparity has a huge impact on the ROI of solar energy projects between the two states. Rational decision makers (i.e., investors) will invest on one side of the border while not on the other. Situations such as this should be corrected on a state by state basis.

In summary, there are many opportunities to apply this model and the results to real-world problems. The model can be used to help determine where to put investments in energy with public funds and that doing so is based on sound principles not political expediency. The results and the model can be a resource when writing and updating laws regarding the incentives for renewable energy. Finally, the results could incentivize the private sector to invest in renewable technologies, not just because they are “green” or sustainable, but because they provide a good return on investment.

9. Summary and conclusions

This paper provides a model that can be used to rank electricity producing technologies based on a comprehensive set of 11 factor representing financial, technical, environmental and socio-economic-political considerations. The AHP model ranked nine primary technologies in terms of overall benefits, with wind and solar–pv topping the list. Performing sensitivity analysis by weighting different clusters according to four types of decision makers resulted in a matrix that was populated by renewable energy technologies in over 85% of the cases. We can conclude that solar, wind, hydropower, and geothermal offer the most overall benefits. Oil and gas offer the most utility in scenarios weighted for financial return and efficiency, but are still lower than wind, solar or hydro. Nuclear does not score as highly as expected, while coal and biomass rank near the bottom in most scenarios.

We can conclude from these results that policies designed to incentivize the production of wind, solar, hydro and geothermal are sound and should be retained or expanded. In contrast, subsidies for non-renewable technologies should be curtailed. In

the U.S.A., states that have not developed Renewable Portfolio Standards (RPS) should consider doing so. States that have adopted RPS policies but currently do not target incentives for wind, solar, hydro and geothermal should consider amending their standards accordingly. Finally, these results provide insight into establishing an optimal mix of renewable and non-renewable electricity producing technologies but more work needs to be done to apply the model in light of very specific constraints such as CO₂ production, available land mass, capital investment, etc., which represent specific goals of the decision makers. Future research includes running additional scenarios and exploring a full range of sensitivity analyses. For example, we could explore the impact of changing each of the eleven criteria on specific outcomes. We might also use experts representing various stakeholder groups to independently assign weights to the four evaluation criteria clusters and run the analyses again. Another way to augment the model would be to include additional criteria in each of the criteria clusters, although the ones used here are believed to provide a comprehensive assessment of the energy options. We could also augment the model by including emerging renewable technologies such as Solar-Thermal.

One additional area for future research is to include demand side factors such as energy efficiency (EE) as part of the analysis. While it makes no sense to calculate the heat value of an EE project, there are relationships between EE and several of the variables used in this study. For example, Wei et al. [64] calculated the contribution of EE projects to job creation. The average value of 0.38 they list is higher than eight of the nine generation technologies profiled in this study (see Table 10). One could also argue that LLE is near zero, financial return is positive, external costs minimal and that EE efforts contribute to energy independence. Consequently, EE would rank among the top “energy” solutions. Future studies could be done to broaden the scope of this model to include both demand and supply side methods that contribute to an effective energy strategy for the U.S.A. and other countries.

References

- [1] (n.d.). Retrieved 2012, from Super Decisions. <<http://www.superdecisions.com>>.
- [2] (2006). Retrieved 2012, from ExternE-External Costs of Energy. <http://www.externe.info/extern_e_2006/>.
- [3] Ahmad N. The design, development and analysis of a multi criteria decision support system model: performance benchmarking of small to medium-sized manufacturing enterprise (SME). Troy, NY: Rensselaer Polytechnic Institute (Doctorate); 2005.
- [4] Al-Yahyai S, Charabi Y, Gastli A, Al-Badi A. Wind farm land suitability indexing using multi-criteria analysis. *Renewable Energy: An International Journal* 2012;44:80–7.
- [5] Aragonés-Beltrán P, Chaparro-González F, Pastor-Ferrando J, Rodríguez-Pozo F. An ANP-based approach for the selection of photovoltaic solar power plant investment projects. *Renewable & Sustainable Energy Reviews* 2010;14(1):249–64.
- [6] Balat M, Ayar G. Biomass energy in the World, use of biomass and potential trends. *Energy Sources* 2005;27:931–40.
- [7] Cain F. Life of the Sun. Retrieved 2012, from Universe Today; March 11 2012. <<http://www.universetoday.com/18847/life-of-the-sun/>>.
- [8] Catalina T, Virgone J, Blanco E. Multi-source energy systems analysis using a multi-criteria decision aid methodology. *Renewable Energy* 2011;36(8):2245–52.
- [9] Cavallaro F. Multi-criteria decision aid to assess concentrated solar thermal technologies. *Renewable Energy* 2009;34(7):1678–85.
- [10] Charabi Y, Gastli A. PV site suitability analysis using GIS-based spatial fuzzy multi-criteria evaluation. *Renewable Energy* 2011;36(9):2554–61.
- [11] Chatzimouratidis AI, Pilavachi PA. Sensitivity analysis of technological, economic and sustainability evaluation of power plants using the analytic hierarchy process. *Energy Policy* 2009;37:788–498.
- [12] Chatzimouratidis A, Pilavachi P. Technological, economic and sustainability evaluation of power plants using the Analytic Hierarchy Process. *Energy Policy* 2009;37(3):778.
- [13] Choudhary D, Shankar R. An STEEP-fuzzy AHP-TOPSIS framework for evaluation and selection of thermal power plant location: a case study from India. *Energy* 2012;42(1):510–21.

- [15] De Jonghe C, Delarue E, Belmans R, D'haeseleer W. Determining optimal electricity technology mix with high level of wind power penetration. *Applied Energy* 2011;88:2231–8.
- [16] Defne Z, Haas KA, Fritz HM. GIS based multi-criteria assessment of tidal stream power potential: a case study for Georgia, USA. *Renewable & Sustainable Energy Reviews* 2011;15(5):2310–21.
- [17] Diakoulaki D, Karangelis F. Multi-criteria decision analysis and cost-benefit analysis of alternative scenarios for the power generation sector in Greece. *Renewable & Sustainable Energy Reviews* 2007;11(4):716–27.
- [19] Environmental Law Institute. Estimating U.S. Government Subsidies to Energy Sources: 2002–2008. Washington, DC: Environmental Law Institute; 2009.
- [20] Euelectric. Efficiency in Electricity Generation. Brussels: Union of the Electricity Industry—Euelectric, VGB; 2003.
- [21] Georgopoulou E, Lalas D, Papagiannakis L. A multicriteria decision aid approach for energy planning problems: the case of renewable energy option. *European Journal of Operational Research* 1997;103(1):38–55.
- [22] Guitioni A, Martel J. Tentative guidelines to help choosing an appropriate MCDA method. *European Journal of Operations Research* 1998;109:501–21.
- [23] Hamalainen R. Computer assisted energy policy analysis in the Parliament of Finland. *Interfaces* 1988;18:12–23.
- [24] Haralambopoulos D, Polatidis H. Renewable energy projects: structuring a multi-criteria decision making framework. *Renewable Energy* 2003;28(6):961–74.
- [25] Heide D, von Bremen L, Greiner M, Hoffmann C, Speckmann M, Bofner S. Seasonal optimal mix of wind and solar power in a future highly renewable Europe. *Renewable Energy* 2010;35:2483–9.
- [26] Heo E, Kim J, Boo K-J. Analysis of the assessment factors for renewable energy dissemination program evaluation using fuzzy AHP. *Renewable & Sustainable Energy Reviews* 2010;14(8):2214–20.
- [27] International Atomic Energy Agency. Uranium fuels the present and future. Retrieved 2012, from International Atomic Energy Agency (IAEA); 2010. <<http://www.iaea.org/newscenter/news/2010/uraniumfuels.html>>.
- [28] Iowa Energy Center. Operating characteristics of wind. Retrieved 2012, from Iowa Energy Center; (n.d.). <<http://www.iowaenergycenter.org/wind-energy-manual/wind-energy-systems/operating-characteristics/>>.
- [29] Kaplan R, Norton D. The Balanced Scorecard—measures that drive performance. *Harvard Business Review* 1992;71–9.
- [30] Kim SC, Min KJ. Determining multi-criteria priorities in the planning of electric power generation: the development of an analytic hierarchy process for using the opinions of experts. *International Journal of Management* 2004;21(2):186–93.
- [32] Lee AH, Chen HH, Kang H-Y. Multi-criteria decision making on strategic selection of wind farms. *Renewable Energy* 2009;34(1):120–6.
- [33] Lobel R. Knowledge@Wharton Today. May 30, 2012. Retrieved from <<http://knowledgeatoday.wharton.upenn.edu/2012/05/sunspots-germany-proves-solar-energy-is-no-mirage/>>.
- [34] Lozano E, Kolios AJ, Brennan F. Multi-criteria assessment of off-shore wind turbine support structures. *Renewable Energy* 2011;36(11):2831–7.
- [35] Muis Z, Hashim H, Manan Z, Douglas P. Optimal planning of renewable energy-integrated electricity generation schemes with CO₂ reduction target. *Renewable Energy* 2010;35:2562–70.
- [36] Nathwani J, Siddall E, Lind N. Energy for 300 years. Waterloo (Canada): Institute for Risk Research, University of Waterloo; 1992.
- [37] National Research Council. Hidden costs of energy: unpriced consequences of energy production and use. Washington, DC: The National Academies Press; 2010.
- [38] National Research Council. Hidden costs of energy: unpriced consequences of energy production and use. Retrieved 2012, from The National Academies Press; 2012. <http://books.nap.edu/catalog.php?record_id=12794>.
- [39] Nigim K, Munier N, Green J. Pre-feasibility MCDM tools to aid communities in prioritizing local viable renewable energy sources. *Renewable Energy* 2004;29(11):1775–91.
- [40] Papadopoulos A, Karagiannidis A. Application of the multi-criteria analysis method Electre III for the optimisation of decentralised energy systems. *Omega* 2008;36(5):766.
- [41] Pohekar S, Ramachandran M. Application of multi-criteria decision making to sustainable energy planning. *Renewable & Sustainable Energy Reviews* 2004;8(4):365–82.
- [42] Polatidis H, Munda GV. Selecting an appropriate multi-criteria decision analysis technique for renewable energy planning. *Energy Sources* 2006;1:181–93.
- [43] Power Plant Performance Factors. Retrieved 2012, from The Engineering Toolbox; (n.d.). <http://www.engineeringtoolbox.com/power-plant-efficiency-d_960.html>.
- [44] Quijano HR, Botero BS, Domínguez BJ. MODERGIS application: integrated simulation platform to promote and develop renewable sustainable energy plans, Colombian case study. *Renewable & Sustainable Energy Reviews* 2012;16(7):5176–87.
- [46] Ribeiro F, Ferreira P, Araújo M. The inclusion of social aspects in power planning. *Renewable & Sustainable Energy Reviews* 2011;15(9):4361–9.
- [48] Saaty T. The analytic hierarchy process. New York: McGraw-Hill; 1980.
- [49] San Cristobal J. Multi-criteria decision making in the selection of a renewable energy project in Spain: the Vikor method. *Renewable Energy* 2011;36(2):498–502.
- [51] Shafiee S, Topal E. When will fossil fuel reserves be diminished? *Energy Policy* 2009;37:181–9.
- [52] Shockley W, Queisser HJ. Detailed balance limit of efficiency of p-n junction solar cells. *Journal of Applied Physics* 1961;32:510–9.
- [54] Streimikiene D, Balezentis T, Krisciukaitienė I, Balezentis A. Prioritizing sustainable electricity production technologies: MCDM approach. *Renewable & Sustainable Energy Reviews* 2012;16(5):3302–11.
- [55] Theodoridou I, Karteris M, Mallinis G, Papadopoulos AM, Hegger M. Assessment of retrofitting measures and solar systems' potential in urban areas using Geographical Information Systems: application to a Mediterranean city. *Renewable & Sustainable Energy Reviews* 2012;16(8):6239–61.
- [56] Tidball R, Bluestein J, Rodriguez N, Knoke S. Cost and performance assumptions for modelling electricity generation technologies. Fairfax, VA: National Renewable Energy Laboratory (NREL); 2010.
- [57] Tsoutsos T, Drandaki M, Frantzeskaki N, Iosifidis E, Kiosses I. Sustainable energy planning by using multi-criteria analysis application in the island of Crete. *Energy Policy* 2009;37(5):1587.
- [58] US Energy Information Administration (2012, 2 7). Frequently asked questions: what is the efficiency of different types of power plants? Retrieved 2012, from US Energy Information Administration (EIA). <<http://205.254.135.7/tools/faqs/faq.cfm?id=107&t=3>>.
- [59] US Energy Information Administration. Glossary. Retrieved 2012, from US Energy Information Administration (EIA); 2012. <<http://205.254.135.7/tools/glossary/index.cfm?id=C>>.
- [60] US Energy Information Agency. EIA 2011 Assumptions to the Annual Energy Outlook. Washington, DC: EIA; 2011.
- [61] van Alphen K, van Sark WG, Hekkert MP. Renewable energy technologies in the Maldives—determining the potential. *Renewable & Sustainable Energy Reviews* 2007;11(8):1650–74.
- [62] van Haaren R, Fthenakis V. GIS-based wind farm site selection using spatial multi-criteria analysis (SMCA): evaluating the case for New York State. *Renewable & Sustainable Energy Reviews* 2011;15(7):3332–40.
- [63] Wang J-J, Jing Y-Y, Zhang C-F, Zhao J-H. Review on multi-criteria decision analysis aid in sustainable energy decision-making. *Renewable & Sustainable Energy Reviews* 2009;13(9):2263–78.
- [64] Wei M, Patadia S, Kammen D. Putting renewables and energy efficiency to work. *Energy Policy* 2010;38:919–31.
- [65] Wiser R, Namovicz C, Gielecki M, Smith R. Renewable portfolio standards: a factual introduction to experience from the United States. Berkeley, CA: Berkeley National Laboratory: Environmental Energy Technologies Division; 2007.
- [66] Yi S-k, Sin H-Y, Heo E. Selecting sustainable renewable energy source for energy assistance to North Korea. *Renewable and Sustainable Energy Reviews* 2011;15(1):554–63.