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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