STOCHASTIC DECISION MAKING FOR SUSTAINABLE ENERGY SYSTEM SELECTION

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ABSTRACT: A sustainability enhancement is generally measurable by its environmental, economic, and socio-cultural effects. To apply this concept, this study developed and empirically tested a risk-based method for evaluating renewable energy policy. The proposed graphical matrix approach coupled with Monte Carlo simulation identifies and measures critical performance indicators at an acceptance level of reliability when comparing alternative renewable energy schemes. The mathematical model reliably prioritizes alternatives by majority voting to address uncertainty in the multi-criteria decision making process. Compared to conventional deterministic method, the stochastic approach provides more reliable estimation accuracy, decision quality, and efficiency in sustainable renewable energy decision making.

Keywords: Multi-criteria Decision Making; Monte Carlo Simulation; Graphical Matrix Approach; Sustainability Assessment; Renewable Energy

1. INTRODUCTION
Renewable energy (RE) is a promising solution to many environmental and social problems associated with fossil and nuclear fuels [10]. However, many barriers to sustainable development (SD) still occur within the RE system life-cycle. For instances, the large barriers to hydropower include the large number of people and animals displaced by dam inundation whereas barriers to geothermal energy schemes include adverse effects on local communities when wastes are improperly managed such as the offensive smell of geothermal processing water due to hydrogen sulfide and contamination of water with ammonia, mercury, radon, arsenic and boron [7].

To facilitate decision makers in coping with complex sustainability issues, evaluation indicators must reflect the overall RE system as well as subsystem interactions. Although numerous studies have demonstrated diverse applications in RE, methods of selecting the best RE scheme based upon sustainability evaluation still receives little attention. Therefore, to fill this gap, this work develops a reliable multi-criteria decision making (MCDM) method that considers sustainability indicators (SIs) when comparing alternative RE schemes.

This study proposes a risk-based MCDM that uses graphical matrix modeling coupled with Monte Carlo simulation (MCS) to facilitate decision making at a desired level of reliability. The results provide policy makers with useful decision information regarding RE schemes given sustainability considerations by synthesizing judgments made by an expert panel.

2. BACKGROUND INFORMATION
Globally, RE sources have widely varying applications. Although they have proven capable of substituting for conventional fuels in most applications, the contribution of alternative energy sources remains low despite considerable technological advances and their increasing economic competitiveness with conventional fuels [17]. Hence, planners and decision makers must identify and suggest interventions for overcoming barriers to their penetration.

2.1 Overview of Decision Making Techniques
Multiple Criteria Decision Making (MCDM) is one decision making tool that managers can use to make accurate decisions. The technique governs the process of
making difficult decisions given seemingly equal objectives. Great progress has been made in developing MCDM approaches for solving real-world problems [12]. For instance, S. D. Pohekar and M. Ramachandran (2004) reviewed the literature to determine the applicability of these various MCDM methods in sustainable energy planning [17]. Industrial applications of MCDM methods include graph theory and matrix approach (GTMA), an alternative MCDM that is particularly suited for RE planning, which is increasingly important for managing future energy demand.

Decision outcomes are often unreliable and uncertain; however, few studies have proposed methods of choosing the best alternative while properly considering reliability and uncertainty. Hence, this study integrated GTMA with MCS to account for uncertainty when making decisions about RE energy schemes.

2.1.1 Graph Theory and Matrix Approaches
The GTMA is a method of solving various problems involving complex criteria with highly dependent relationships across different levels [13, 26]. GTMA is a logical and systematic approach that considers inherent errors and multiple qualitative and quantitative attributes simultaneously, which is especially important when studying interconnections among elements in natural and man-made systems.

Although many studies have demonstrated the effectiveness and efficacy of GTMA [5, 13, 19], conventional GTMA generates single-point estimation which is often unreliable and does not consider probabilistic range so as to distinguish adjacent importance values when comparing attributes assessed by different experts.

2.1.2 Monte Carlo Simulation Method
Monte Carlo simulation (MCS) is a risk-analysis technique that facilitates the use of decision science in management decisions [3]. It also optimizes the results of group evaluations. The advantage of this method is its limitation of Monte Carlo approximation error to below a given value with a certain probability and the method can support in making decisions that involve uncertainty or numerous variables. For instance, Chou et al. (2009) proposed a probabilistic simulation approach using MCS to analyze procedures for estimating construction project cost and correlation effects of incorporated risk [4].

2.2 Relationships among Sustainability and Renewable Energy Schemes
Sustainable development (SD) is conventionally defined as development that meets the needs of the present generation without compromising those of future generations [27]. According to this definition, society must minimize the use of consumable resources.

Although the application of RE should consider social equity, environmental responsibility, and economic viability, studies of RE schemes tend to evaluated only one aspect. Sreekumar (2010) developed and tested a roof-integrated solar air heater with a batch dryer [21]. This study, however, focused on the economic aspects of implementing RE schemes to solve the energy demand problem. The environmental effects of conventional energy production must be addressed. For instance, Varun et al. (2009) studied the economic and environment impacts of RE generation technologies [24]. Development of RE supports the viability of society and is expected to provide long term benefits to social and economic development.

SIs and composite index are increasingly recognized as useful tools for policy making and public communication of information about countries and corporate performance in terms of effects on the environment, the economy, society and, technological improvement [20]. Thus, the interaction among interpersonal factors or different indicators within the sustainability is essential for successful implementation of sustainable RE systems.

3. METHODOLOGY AND MODELING OF RISK-BASED DECISION MAKING
Achieving strategic sustainable objectives by RE deployment is a complex task. To overcome this concern, this study proposes a stochastic graphical matrix modeling technique for assessing the sustainability of RE schemes.
when comparing alternatives under uncertainties. Specifically, this study assesses six RE schemes, namely wind power, solar energy, hydroelectric power, geothermal energy; ocean power, and biomass. Table 1 shows how this work defined SIs based on findings in the literature.

### 3.1 Risk-based Group Decision Making Process

The GTMA lacks a probability explanation for distinguishing between adjacent alternatives in final ordering. In response to this specific drawback, this study suggests that, when distributing relative importance value, the pairwise value \( S_{ij} \) can be considered a random variable. The value of a random variable \( S_{ij} \) is dependent on \( S_{ij} \).

Assumedly, therefore, \( \{S_{i} | i > j \} \) is independent, and the final scores \( H_1, H_2, ..., H_N \) are stochastic. In the case of \( S_i > S_j \), alternative \( i \) is superior to alternative \( j \) at a certain error level (\( \alpha \)). To compare the alternatives associated with SIs within alternative schemes, both qualitative and quantitative indicators need an appropriate normalized assessment method [18]. Beneficial attributes in which higher measures are more desirable for the given application can be calculated by \( k_i/k_j \), where \( k_i \) is a measure of the attribute for \( i \)th alternative and \( k_j \) is measure of the attribute for \( j \)th alternative that has a higher measure of the attribute among the considered alternatives. Meanwhile, non-beneficial attributes are those in which the lower measures are desirable and in which normalized values assigned to the alternatives are calculated by \( k_j/k_i \). In this case, \( k_i \) is a measure of the \( j \)th attribute among the considered alternatives.

### 3.2.1 Matrix Representation of the Digraph

Let nodes \( E = \{e_i \} \) with \( i = 1, 2, ..., M \) correspond to the \( i \)th factor represented by node \( n_i \) as the RE attributes and edges \( S = \{s_i\} \), as the relative importance of the \( i \)th attributes over the \( j \)th attributes. If a node “\( i \)” has a higher relative importance compared to another node “\( j \)” when evaluating the indicator for the given RE, then a directed edge or arrow is drawn from node “\( i \)” to node “\( j \)” (\( d_{ij} \)), and vice versa.

Table 2 aids in assigning \( S_{ij} \) as a relative importance value for SIs. Further, matrix representation of the selection factors graph enables a one-to-one representation. Thus, the selection factors for matrix \( H \) is defined by \( H \times i \) matrix, which considers all factors (\( E_i \)) and their relative importance between the attributes (\( S_{ij} \)). Notably, GTMA

<table>
<thead>
<tr>
<th>Key sustainability</th>
<th>Indicator name</th>
<th>Description</th>
<th>Attribute annotation</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Economic</td>
<td>Installed capacity</td>
<td>Installed capacity for each renewable energy system</td>
<td>Beneficial</td>
<td>[16,25]</td>
</tr>
<tr>
<td></td>
<td>Energy cost</td>
<td>Monetary and non-monetary costs (e.g., environmental impact) associated with the production, transmission, and consumption of energy</td>
<td>Non-beneficial</td>
<td>[2,16,24]</td>
</tr>
<tr>
<td></td>
<td>Initial investment</td>
<td>Initial cost building and operating each renewable energy system</td>
<td>Non-beneficial</td>
<td>[1,16,22,23]</td>
</tr>
<tr>
<td></td>
<td>Operation and Maintenance cost</td>
<td>Annual cost maintaining and operating the system during the operation time</td>
<td>Non-beneficial</td>
<td>[8,16,22-24]</td>
</tr>
<tr>
<td></td>
<td>Mean price of electricity</td>
<td>Mean (unit) price that society must pay to use for 1 hour of electricity</td>
<td>Non-beneficial</td>
<td>[1,7,23,24]</td>
</tr>
<tr>
<td>Environment</td>
<td>CO2 emission</td>
<td>CO2 emitted by each system during its operation time to produce 1 kwH electricity</td>
<td>Non-beneficial</td>
<td>[7,8,11,15,16,22,24]</td>
</tr>
<tr>
<td></td>
<td>Water consumption</td>
<td>Water needed by each system during its operation time to produce 1 kwH electricity</td>
<td>Non-beneficial</td>
<td>[7,8,14,16,22,23]</td>
</tr>
<tr>
<td></td>
<td>Land use</td>
<td>Amount of land required for utility-scale converter plants/systems, including land acquisition, extent of tree felling and extent of loss of habitat or feeding grounds</td>
<td>Non-beneficial</td>
<td>[2,7,15,16,22,23]</td>
</tr>
<tr>
<td></td>
<td>Employment</td>
<td>Employment associated with each renewable energy project</td>
<td>Non-beneficial</td>
<td>[1,2,6,14,16,22,23]</td>
</tr>
</tbody>
</table>

Table 1. Summary data of sustainability indicators
adopt symmetrical complementary matrices by using equation $S_i = L - S_i$.

Moreover, permanent function can be used to calculate the final results needed to compare $i$ attributes. The function resembles the determinant manner of a matrix function and is used in combinatorial mathematics [5]. The permanent function of matrix $H$ is expressed by Equation [1].

$$\text{Per}(H) = \sum_{\text{permutation}} \prod_{i,j} H_{ij}$$

where $H$ is the selection function matrix, $E_i$ is the value of the $i$th factor represented by node $n_i$ as renewable energy attributes, and $S_j$ is the relative importance of the $i$th factor over the $j$th factor.

### 3.2.2 Experts Judgment Considering Uncertainties

As judgment capabilities differ among professional employees, the estimation results may exhibit differences that have no scientific basis [3]. The comparison for $i$th attribute over $j$th attribute made by expert judgments can be assessed by assuming $g(x)$ functions as a random variable where $x = (S_i, S_j)$ and $f(x)$ be the probability density function (PDF). The expectation of $g(X)$ denoted by $E[g(X)]$ can be calculated by the following equation:

$$E[g(X)] = \int g(x) f(x) dx$$

where $M$ is the space of $X$. However, the PDF is difficult to obtain in practice. Generally, MCS can obtain a numerical solution via the above equation. This study further uses the triangle distribution from MCS for efficiently representing the pessimistic, most likely, and optimistic propensity of using the relative importance value to evaluate the attribute comparison.

### 4. EMPIRICAL APPLICATION

The proposed risk-based MCDM process is simulated to enable an expert panel to analyze the alternative RE schemes in terms of sustainability.

#### 4.1. Simulation Model Development

![Fig. 1 Direct graph for renewable energy schemes.](image)

Attributes: (1) IC; (2) EC; (3) II; (4) OM; (5) MP; (6) CE; (7) WC; (8) LU; (9) EM; (10) PA.
Table 3. Data summary for SIs within RE.

<table>
<thead>
<tr>
<th>Renewable Energy/Sustainability Indicator</th>
<th>Installed Capacity (GW)</th>
<th>Energy Cost (cent/kWh)</th>
<th>Initial Investment (US$)</th>
<th>Operation and Maintenance Cost (US$)</th>
<th>Mean Price of Electricity (cent/kWh)</th>
<th>CO2 Emission (gr/kWh)</th>
<th>Water Consumption (kg/kWh)</th>
<th>Land Use (km²/TWh)</th>
<th>Employment (person)</th>
<th>Public Attention</th>
<th>GTMA scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind Power (Off &amp; Onshore)</td>
<td>158.505</td>
<td>12</td>
<td>67</td>
<td>2.7</td>
<td>7</td>
<td>25</td>
<td>1</td>
<td>72</td>
<td>50000</td>
<td>0.625</td>
<td>7</td>
</tr>
<tr>
<td>Geothermal Energy</td>
<td>11</td>
<td>7.5</td>
<td>13</td>
<td>2.29</td>
<td>7</td>
<td>170</td>
<td>156</td>
<td>46</td>
<td>595100</td>
<td>0.011</td>
<td>6</td>
</tr>
<tr>
<td>Solar Energy (PV)</td>
<td>22</td>
<td>23</td>
<td>40</td>
<td>0.64</td>
<td>24</td>
<td>90</td>
<td>10</td>
<td>46</td>
<td>300000</td>
<td>0.353</td>
<td>3</td>
</tr>
<tr>
<td>Hydropower (Large &amp; Small Dam)</td>
<td>1040</td>
<td>7.5</td>
<td>42.5</td>
<td>3</td>
<td>5</td>
<td>41</td>
<td>36</td>
<td>750</td>
<td>11752000</td>
<td>0.003</td>
<td>7</td>
</tr>
<tr>
<td>Biomass</td>
<td>54</td>
<td>8.5</td>
<td>17.7</td>
<td>0.91</td>
<td>8.85</td>
<td>11</td>
<td>1</td>
<td>491</td>
<td>980000</td>
<td>0.015</td>
<td>8</td>
</tr>
<tr>
<td>Ocean Power</td>
<td>0.3</td>
<td>12</td>
<td>0.2</td>
<td>1.5</td>
<td>5.5</td>
<td>22.8</td>
<td>1</td>
<td>1</td>
<td>40000</td>
<td>0.002</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 4. Normalized value for SIs.

Table 6. Ranking of perceived RE schemes by SGMM.

4.2 Stochastic Judgment Representation Model

To obtain probability information for $S_{i}$ in the context of each decision maker, this case study assumes that the likelihood $S_{i}$ is equal. Using MCS, simulation values were recorded into the selection factor matrix while comparing the attributes. Each alternative was then ranked using the permanent function based on the selection factor matrix.

This study performed 500 simulations of the relative importance value between attributes to obtain reference rankings for each RE scheme. Table 6 shows the rankings for RE alternative schemes based on the repetitive decision processes along with their corresponding frequencies. Specifically, inconsistency in describing the results contributed to the variation in the most likely ranking.

GTMA scores can be prioritized by ocean power as the first rank followed by biomass, wind power, hydropower,
geothermal energy and solar thermal energy. Conversely, when using SGMM, the ranking order differs from GTMA.

Table 7. Analytical results for GTMA and SGMM.

<table>
<thead>
<tr>
<th>Renewable Energy Scheme</th>
<th>GTMA Score (/1000)</th>
<th>GTMA Ranking</th>
<th>SGMM Ranking</th>
<th>Remarks*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind Power</td>
<td>10.394</td>
<td>3</td>
<td>4</td>
<td>↓</td>
</tr>
<tr>
<td>Geothermal Energy</td>
<td>8.058</td>
<td>5</td>
<td>5</td>
<td>●</td>
</tr>
<tr>
<td>Solar Energy (PV)</td>
<td>7.862</td>
<td>6</td>
<td>6</td>
<td>●</td>
</tr>
<tr>
<td>Hydropower</td>
<td>9.235</td>
<td>4</td>
<td>2</td>
<td>↑</td>
</tr>
<tr>
<td>Biomass</td>
<td>10.966</td>
<td>2</td>
<td>3</td>
<td>↓</td>
</tr>
<tr>
<td>Ocean Power</td>
<td>12.414</td>
<td>1</td>
<td>1</td>
<td>●</td>
</tr>
</tbody>
</table>

* (↑) Ascended, (↓) Descended, (●) Unchanged

5. CONCLUDING REMARKS

This study presents a risk-based SGMM approach that integrates Monte Carlo simulation with traditional GTMA to estimate and support MCDM in selecting the best RE scheme given sustainability considerations. Although both GTMA and SGMM methods rank ocean power first among sustainable RE schemes, SGMM provides a relatively more reliable priority list. Further, by repetitively emulating the comparison process, this novel GDM method improves not only estimation accuracy and reliability, but also decision making quality and efficiency. This case study of the problem of selecting the best RE scheme demonstrated the excellent performance SGMM.

Particularly, the SGMM delineates the uncertainty in comparison values obtained by subject ratings by experts. Moreover, the risk-based method systematically obtains the range estimation of decision variables from decision makers and is applicable in other similar decision making problems. Specifically, the proposed method does not require criteria weighting or accurate quantitative calculation as it simplifies the decision making process by solving problems based on qualitative or quantitative information.

REFERENCES


