STOCHASTIC DECISION MAKING FOR SUSTAINABLE ENERGY SYSTEM SELECTION

Jui-Sheng Chou* and Citra Satria Ongkowijoyo

Department of Construction Engineering, National Taiwan University of Science and Technology, Taipei, Taiwan
*****Corresponding author (jschou@mail.ntust.edu.tw)*

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

Table 1. Summary data of sustainability indicators

Key sustainability	Indicator name	Description	Attribute annotation	References
Economic	Installed capacity	Installed capacity for each renewable energy system	Beneficial	[16,25]
	Energy cost	Monetary and non-monetary costs (*e.g.,* environmental impact) associated with the production, transmission, and consumption of energy	Non-beneficial	[2,16,24]
	Initial investment	Initial cost building and operating each renewable energy system	Non-beneficial	[1,16,22,23]
	Operation and Maintenance cost	Annual cost maintaining and operating the system during the operation time	Non-beneficial	[8,16,22-24]
	Mean price of electricity	Mean (unit) price that society must pay to use for 1 hour of electricity	Non-beneficial	[1,7,23,24]
Environment	CO_2 emission	CO_2 emitted by each system during its operation time to produce 1 kwH electricity	Non-beneficial	[7,8,11,15,16,22,24]
	Water consumption	Water needed by each system during its operation time to produce 1 kwH electricity	Non-beneficial	[7,8,14,16,22,23]
	Land use	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	Non-beneficial	[2,7,15,16,22,23]
Social	Employment	Employment associated with each renewable energy project	Non-beneficial	[1,2,6,14,16,22,23]
	Public Attention	Wind energy: land use, visual impact, noise, electromagnetic interference, effects upon birds and wildlife, human safety hazards.	Non-beneficial	[2,7-9,16,22]
		Geothermal energy: air pollution, water pollution, land subsidence, induced seismicity, noise, escaping steam.		
		Solar energy (PV): land use, large material requirements, health hazard.		
		Hydropower: population movements, health hazards, fish culture, flora and fauna, groundwater, excessive fertilization, transport of nutrients.		
		Biomass: land and water resources, soil erosion and water runoff, nutrient removal and loss, loss of natural biota, habitat and wild life		
		Ocean power: disturbance of marine life, visual impact, noise, threat to navigation, coastal erosion.		

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_{ji} is dependent on S_{ij}.

Assumedly, therefore, $\left(S_{ij} \middle| i > j\right)$ is independent, and the final scores $H_1, H_2, \ldots, H_N$ are stochastic. In the case of $S_i > S_j$, alternative i is superior to alterative j at a certain error level (α). 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 ith alternative and k_j is measure of the attribute for jth 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_j is a measure of the jth attribute among the considered alternatives.

3.2.1 Matrix Representation of the Digraph

Let nodes $E = \{E_i\}$, with $i = 1,2,\ldots,M$ correspond to the ith factor represented by node n_i as the RE attributes and edges $S = \{S_{ij}\}$, as the relative importance of the ith attributes over the jth 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 $i \times i$ matrix, which considers all factors (E_i) and their relative importance between the attributes (S_{ij}). Notably, GTMA adopt symmetrical complementary matrices by using equation $S_{ji} = L - S_{ij}$.

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].

$$
\begin{aligned}
Per(H) = {} & \prod_{i=1}^{m} E_i + \sum_{i=1}^{M-1}\sum_{j=i+1}^{M}\cdots\sum_{M=t+1}^{M}(S_{ij}S_{ij})\underset{\ldots,M\neq pus}{E_{kl}E_mE_nE_o\ldots E_tE_M} \\
& + \sum_{i=1}^{M-2}\sum_{j=i+1}^{M-1}\sum_{k=j+1}^{M}\cdots\sum_{l=1\,M=t+1}^{M}(S_{ij}S_{jk}S_{ki}+S_{ik}S_{kj}S_{ji})\underset{k,\ldots,M\neq pus}{E_lE_mE_nE_o\ldots E_tE_M} \\
& + [\sum_{i=1}^{M-3}\sum_{j=i+1}^{M}\sum_{k=i+1}^{M-1}\sum_{l=i+2}^{M}\cdots\sum_{M=t+1}^{M}(S_{ij}S_{ji})(S_{kl}S_{lk})\underset{k,l,\ldots M\neq pus}{E_mE_nE_o\ldots E_tE_M} \\
& + \sum_{i=1}^{M-3}\sum_{j=i+1}^{M-1}\sum_{k=i+1}^{M}\sum_{l=j+1}^{M}\cdots\sum_{M=t+1}^{M}(S_{ij}S_{jk}S_{kl}S_{li}+S_{il}S_{lk}S_{kj}S_{ji})\underset{k,l,\ldots M\neq pus}{E_mE_nE_o\ldots E_tE_M}] \\
& + [\sum_{i=1}^{M-2}\sum_{j=i+1}^{M-1}\sum_{k=j+1}^{M}\sum_{l=1}^{M-1}\sum_{m=i+1}^{M}\cdots\sum_{M=l+1}^{M}(S_{ij}S_{jk}S_{ki}+S_{ik}S_{kj}S_{ji})(S_{lm}S_{ml})\underset{k,l,m,\ldots M\neq pus}{E_nE_o\ldots E_tE_M} \\
& + \sum_{i=1}^{M-4}\sum_{j=i+1}^{M-1}\sum_{k=i+1}^{M}\sum_{l=i+1}^{M}\sum_{m=j+1}^{M}\cdots\sum_{M=t+1}^{M}(S_{ij}S_{jk}S_{kl}S_{lm}S_{mi}+S_{im}S_{ml}S_{lk}S_{kj}S_{ji})\underset{k,l,m,\ldots,M\neq pus}{E_nE_o\ldots E_tE_M}] \\
& + [(\sum_{i=1}^{M-3}\sum_{j=i+1}^{M-1}\sum_{k=i+1}^{M}\sum_{l=j+1}^{M}\sum_{m=1}^{M-1}\sum_{n=m+1}^{M}\cdots\sum_{M=1+1}^{M}(S_{ij}S_{jk}S_{kl}S_{li}+S_{il}S_{lk}S_{kj}S_{ji})(S_{mn}S_{nm})\underset{k,l,m,n,\ldots M\neq pus}{E_o\ldots E_tE_M} \\
& + \sum_{i=1}^{M-5}\sum_{j=i+1}^{M-1}\sum_{k=j+1}^{M}\sum_{l=1}^{M-2}\sum_{m=1}^{M-1}\sum_{n=m+1}^{M}\cdots\sum_{M=1+1}^{M}(S_{ij}S_{jk}S_{ki}+S_{ik}S_{kj}S_{ji})(S_{lm}S_{mn}S_{nl}+S_{ln}S_{nm}S_{ml})\underset{k,l,m,n,\ldots M\neq pus}{E_o\ldots E_tE_M} \\
& + \sum_{i=1}^{M-5}\sum_{j=i+1}^{M}\sum_{k=i+1}^{M-3}\sum_{l=i+2}^{M}\sum_{m=k+1}^{M-1}\sum_{n=k+2}^{M}\cdots\sum_{M=t+1}^{M}(S_{ij}S_{ji})(S_{kl}S_{lk})(S_{mn}S_{nm})\underset{k,l,m,n,\ldots M\neq pus}{E_o\ldots E_tE_M} \\
& + \sum_{i=1}^{M-5}\sum_{j=i+1}^{M-1}\sum_{k=i+1}^{M}\sum_{l=i+1}^{M}\sum_{m=i+1}^{M}\sum_{n=j+1}^{M}\cdots\sum_{M=t+1}^{M}(S_{ij}S_{jk}S_{kl}S_{1m}S_{mn}S_{ni}+S_{in}S_{nm}S_{ml}S_{lk}S_{kj}S_{ji})\underset{k,l,m,\ldots,M\neq pus}{E_o\ldots E_tE_M})]+\ldots
\end{aligned}
\qquad (1)
$$

where H is the selection function matrix, E_i is the value of the ith factor represented by node n_i as renewable energy attributes, and S_{ij} is the relative importance of the ith factor over the jth 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 ith attribute over jth attribute made by expert judgments can be assessed by assuming $g(\mathbf{X})$ functions as a random variable where $\mathbf{X} = (S_{ij} | i > j)$. Let $f(\mathbf{X})$ be the probability density function (PDF). The expectation of $g(\mathbf{X})$ denoted by $E[g(\mathbf{X})]$ can be calculated by the following equation:

$$E\left[g(\mathbf{X})\right] = \int_{X\in \mathrm{M}} g(\mathbf{X})\cdot f(\mathbf{X})d\mathbf{X} \qquad (2)$$

where M is the space of $\mathbf{X}$. 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.

Table 2. Relative importance used as the attributes.

Subjective measure of attribute	**Relative importance of attributes**	
	S_{ij}	$S_{ji}=L-S_{ij}$
One attribute is exceptionally less important than the other	0.0	1.0
One attribute is extremely less important than the other	0.1	0.9
One attribute is very less important than the other	0.2	0.8
One attribute is less important than the other	0.3	0.7
One attribute is slightly less important than the other	0.4	0.6
Two attributes are equally important than the other	0.5	0.5
One attribute is slightly more important than the other	0.6	0.4
One attribute is more important than the other	0.7	0.3
One attribute is much more important than the other	0.8	0.2
One attribute is extremely more important than the other	0.9	0.1
One attribute is exceptionally more important than the other	1.0	0.0

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

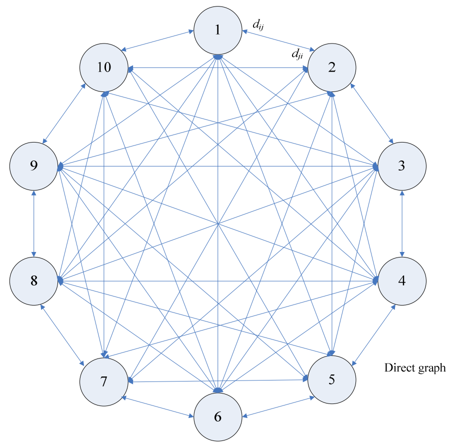

Fig. 1 Direct graph for renewable energy schemes. Attributes: (1) IC; (2) EC; (3) II; (4) OM; (5) MP; (6) CE; (7) WC; (8) LU; (9) EM; (10) PA.

Table 3. Data summary for SIs within RE.

Renewable Energy/Sustainability Indicator	Installed Capacity (GW) (E_1)	Energy Cost (cent/kWh) (E_2)	Initial Investment (US$) ($E_3$)	Operation and Maintenance Cost cent/kWh (US$) ($E_4$)	Mean Price of Electricity (cent US$/kWh) ($E_5$)	CO_2 Emission (gr/kWh) (E_6)	Water Consumption (kg/kWh) (E_7)	Land Use (km^2/TWh) (E_8)	Employment (person) (E_9)	Public Attention (E_{10})
	Global Report Renewable Energy									
Wind Power (Off & Onshore)	158.505	12	67	2.7	7	25	1	72	500000	6
Geothermal Energy	11	7.5	13	2.29	7	170	156	46	595100	6
Solar Energy (PV)	22	23	40	0.64	24	90	10	46	300000	3
Hydropower (Large & Small Dam)	1040	7.5	42.5	3	5	41	36	750	11752000	7
Biomass	54	8.5	17.7	0.91	8.85	11	1	491	980000	8
Ocean Power	0.3	12	0.2	1.5	5.5	22.8	1	1	40000	5

Table 4. Normalized value for SIs.

Renewable Energy/Sustainability Indicator	Installed Capacity (GW) (E_1)	Energy Cost (cent/kWh) (E_2)	Initial Investment (US$) ($E_3$)	Operation and Maintenance Cost cent/kWh (US$) ($E_4$)	Mean Price of Electricity (cent US$/kWh) ($E_5$)	CO_2 Emission (gr/kWh) (E_6)	Water Consumption (kg/kWh) (E_7)	Land Use (km^2/TWh) (E_8)	Employment (person) (E_9)	Public Attention (E_{10})
	Global Report Renewable Energy									
Wind Power (Off & Onshore)	0.152	0.625	0.003	0.237	0.714	0.440	1.000	0.014	0.043	0.500
Geothermal Energy	0.011	1.000	0.015	0.279	0.714	0.065	0.006	0.022	0.051	0.500
Solar Energy (PV)	0.021	0.326	0.005	1.000	0.208	0.122	0.100	0.022	0.026	1.000
Hydropower (Large & Small Dam)	1.000	1.000	0.005	0.213	1.000	0.268	0.028	0.001	1.000	0.429
Biomass	0.052	0.882	0.011	0.703	0.565	1.000	1.000	0.002	0.083	0.375
Ocean Power	0.0003	0.625	1.000	0.427	0.909	0.482	1.000	1.000	0.003	0.600

Table 3 shows the prior information summary for each SI within the RE schemes. To incorporate the same evaluation indicators for a different RE scheme, the value for each attribute must be normalized according to the attribute annotations. Table 4 summarizes the results. To describe the RE digraph in a single multinomial permanent function, a new matrix called permanent system matrix is defined. This matrix, which shows all RE schemes as a direct graph (Fig. 1) presents all possible structural information of the RE as it contains no negative signs.

$$
\begin{array}{cc}
 & \begin{array}{cccccccccc} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 \end{array} \quad \text{attributes} \\
H = & \begin{bmatrix}
E_1 & s_{12} & s_{13} & s_{14} & s_{15} & s_{16} & s_{17} & s_{18} & s_{19} & s_{110} \\
s_{21} & E_2 & s_{23} & s_{24} & s_{25} & s_{26} & s_{27} & s_{28} & s_{29} & s_{210} \\
s_{31} & s_{32} & E_3 & s_{34} & s_{35} & s_{36} & s_{37} & s_{38} & s_{39} & s_{310} \\
s_{41} & s_{42} & s_{43} & 4_4 & s_{45} & s_{46} & s_{47} & s_{48} & s_{49} & s_{410} \\
s_{51} & s_{52} & s_{53} & s_{54} & E_5 & s_{56} & s_{57} & s_{58} & s_{59} & s_{510} \\
s_{61} & s_{62} & s_{63} & s_{64} & s_{65} & E_6 & s_{67} & s_{68} & s_{69} & s_{610} \\
s_{71} & s_{72} & s_{73} & s_{74} & s_{75} & s_{76} & E_7 & s_{78} & s_{79} & s_{710} \\
s_{81} & s_{82} & s_{83} & s_{84} & s_{85} & s_{86} & s_{87} & E_8 & s_{89} & s_{810} \\
s_{91} & s_{92} & s_{93} & s_{94} & s_{95} & s_{96} & s_{97} & s_{98} & E_9 & s_{910} \\
s_{101} & s_{102} & s_{103} & s_{104} & s_{105} & s_{106} & s_{107} & s_{108} & s_{109} & E_{10}
\end{bmatrix}
\begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \\ 9 \\ 10 \end{array}
\end{array}
\tag{3}
$$

4.2 Stochastic Judgment Representation Model

To obtain probability information for S_{ij} in the context of each decision maker, this case study assumes that the likelihood S_{ij} 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.

Table 6. Ranking of perceived RE schemes by SGMM.

Scheme/Rank	1	2	3	4	5	6
Wind Power	0	3	114	386	0	0
Geothermal Energy	0	0	0	1	499	0
Solar Energy (PV)	0	0	0	0	0	500
Hydropower	219	236	26	19	0	0
Biomass	3	61	341	0	1	0
Ocean Power	278	203	19	94	3	0

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.

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

* (↑) 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

[1]N.H. Afgan, M.G. Carvalho, N.V. Hovanov, Energy system assessment with sustainability indicators, Energy Policy 28 (9) (2000) 603-612.

[2] M. Beccali, M. Cellura, M. Mistretta, Decision-making in energy planning. Application of the Electre method at regional level for the diffusion of renewable energy technology, Renewable Energy 28 (13) (2003) 2063-2087.

[3] J.-S. Chou, Cost simulation in an item-based project involving construction engineering and management, International Journal of Project Management In Press, Corrected Proof.

[4] J.-S. Chou, I.T. Yang, W.K. Chong, Probabilistic simulation for developing likelihood distribution of engineering project cost, Automation in Construction 18 (5) (2009) 570-577.

[5] M. Darvish, M. Yasaei, A. Saeedi, Application of the graph theory and matrix methods to contractor ranking, International Journal of Project Management 27 (6) (2009) 610-619.

[6] P. del Río, M. Burguillo, Assessing the impact of renewable energy deployment on local sustainability: Towards a theoretical framework, Renewable and Sustainable Energy Reviews 12 (5) (2008) 1325-1344.

[7] A. Evans, V. Strezov, T.J. Evans, Assessment of sustainability indicators for renewable energy technologies, Renewable and Sustainable Energy Reviews 13 (5) (2009) 1082-1088.

[8] G. Fernández-Sánchez, F. Rodríguez-López, A methodology to identify sustainability indicators in construction project management--Application to infrastructure projects in Spain, Ecological Indicators 10 (6) (2010) 1193-1201.

[9] M. Kaltschmitt, W. Streicher, A. Wiese, Renewable Energy, Springer, New York, 2007.

[10] K. Kaygusuz, Sustainable development of hydropower and biomass energy in Turkey, Energy Conversion and Management 43 (8) (2002) 1099-1120.

[11] H.H. Khoo, Life cycle impact assessment of various waste conversion technologies, Waste Management 29 (6) (2009) 1892-1900.

[12] R.A. Krohling, V.C. Campanharo, Fuzzy TOPSIS for group decision making: A case study for accidents with oil spill in the sea, Expert Systems with Applications 38 (4)

(2011) 4190-4197.

[13] A. Kumar, S. Clement, V.P. Agrawal, Structural modeling and analysis of an effluent treatment process for electroplating--A graph theoretic approach, Journal of Hazardous Materials 179 (1-3) (2010) 748-761.

[14] J.R. May, D.J. Brennan, Sustainability Assessment of Australian Electricity Generation, Process Safety and Environmental Protection 84 (2) (2006) 131-142.

[15] A.R. Neves, V. Leal, Energy sustainability indicators for local energy planning: Review of current practices and derivation of a new framework, Renewable and Sustainable Energy Reviews 14 (9) (2010) 2723-2735.

[16] N. Onat, H. Bayar, The sustainability indicators of power production systems, Renewable and Sustainable Energy Reviews 14 (9) (2010) 3108-3115.

[17] S.D. Pohekar, M. Ramachandran, Application of multi-criteria decision making tosustainable energy planning - A review, Fuel and Energy Abstracts 84 (4) (2004) 365-381.

[18] R. Rao, A decision-making framework model for evaluating flexible manufacturing systems using digraph and matrix methods, The International Journal of Advanced Manufacturing Technology 30 (11) (2006) 1101-1110.

[19] R.V. Rao, K.K. Padmanabhan, Rapid prototyping process selection using graph theory and matrix approach, Journal of Materials Processing Technology 194 (1-3) (2007) 81-88.

[20] R.K. Singh, H.R. Murty, S.K. Gupta, A.K. Dikshit, An overview of sustainability assessment methodologies, Ecological Indicators 9 (2) (2009) 189-212.

[21] A. Sreekumar, Techno-economic analysis of a roof-integrated solar air heating system for drying fruit and vegetables, Energy Conversion and Management 51 (11) (2010) 2230-2238.

[22] O.O. Ugwu, T.C. Haupt, Key performance indicators and assessment methods for infrastructure sustainability--a South African construction industry perspective, Building and Environment 42 (2) (2007) 665-680.

[23] O.O. Ugwu, M.M. Kumaraswamy, A. Wong, S.T. Ng, Sustainability appraisal in infrastructure projects (SUSAIP): Part 1. Development of indicators and computational methods, Automation in Construction 15 (2) (2006) 239-251.

[24] Varun, R. Prakash, I.K. Bhat, Energy, economics and environmental impacts of renewable energy systems, Renewable and Sustainable Energy Reviews 13 (9) (2009) 2716-2721.

[25] Varun, R. Prakash, I.K. Bhat, A figure of merit for evaluating sustainability of renewable energy systems, Renewable and Sustainable Energy Reviews 14 (6) (2010) 1640-1643.

[26] R. Venkatasamy, V.P. Agrawal, A DIGRAPH APPROACH TO QUALITY EVALUATION OF AN AUTOMOTIVE VEHICLE, Quality Engineering 9 (3) (1997) 405 - 417.

[27] WCED, Our common future, World Comission on Environment and Development, New York, 1987.