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Optimal Selection of Low Carbon Technologies using a Stochastic Fuzzy Multi-Criteria Decision Modelling Approach

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Power sectors, as the world's demand for electricity is increasing, are recognized to be as significant contributors of CO_2 emissions in a fossil-fuel based economy. Low carbon energy systems are thus being developed, promoted and deployed as part of the solution portfolios to address climate change. However, certain issues are associated with each technology such that each one needs to be deployed in appropriate scenarios. Optimal selection of such systems should consider the technical, economic, environmental and social aspects of the decision problem. In addition, some emerging technologies may have imprecise information which make it difficult to understand the behavior of the alternatives with respect to some criteria with certainty. The decision maker also needs to conduct trade-off analysis when prioritizing the alternatives in a complex problem involving multiple conflicting criteria. In this work, a Stochastic Fuzzy Analytic Network Process (SFANP) model was developed and applied in the prioritization of low carbon energy systems considering such uncertainty. This technique decomposes the complex problem into a hierarchic network structure and derives priority weights to rank the alternatives. The decision model incorporated the ambiguity-type uncertainty wherein a calibrated fuzzy scale was used to represent the judgment in pairwise comparisons of alternatives and criteria. Monte Carlo simulations were also done for the uncertainty analysis of the priorities derived from the model. An illustrative case study in the Philippines was presented. The case study involves biomass, geothermal, solar, hydro, and wind power which were evaluated with respect to tangible criteria such as levelized cost of electricity, carbon footprint, land footprint and water footprints, as well as, intangible criteria such as maturity of technology, social acceptance, and social benefits.

1. Introduction

This past decade has seen the rising threat of climate change, and we are becoming more aware and alarmed on our planet's limited ability to support the unrestrained progress of human civilization. For example, energy systems are not only a driver of economic and technological growth but also the driver of climate change as the fossil fuel-based power sector in particular is a major contributor of the global CO_2 emissions (IPCC, 2014). Many nations and institutions have already included low carbon technologies using renewable energy (RE) sources as one of their strategies in their energy policies leading to legislations, directives, and programs that develop and promote such systems. The Philippines had made also some initiatives as mandated by Renewable Energy Act of 2008 to shift the energy dependency from fossil fuels to low carbon energy sources. Accordingly, the country's Department of Energy under the National Renewable Energy Plan aims to increase the renewable energy generation to around 9,500 MW by year 2030 (DOE, 2016). These involve potential RE projects to generate electricity from hydropower, biomass, wind, solar and geothermal resource. Proper planning and optimal selection of sustainable energy systems for the country involve crucial and long-term decisions, and require a systematic methodology to deal with such complex and multi-faceted decision problem.
Multiple criteria decision analysis (MCDA) have been demonstrated to be useful in solving such complex energy planning problems (Pohekar and Ramachandran, 2004). For example, Wang et al. (2009) review several

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techniques on criteria weighting, and methods for energy planning based on priority setting, weighted sum, outranking approach, fuzzy set theory, among others. In the said paper, the Analytic Hierarchy Process (AHP) is mentioned as the most widely used MCDA tool. In addition, fuzzy set methodology is also increasingly applied to address the imprecision or vagueness inherent in the decision making (Zimmermann, 2011). AHP's popularity in many parts of the world is mainly attributed to its intuitive appeal, simplicity and flexibility to integrate with other techniques and handling multiple and conflicting criteria that are either qualitative or quantitative in nature. This same trend on the popularity of AHP and its variant such as Fuzzy AHP has also been observed in decision analysis for sustainable renewable energy development (Kumar et al., 2017) and for energy management problems (Mardani et al., 2017). For example, it has been used to select renewables in developing countries like Pakistan (Amer and Daim, 2011) and Algeria (Haddad et al., 2017). In the Philippines, AHP was used in prioritizing climate change mitigation options (Promentilla et al., 2013), and a variant of Fuzzy AHP has also been developed for optimal selection of low carbon technologies for energy storage (Promentilla et al., 2015). However, these applications did not consider the complex interdependencies of the decision structure and uncertainties involved in it. For example, the available information could be imprecise, incomplete and sometimes unreliable due to lack of knowledge or the unquantifiable nature of data. In the absence of quantitative data, experts and stakeholders tend also to provide their judgments in linguistic but ambiguous terms.

This work thus extends the previous work of the authors (Promentilla et al., 2016) to address these problems using the concept of Analytic Network Process (ANP) while addressing the fuzzy and probabilistic uncertainties involved simultaneously. Note that ANP is a generalization of AHP that represents the decision structure as a network with dependence and feedback in a super matrix framework (Saaty, 2001). Our proposed decision model based on fuzzy ANP involves optimal selection of low carbon energy systems for power generation wherein interdependence among criteria and between criteria and alternatives are considered in the evaluation framework. In addition, the decision model incorporates the ambiguity-type uncertainty wherein a fuzzy preference programming technique was used to derive the priority weights from a calibrated fuzzy scale. Monte Carlo simulations are then made to model the variability of the priority weights and treat those variables characterized by multiple sources that are imprecise or lacking with reliable sources of information.

2. Methodology

An outline of the procedure for the proposed decision modeling approach is described as follows:

1. The decision problem is decomposed in a hierarchical network structure. This is represented as a super matrix based on a digraph (Promentilla et al., 2008). Note that this super matrix is a partitioned matrix to organize the priorities wherein each submatrix represents the interdependencies between or within the level or cluster. A more detailed discussion on these interdependencies is provided in Section 3.

2. Data is collected from the literature or through questionnaire, interview or survey to quantify the priority weights. Those priority weights that can be derived directly from quantitative data are computed by normalizing the data with the maximum value in the set if larger value is better. Otherwise, if smaller value is better, e.g., cost, the reciprocal of the data is computed first before the normalization. In the absence of quantitative data, elicit value judgments from experts or stakeholders to derive the initial priorities that describe the relative preference of an alternative, the relative importance of a criterion, or the relative dominance of an element over the other element belonging in the same level. The verbal judgment is described by triangular fuzzy numbers (TFN) to address the ambiguity of the judgments provided by the respondents. The TFN is represented by triples <*l*,***m***,*u*> to represent the lower bound, modal value, and upper bound of the fuzzy number. Based on the recent study in Promentilla et. al. (2016), the calibrated fuzzy scale for pairwise comparative judgment ($\hat{a}_{ij}$) pertaining to "equally", "slightly more", "moderately more", "strongly more" and "very strongly more" are TFNs <1.0, **1**, 1.0>, <1.2, **2**, 3.2>, <1.5, **3**, 5.6>, <3.0, **5**, 7.9>, <6.0, **8**, 9.5>, respectively. Note that the modal value follows the Fibonacci sequence and the degree of fuzziness, i.e., the difference between the upper bound and lower bound, is greater to those verbal judgments with "strongly more" and "very strongly more". For a number of decision makers, the individual judgements expressed as fuzzy numbers can be aggregated using geometric mean method (Orbecido et al., 2016). The pairwise comparative judgment matrx is shown in Eq. (1).

$$\hat{A}=\begin{bmatrix} \langle 1,1,1\rangle & \hat{a}_{12} & \cdots & \hat{a}_{1n} \\ \hat{a}_{21} & \langle 1,1,1\rangle & \cdots & \hat{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{a}_{n1} & \hat{a}_{n1} & \cdots & \langle 1,1,1\rangle \end{bmatrix} \text{ where } \hat{a}_{ji}=\left\langle l_{ij}, m_{ij}, u_{ij}\right\rangle;\ \hat{a}_{ji}=\left\langle \frac{1}{u_{ij}}, \frac{1}{m_{ij}}, \frac{1}{l_{ij}}\right\rangle \tag{1}$$

3. The priority weights are computed using the nonlinear fuzzy preference programming approach described in Promentilla et.al. (2015):

$$\max \lambda \quad \text{(2a)}$$
s.t.:
$$a_{ij} - l_{ij} \geq \lambda(m_{ij} - l_{ij}) \quad ; \quad a_{ji} - l_{ji} \geq \lambda(m_{ji} - l_{ji}) \quad \text{(2b)}$$
$$u_{ij} - a_{ij} \geq \lambda(u_{ij} - m_{ij}) \quad ; \quad u_{ji} - a_{ji} \geq \lambda(u_{ji} - m_{ji}) \quad \text{(2c)}$$
$$\text{where } a_{ij} = {w_i}/{w_j} \quad ; \quad a_{ji} = {w_j}/{w_i} \qquad \forall \text{ i} = 1,..., \text{n-1; j} = 2,..., \text{n; j} > \text{i} \quad \text{(2d)}$$
$$\sum_{k=1}^{n} w_k = 1; \quad w_k > 0 \quad \text{(2e)}$$

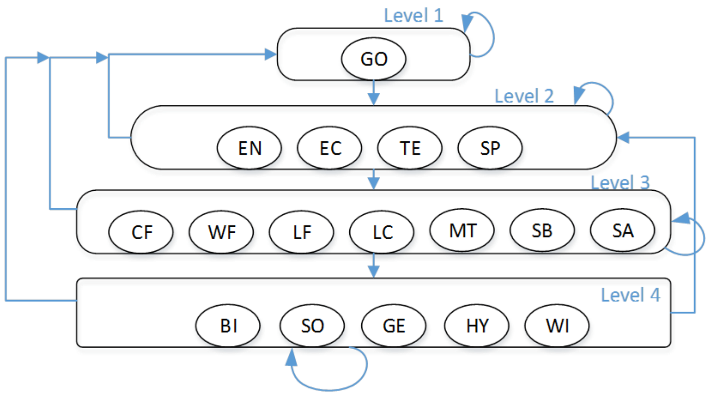
These ratio-scale weights (w_k) is approximated by maximizing degree of satisfaction λ, which is also a measure of consistency wherein the ratio of these computed weights also satisfy the initial fuzzy judgments. A λ of 1.0 indicates perfect consistency whereas a value of λ equal to 0.0 indicates that fuzzy judgments are only satisfied at their boundaries (Tan et al., 2014).

4. The super matrix (*S*) representation of the decision structure with normalized priority vectors is populated. Note that the priority vectors derived from the pairwise comparative judgment or from quantitative data are normalized by the maximum priority in the set. After constructing the initial super matrix, overall priorities are then derived from the principal eigenvector (v) of the said super matrix, which were normalized according to pertinent clusters. Please refer to Promentilla et al. (2008) for the description of algorithm in Eq(3). Note that *q* is a scalar multiple of the eigenvector (v) derived from the irreducible primitive matrix *S*. The computation of this eigenvector can be easily implemented in a spreadsheet by consecutively squaring the matrix until the normalized row sum of the squared matrix converged to a limiting value.

$$\operatorname*{limit}_{p\to\infty} \frac{S^p e}{e^T S^p e} = qv \quad \text{(3)}$$

5. Stochastic simulations are performed using Monte Carlo (MC) method to model the uncertainty involved in computing the overall priorities. The variability in the initial priority is simulated by assuming a predefined probability distribution of the random variables for quantitative and qualitative data. In this study, Beta-PERT distribution was used to model the variability in the input priorities to the super matrix. Beta-PERT distribution is a special case of Beta distribution that requires only the the minimum, most likely and maximum estimate of the variable, which has been widely used for modelling experts judgment with less demand for data (Jing et al., 2013). Repeat Step 4 for a number of iterations or simulations (e.g., 5,000; 10,000). Plot the probability distribution of the normalized priority weights.

3. Numerical example: prioritization of low carbon energy systems in the Philippines



$$S = \begin{bmatrix} W_{11} & W_{12} & W_{13} & W_{14} \\ W_{21} & W_{22} & O & W_{24} \\ O & W_{32} & W_{33} & O \\ O & O & W_{43} & W_{44} \end{bmatrix}$$

Figure 1: A sample digraph of hierarchical network structure and its super matrix representation.

In this case study, an illustrative hierarchical network decision structure in a form of digraph and its super matrix are shown in Figure 1. The uppermost level is the goal (GO), i.e., to determine the most preferred alternatives. The second level or cluster includes the four main criteria namely environmental (EN), economic (EC), technological (TE), and socio-political (SP) aspects. The next level contains the indicators for each criterion. For example, the environmental aspect is defined by three indicators namely: carbon footprint (CF), water footprint (WF), and land footprint (LF). The levelized cost (LC) is used as an indicator for economic aspect whereas the maturity of technology (MT) is an indicator for technological aspect. As for the socio-political aspect, social benefits (SB) and social acceptability (SA) are the indicators. At the lowest level, low carbon technologies for electricity generation are identified as alternatives namely: biomass (BI), solar power (SO), geothermal power (GE), hydropower (HY), and wind power (WI).

The super matrix ***S*** organizes the interdependencies among the elements in the decision structure. For example, W_{21} is the submatrix containing the priority vectors of elements in Level 2 as influenced by an element in Level 1. This is represented in the digraph by the downward arrow of influence from Level 1 to Level 2. Note that these priorities are the relative importance of the main criteria with respect to the goal. W_{32} is the submatrix containing the priority vectors of elements in Level 3 as influenced by elements in Level 2. This is represented in the digraph by the downward arrow of influence from Level 2 to Level 3. These priorities are the relative importance of the indicators with respect to the associated criteria. On one hand, W_{43} is the submatrix containing priority vectors of elements in Level 4 as influenced by elements in Level 3 and is represented in the digraph by the downward arrow of influence from Level 3 to Level 4. These priorities are the relative preference of the alternatives with respect to the indicators. These downward arrows from Level 1 to Level 4 are analogous with the typical hierarchical structure of AHP. However, the proposed decision structure extends the AHP model to other possible interdependencies such as the interdependence among elements within the level or the feedback dependence from the lower level to an upper level. For example, the arc loop to each level denotes interdependence of elements within the level as represented by W_{11}, W_{22}, W_{33}, and W_{44}. Note that these submatrices are identity matrices if the elements within the level or cluster depend only on itself and independent from other elements. For example, $W_{44} = I$ since the alternatives are assumed to be independent from each other. As for the feedback dependencies, an example is W_{24} which is a submatrix containing the priority vectors of elements in Level 2 as influenced by the elements in Level 4. These priorities are the relative importance of criteria as being influenced by the characteristics of alternatives. This is represented by the upward arrow from Level 4 to Level 2. The null matrix, for example, in submatrices W_{41}, W_{42}, and W_{23} described in super matrix ***S*** indicates that there is no direct dependence between those levels in that direction. In other words, W_{41} is a null matrix such that there is no downward arrow from Level 1 that directly connects to Level 4 as a result of the problem decomposition wherein the alternatives have no direct impact on the goal. On the other hand, W_{12}, W_{13}, and W_{14} are row vectors of 1.0 as these represent feedback control loops to the single controlling element in Level 1, i.e., the goal. The upward arrow to the goal from the lower levels describes structural dependence and ensures that the structure is a strongly connected network which will provide meaningful overall priorities by capturing all the possible direct and indirect interactions among elements in the system (Promentilla et al., 2006).

	GO	EN	EC	TE	SP	CF	WF	LF	LC	MT	SB	SA	BI	SO	GE	HY	WI	*priority*
GO	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1.000**
EN	**0.03**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.35**	**1.00**	**0.89**	**0.64**	**0.79**	**0.129**
EC	**0.02**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1.00**	**0.42**	**1.00**	**0.91**	**0.29**	**0.144**
TE	**0.57**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.53**	**0.60**	**0.65**	**1.00**	**1.00**	**0.303**
SP	**1.00**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.21**	**1.00**	**0.60**	**0.98**	**0.30**	**0.424**
CF	**0**	**0.04**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.005**
WF	**0**	**0.04**	**0**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.005**
LF	**0**	**1.00**	**0**	**0**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.125**
LC	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.140**
MT	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.293**
SB	**0**	**0**	**0**	**0**	**0.05**	**0**	**0**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0.021**
SA	**0**	**0**	**0**	**0**	**1.00**	**0**	**0**	**0**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0.410**
BI	**0**	**0**	**0**	**0**	**0**	**0.03**	**0.01**	**0.00**	**0.89**	**1.00**	**1.00**	**1.00**	**1**	**0**	**0**	**0**	**0**	**0.369**
SO	**0**	**0**	**0**	**0**	**0**	**0.03**	**0.61**	**1.00**	**0.39**	**0.14**	**0.64**	**0.74**	**0**	**1**	**0**	**0**	**0**	**0.236**
GE	**0**	**0**	**0**	**0**	**0**	**0.17**	**0.01**	**0.01**	**1.00**	**0.50**	**0.37**	**0.18**	**0**	**0**	**1**	**0**	**0**	**0.162**
HY	**0**	**0**	**0**	**0**	**0**	**1.00**	**0.04**	**0.49**	**0.76**	**0.27**	**0.21**	**0.14**	**0**	**0**	**0**	**1**	**0**	**0.135**
WI	**0**	**0**	**0**	**0**	**0**	**0.50**	**1.00**	**0.19**	**0.53**	**0.14**	**0.10**	**0.19**	**0**	**0**	**0**	**0**	**1**	**0.098**

Figure 2: Initial super matrix populated by priority weights derived from quantitative data or expert judgments and the computed overall priorities.

Details of pairwise comparison matrices are not discussed here for the purpose of brevity. Only a sample of the numerical calculations is shown to demonstrate the proposed method particularly in the computation of priority vectors. Figure 2 describes an example of initial supermatrix populated by the appropriate priority weights including the computed overall priorities from the eigenvector of the said supermatrix. Note that the final or overall priority weights in each level or cluster are derived by capturing all the possible interactions in the decision structure as described by the initial priorities. These non-zero priorities in this supermatrix refer to the relative dominance of elements in the corresponding block's column with respect to the element in the block's row. Accordingly, an element with a value of '1' in a column vector of a submatrix suggests that element is the most dominant element (see Figure 2). For example, the socio-political aspect criterion in W_{12} is perceived to be the most important with respect to the goal. As for feedback dependence described in W_{24}, the economic aspect criterion is perceived to be the most attractive attribute of biomass and geothermal-based energy system. Table 1 summarizes the sample parameters used for the Beta-PERT distributions of performance of the alternatives with respect to tangible and intangible criteria. Figure 3 illustrates the probability distributions of the overall priorities after 10,000 simulations, implying biomass as the most preferred alternative followed by solar power whereas wind or hydropower as the least preferred.

Table 1: Beta-PERT distributions of the selected random variables for Monte Carlo simulations

Indicators	Alternatives (Minimum, Most likely, Maximum)[a]				
	BI	SO	GE	HY	WI
CF ($kg\ CO_2/kWh$)	(0.00, 0.38, 0.38)	(0.102, 0.33, 0.949)	(0.019, 0.06, 0.128)	(0.008, 0.01, 0.022)	(0.0107, 0.02, 0.03)
WF (m^3/GWh)	(86400, 221121, 514800)	(1080, 3286, 10000)	(142200, 158000, 173800)	(37000, 54133, 79200)	(1800, 2000, 2200)
LF (m^2/GWh)	(363600, 474692, 694800)	(164, 665, 45000)	(43200, 48000, 52800)	(3, 1367, 737000)	(1030, 3503, 72000)
LC ($/KWh)	(0.037, 0.091, 0.143)	(0.024, 0.331, 1.20)	(0.048, 0.080, 0.155)	(0.053, 0.113, 0.168)	(0.053, 0.566, 3.855)
MT*	(0.28,0.46,0.63)	(0.03,0.06,0.41)	(0.12,0.23,0.37)	(0.06,0.12,0.23)	(0.03,0.06,0.12)
SB*	(0.25,0.42,0.73)	(0.15,0.27,0.47)	(0.05,0.16,0.28)	(0.03,0.09,0.19)	(0.02,0.04,0.09)
SA*	(0.37,0.44,0.55)	(0.26,0.32,0.39)	(0.05,0.08,0.12)	(0.04,0.06,0.12)	(0.06,0.08,0.10)

[a]based from the data compiled in Antonio et al., 2015 and references therein
*priority weights derived from expert's judgment

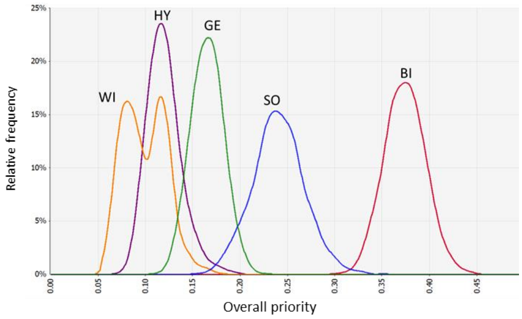


Figure 3: Probability distribution of the overall priorities of the alternatives

4. Conclusions

This work demonstrates the application of a decision modelling approach based on a hierarchical network structure to the optimal selection of low-carbon technologies for power generation. Five alternatives were considered for the Philippine setting namely biomass, geothermal, solar, hydro, and wind power. These energy systems were evaluated with respect to tangible criteria such as levelized cost of electricity, carbon footprint, land footprint and water footprints, as well as, intangible criteria such as maturity of technology, social acceptance, and social benefits. The overall priorities from the super matrix are computed from the Monte Carlo aided Fuzzy ANP. For this case study, the most desirable alternative is the biomass-based energy systems for electricity generation followed by solar power. The proposed technique provides a systematic and robust mathematical approach where results can aid decision makers in spite of the uncertainty involved in the decision-making process. The proposed approach can offer some advantages such as to capture ambiguity and address the effects of uncertain information due to imprecise and insufficient data, or biased opinions. Furthermore, approaches like this make the decision-making process transparent and open for new information whenever relevant data becomes available. Future work will also consider the sensitivity of model results on the other type of dependencies which takes into account electricity demand and the capacities of biomass, solar and other alternatives available within the region in the decision structure.

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