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# A Risk-based Decision Support Tool for Selection and Evaluation of Negative Emissions Technologies

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As the rate at which climate change is increasing in making an impact to the planet, the need to develop and deploy technologies to reduce greenhouse gas (GHG) emissions becomes increasingly necessary. The United Nations' Sustainable Development Goal 13 (SDG 13) of reducing the effects of climate change would require ambitious actions and implementation towards achieving it. Negative emissions technologies (NETs) will contribute to this goal by reducing GHG concentrations in the atmosphere. Options for NETs are available for integration into energy and climate change policies. Barriers for large-scale implementation are present in each of these technologies; risks are present when it comes to integrating them into climate change mitigation strategies. In this paper, a novel multi-criteria decision analysis (MCDA) tool is developed for ranking and evaluating NETs under different risk levels. The tool is based on integrating the concept of neutrosophic sets into data envelopment analysis, or neutrosophic data envelopment analysis (NDEA) to examine the consequential effect of inefficiencies and uncertainties in the characteristics of different NETs. This considers a decoupled approach to the inherent efficiency, inefficiency, and uncertainty of each technology. A case study is presented to illustrate this tool. Results show the advantages of different NETs under different levels of expert's risk attitude and perception, i.e. tolerance factors. Soil carbon sequestration technology is efficient at tolerance levels from 60 % to 100 % as presented in the results. This can be an effective tool to select which technologies is appropriate in different scenarios.

## 1. Introduction

The increase in fossil fuel-based energy consumption is attributed to the growing global population, industrial development, and economic growth. Seventeen (17) sustainable development goals (SDGs) are developed as a framework to address issues in attaining sustainable development; one of which entails the reduction of $CO_2$ emissions in the atmosphere. As the window of opportunity to achieve this goal gets smaller, the need to reduce atmospheric $CO_2$ concentration becomes more relevant in the climate change problem (Haszeldine et al., 2018). Implementation of negative emissions technologies (NETs) will play an important role in addressing this need.

NETs not only involve the reduction of $CO_2$ emissions from sources but also produce a net negative carbon footprint in its life cycle. Technologies considered as NETs include bioenergy with CCS (BECCS), direct air capture systems (DACS), afforestation and reforestation (AR), biochar technology, soil carbon sequestration (SCS) and enhanced weathering (EW) (McLaren, 2012). Aside from being a technology with negative emissions, some technologies have added benefits. Biochar helps improves soil quality (El Naggar et al., 2019). Despite their environmental benefits, these technologies entail some issues pertaining to economic and environmental impacts, and technological readiness. Mathematical tools are important to assess these technologies in large-scale applications and to integrate these in energy policies.

Recent studies on integrating NETs into energy and environmental policies reveals its potential as contributors in addressing the climate change problem (Smith et al., 2016). Mathematical models have been developed for planning and large-scale implementation of selected NETs such as EW (Tan and Aviso, 2019), ocean-capture technology (Tan et al., 2019), DACS (Darton and Yang, 2018) and biochar-producing power plants (Aviso et al., 2019). These studies aid the deployment of NETs in regional energy planning and provide useful insights to improve their technological maturity. Decision tools for selection of multiple NETs are limited; the recent one

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is by Tan et al. (2019). Improved decision tools in selection of multiple NET options is needed to be developed considering the risks entailed to it. The objective of this study is to develop a decision-making tool for selection and evaluation of NET options accounting for the uncertainties in their characteristics.

This study develops a neutrosophic data envelopment analysis (NDEA) tool that evaluates technologies for negative emissions under uncertainty. The uncertainty is modelled using neutrosophic sets to consider the different aspects of decision-making and risk management. The concept of neutrosophic sets was developed by Smarandache (2006) to generalize fuzzy-like uncertainties such as incomplete and vague information present in emerging technologies like NETs. Neutrosophic sets were applied in various engineering applications such as water-shale gas network (Ahmad et al., 2019) and energy policies in the European Union (Siksnelyte et al., 2019). Data envelopment analysis (DEA) was effectively used as an MCDA tool for selection where the options are described quantitatively (Tapia et al., 2017). The application of neutrosophic sets in DEA has been developed by Abdelfattah (2019). It only utilizes the mathematical concept of neutrosophic numbers. The innovation and contribution of this paper is the application of NDEA in important sustainability issues such as climate change. Combining the concept of DEA as an effective MCDA tool and neutrosophic sets to model uncertainty is a potentially powerful tool to evaluate NETs under uncertainty. NDEA is applied in this study for the selection of multiple NET options under uncertainty. This paper also generates important insights about the relationship between performance of NETs and uncertainty tolerance levels. The rest of this paper is organized as follows. Section 2 discusses the problem statement while Section 3 discusses the mathematical model. Section 4 illustrates the model for a case study involving multiple NETs options and Section 5 presents the conclusions.

## 2. Problem Statement

For the development of decision tools for NETs, the formal problem statement is discussed as follows:

- The system consists of *n* options for negative emissions which are treated as decision-making units (DMUs).
- Each option *i* = {1,2,3, …, n} is characterized by *p* outputs. These are criteria in which higher values are favorable such as technological readiness levels (TRLs) and storage capacity.
- Each option *i* = {1,2,3, …, n} is characterized by *m* output. These are criteria in which lower values are favorable such as energy requirement, land and water footprint, costs, and soil albedo effect.
- Both input and output parameters are treated as neutrosophic sets, which characterizes them with membership, non-membership, and indeterminacy degrees. In Figure 1, the performance satisfaction is expressed as a function of the membership function where the highest value is given at high outputs and low inputs. Characterizing each technology creates consequences in terms of performance dissatisfaction for low outputs and high inputs, and uncertainty to attain high outputs and low inputs. Performance dissatisfaction is modelled in terms of non-membership function and uncertainty is modelled as indeterminacy function.
- The goal is to determine the ranking of each NET options subject to the constraints of data envelopment analysis (DEA). The expert's risks attitude is also incorporated to the decision as tolerance factors to performance dissatisfaction or inefficiency (TE) and uncertainty (TI). These are factors which can vary from one expert to another, depending on how averse the experts are to risks.

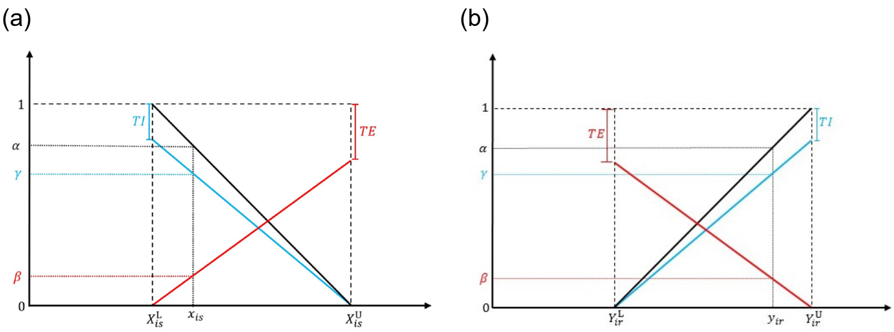


*Figure 1: Representation of (a) input data and (b) output data as neutrosophic sets*

## 3. Mathematical Formulation

The objective function of the model is to maximize the overall degree of satisfaction, minimize the overall degree of dissatisfaction and the overall degree of uncertainty as shown in Eq(1). Eq(2) ensures that the efficiency of observed DMU *o* is maximized while Eq(3) to Eq(5) maximize the minimum degree of satisfaction and minimizes the maximum degrees of dissatisfaction and uncertainty. Eq(6) ensures that the efficiency is higher than the overall degree of satisfaction while Eq(7) ensures that the aggregated input of the observed DMU is equal to one. Eq(8) represents the constraint that the efficiency of all other DMUs are equal to or less than one. Six bilinear factors in Eq(9) to Eq(11) are bounded so that their values do not exceed the input weight, $v_s$ and output weight, $u_r$. These bilinear factors are expressed as follows in Eq(18) to Eq(20). The membership function shown in Figure 1 is represented by Eq(12) for input parameters and Eq(13) for output parameters. The non-membership function is represented by Eq(14) and Eq(15) while the indeterminacy function is expressed in Eq(16) and Eq(17). The efficiency is optimized by determining the best weights for the inputs and outputs of the observed DMU.

$$\max \alpha - \beta - \gamma + \frac{\theta_0}{\mathrm{M}} \tag{1}$$

Subject to:

$$\theta_0 = \textstyle\sum_r b_{ir} \tag{2}$$

$$\alpha \le \alpha_s^{\mathrm{Iw}} \quad \forall s, \quad \alpha \le \alpha_r^{\mathrm{Ow}} \quad \forall r \tag{3}$$

$$\beta \ge \beta_s^{\mathrm{Iw}} \quad \forall s, \quad \beta \ge \beta_r^{\mathrm{Ow}} \quad \forall r \tag{4}$$

$$\gamma \ge \gamma_s^{\mathrm{Iw}} \quad \forall s, \quad \gamma \ge \gamma_r^{\mathrm{Ow}} \quad \forall r \tag{5}$$

$$\alpha \ge \theta_0 \tag{6}$$

$$\textstyle\sum_s a_{is} = 1 \tag{7}$$

$$\textstyle\sum_r b_{ir} \le \sum_s a_i \quad \forall i \tag{8}$$

$$0 \le \alpha_s^{\mathrm{Iw}} \le v_s \quad \forall s, \quad 0 \le \alpha_r^{\mathrm{Ow}} \le u_r \quad \forall r \tag{9}$$

$$0 \le \beta_s^{\mathrm{Iw}} \le v_s(1-\mathrm{TE}) \quad \forall s, \quad 0 \le \beta_r^{\mathrm{Ow}} \le u_r(1-\mathrm{TE}) \quad \forall r \tag{10}$$

$$0 \le \gamma_s^{\mathrm{Iw}} \le v_s(1-\mathrm{TI}) \quad \forall s, \quad 0 \le \gamma_r^{\mathrm{Ow}} \le u_r(1-\mathrm{TI}) \quad \forall r \tag{11}$$

$$a_{is} = \alpha_s^{\mathrm{Iw}}\left(\mathrm{X}_{is}^{\mathrm{L}} - \mathrm{X}_{is}^{\mathrm{U}}\right) + v_s\mathrm{X}_{is}^{\mathrm{U}} \quad \forall i, s \tag{12}$$

$$b_{ir} = \alpha_r^{\mathrm{Ow}}\left(\mathrm{Y}_{ir}^{\mathrm{U}} - \mathrm{Y}_{ir}^{\mathrm{L}}\right) + u_r\mathrm{Y}_{is}^{\mathrm{L}} \quad \forall i, r \tag{13}$$

$$a_{is}(1-\mathrm{TE}) = \beta_s^{\mathrm{Iw}}\left(\mathrm{X}_{is}^{\mathrm{U}} - \mathrm{X}_{is}^{\mathrm{L}}\right) + v_s\mathrm{X}_{is}^{\mathrm{L}} \quad \forall i, s \tag{14}$$

$$b_{ir}(1-\mathrm{TE}) = \beta_r^{\mathrm{Ow}}\left(\mathrm{Y}_{ir}^{\mathrm{L}} - \mathrm{Y}_{ir}^{\mathrm{U}}\right) + u_r\mathrm{Y}_{is}^{\mathrm{U}} \quad \forall i, r \tag{15}$$

$$a_{is}(1-\mathrm{TI}) = \gamma_s^{\mathrm{Iw}}\left(\mathrm{X}_{is}^{\mathrm{L}} - \mathrm{X}_{is}^{\mathrm{U}}\right) + v_s\mathrm{X}_{is}^{\mathrm{U}} \quad \forall i, s \tag{16}$$

$$b_{ir}(1-\mathrm{TI}) = \gamma_r^{\mathrm{Ow}}\left(\mathrm{Y}_{ir}^{\mathrm{U}} - \mathrm{Y}_{ir}^{\mathrm{L}}\right) + u_r\mathrm{Y}_{is}^{\mathrm{L}} \quad \forall i, r \tag{17}$$

$$\alpha_s^{\mathrm{Iw}} = \alpha v_s \quad \forall s,\ \alpha_r^{\mathrm{Ow}} = \alpha u_r \quad \forall s \tag{18}$$

$$\beta_s^{\mathrm{Iw}} = \beta v_s \quad \forall s,\ \alpha_r^{\mathrm{Ow}} = \alpha u_r \quad \forall s \tag{19}$$

$$\gamma_s^{\mathrm{Iw}} = \gamma v_s \quad \forall s,\ \alpha_r^{\mathrm{Ow}} = \alpha u_r \quad \forall s \tag{20}$$

This model is run for each candidate options. The model is formulated with an objective function in Eq(1) subject to constraints in Eq(2) to Eq(17). The model is implemented in AIMMS 4.68.2.4 in a PC with 8.00 GB RAM and 2.60 GHz processor with negligible computational times.

## 4. Case Study

To illustrate the model, a case study using the data in Smith et al. (2016) and Smith (2016) are used. The data for DACS, BECCS, AR and EW are adopted from Smith et al. (2016) and for SCS and biochar are adopted from Smith (2016). The input data is shown in Table 1 as stated in the literature provided while the output data is shown in Table 2. The input criteria used are the energy and land requirement, costs, soil albedo effect and water requirement. On the other hand, the output criteria used are TRL and potential storage capacity. The data were given as interval-valued neutrosophic numbers. The neutrosophic nature of the input and output parameters in the selection of NETs are explained as follows. Higher degrees of satisfaction are given for lower input and higher output to achieve higher efficiency. This entails two consequences: one is the risks attributed to poor performance as represented by the degree of dissatisfaction and the other is the risks due to the uncertainty of attaining better technological characteristics as represented by the degree of uncertainty. The degree of dissatisfaction is higher at high inputs and low outputs while the degree of uncertainty is higher at low inputs and high outputs.

*Table 1: Input data for the case study*

| NETs | Energy Requirement (GJ/t$CO_2$-eq) | Land Area Requirement (ha/ t$CO_2$-eq /y) | Water Requirement ($m^3$/ t$CO_2$-eq) | Costs (USD/ t$CO_2$-eq) | Albedo Effect (% change/ t$CO_2$-eq) |
|---|---|---|---|---|---|
| DACS | 0.49 to 12.27 | 0.0027 to 0.03 | 0.0027 to 0.05 | 436.36 to 567.27 | 0 to 0.00003 |
| BECCS | -10.91 to -0.82 | 0.03 to 0.46 | 0.35 to 0.57 | 27.27 to 36.00 | 0.0027 to 1.36 |
| AR | -10.91 to -4.09 | 0.03 to 0.16 | 0.41 to 0.74 | 17.73 to 29.45 | 0.027 to 15 |
| SCS | 0.03 to 0.27 | 0.27 to 9.00 | 0.00014 to 0.0027 | -45 to 10.91 | 0 to 0.0027 |
| Biochar | -9.55 to -3.82 | 0.01 to 0.27 | 0.00014 to 0.0027 | -226.36 to 327.27 | 2.18 to 3.27 |
| EW | 0.20 to 12.55 | 0.0003 to 0.0014 | 0.05 to 0.41 | 24 to 548.73 | 0 to 0.00003 |

*Table 2: Output data for the case study*

| NETs | TRL | Potential Capacity (Gt/y) |
|---|---|---|
| DACS | 3.0 to 6.0 | 8 to 11 |
| BECCS | 4.0 to 6.0 | 2.4 to 10 |
| AR | 5.5 to 6.5 | 1.5 to 3.0 |
| SCS | 2.0 to 7.0 | 1.0 to 2.3 |
| Biochar | 4.8 to 5.3 | 0.9 to 1.0 |
| EW | 1.0 to 5.0 | 0.1 to 1.0 |

The optimization model for the case study has 76 continuous variables and 179 constraints. The NDEA model developed can be transformed into a fuzzy DEA when the degrees of dissatisfaction and uncertainty are not considered, i.e. when TE=1 and TI=1. It can also be transformed into an intuitionistic fuzzy DEA when the degree of uncertainty is not considered, i.e., when TE=0 and TI=1. Solving the case study as fuzzy, intuitionistic fuzzy and neutrosophic in nature, the results is shown in Table 3. When the expert is does not consider the risks in inefficiency and uncertainty, the ranking does not clearly indicate the best option. The ranking becomes evident when the risks in performance dissatisfaction is considered. In this case, the most efficient technology is DACS followed by BECCS while the lowest is SCS. The changes in ranking shows the effect of considering the uncertainty of attaining high performance of NETs. The changes in the ranking of DACS for the most efficient to the least efficient option make it vulnerable to performance uncertainty when implemented in the future. BECCS shows high preference in three cases while the preference for EW is consistently at lower ranks considering least tolerance to inefficiency and to both inefficiency and uncertainty. These clearly shows that NDEA gives more insight than fuzzy DEA or intuitionistic fuzzy DEA as it gives the ranking of NETs in different expert risk perception levels. These insights are useful in planning, given the conditions and capacity of a given region or country.

*Table 3: Case study result showing the efficiencies $\theta_0$ as different tolerance values*

| NETs | Fuzzy DEA ($TE$=1 and $TI$=1) | Intuitionistic Fuzzy DEA ($TE$=0 and $TI$=1) | Ranking | Neutrosophic DEA ($TE$=0 and $TI$=0) | Ranking |
|---|---|---|---|---|---|
| DACS | 1.00000 | 1.00000 | 1 | 0.002585 | 5 |
| BECCS | 1.00000 | 0.09207 | 2 | 0.040467 | 2 |
| AR | 1.00000 | 0.05468 | 3 | 0.022557 | 3 |
| SCS | 1.00000 | 0.00023 | 6 | 0.040530 | 1 |
| Biochar | 1.00000 | 0.04787 | 4 | 0.004699 | 4 |
| EW | 1.00000 | 0.03491 | 5 | 0.001222 | 6 |

To show the effect of the tolerance factors in the ranking of different NET options, a sensitivity analysis is performed for varying inefficiency tolerance levels at a specific values of uncertainty tolerance. The result of the sensitivity analysis is shown in Figure 2. The choice of uncertainty tolerance is arbitrary; Figure 2 just illustrates a comparison between two levels of uncertainty tolerance factors. Results shows that most options are efficient only at high tolerances of performance dissatisfaction (i.e. TE). SCS has the widest range of efficient performance from TE = 0.6 to TE = 1 at TI = 0.95 among the options. It also shows that the most efficient option when all options are not fully efficient is BECCS and SCS. At TI = 0.60 and TE = 0.95, the TE values that enables DACS and EW options to be fully efficient both starts with 0.95. This shows that both options should only be considered when the expert is focused on the possibility that the characteristics of the given options are attainable. The efficiency of AR gradually increases in increasing TE and TI factors compare to other options where no changes occur at low TE levels and an abrupt increase to full efficiency at higher TE levels. The trend for biochar is the same as that of BECCS where full efficiency is achieved at TE = 0.75. The sensitivity of different NET options shows certain levels of risk can greatly affect the performance of these options. The results offer insights that allows policymakers to select which option is best suitable in the condition of their regional capacity.

(a) (b)

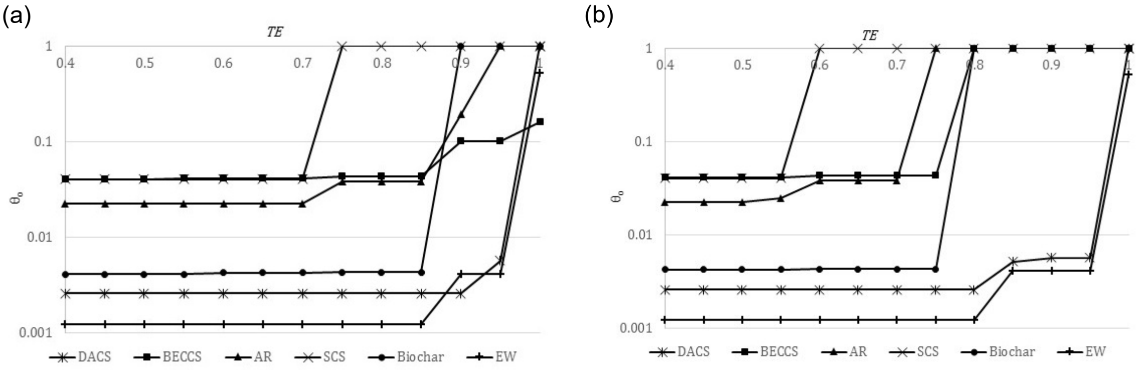


*Figure 2: Sensitivity analysis of the efficiencies ($\theta_0$) obtained by varying the inefficiency tolerance factor (TE) at uncertainty tolerance factor at (a) TI = 0.60 and (b) TI = 0.95*

Results from the study shows the following insights in evaluating NET options:

- DACS is only an efficient option when risks arising from uncertainty is not considered. It is suitable for small regions with enough financial capacity and renewable energy source.
- BECCS is an to consider as it is robust to varying levels of tolerance in inefficiency and uncertainty. It is suitable for regions with large available land.
- Based on the results, AR is comparable to BECCS in terms of performance and robustness. This can be a viable option if the effect on soil albedo is reduced
- SCS is a decent option at high tolerance levels of inefficiency and uncertainty. The challenge to this technology is the availability of land area.
- At high tolerance factors, biochar is a good option with potential for profit and energy source. Considering its potentially high economic impact, improvements to the technology to reduce cost is much needed.

- Improvements are need to EW it does not perform enough compared to other options. The advantage of this option are low albedo effect and low land requirement which can still be a viable option in the future.

## 5. Conclusions

A neutrosophic data envelopment analysis (NDEA) model is developed for the selection and assessment of negative emissions technologies (NETs). The model accounts for the degrees of satisfaction, dissatisfaction and uncertainty in the input and output data. By setting the tolerance factors for the risks in inefficiency and uncertainty, the model can be transformed into a fuzzy DEA and an intuitionistic fuzzy DEA. The selection of NETs shows different ranking when the tolerance factors are set into different levels. This model can be used for future energy planning and policies involving multiple NET options for consideration.

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