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Fuzzy Optimization Model for the Selection of Negative Emissions Technologies Portfolios with Uncertain Cost and Performance

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The delay in climate action forces Carbon Dioxide Removal (CDR) or Negative Emissions Technologies (NETs) to become unavoidable. Different types of NETs (afforestation/reforestation, biochar application, soil carbon sequestration, bioenergy with carbon capture and storage, enhanced weathering, and direct air carbon capture and storage) have uncertain costs and performance that are difficult to predict precisely, a characteristic of unproven, emerging technologies. At the same time, the implementation of NETs will be subject to target negative emissions and resource constraints that lack precision. If unaddressed, these uncertainties will lead to techno-economic risks on the part of the stakeholder or decisionmaker. This study utilizes Fuzzy Mathematical Programming to optimize a NETs portfolio with uncertain performance and costs. The model gives the best compromising solution that maximizes the total negative emissions while conserving the resources. The performance of the model is demonstrated by case studies.

1. Introduction

Negative Emissions Technologies (NETs) will be required to address the residual emissions from fossil fuels (IPCC, 2022). NETs extract carbon dioxide away from the atmosphere for storage deep underground, in biomass, in the ocean, or the built environment (Minx et al., 2018). Examples of land-based NETs include bioenergy with carbon capture and storage (BECCS), afforestation/reforestation (AR), soil carbon sequestration (SCS), biochar (BC), enhanced weathering (EW), wetland restoration (WR), and direct air carbon capture and storage (DACCS) (Minx et al., 2018). Although the fundamentals of these technologies have been demonstrated, most of the emerging technologies are still unproven on the large scale (Minx et al., 2018). The large-scale deployment of NETs may have unintended consequences on sustainable development if poorly implemented (IPCC, 2022). For example, the maladaptation of biomass-based NETs such as BECCS and AR may impact water and food security, biodiversity, and livelihoods (IPCC, 2022). Deploying NETs portfolios on smaller scales as opposed to single technologies on larger scales will help address the risks and sustainability concerns present in these technologies (Fuss et al., 2018).

NET performance in terms of environmental footprint and cost has been evaluated across literature but there is a significant disagreement among studies (Minx et al., 2018). These differences arise not only from the differences in the assumptions used in the studies but also from epistemic uncertainties or the lack of knowledge of these systems, which is a characteristic of emerging technologies (Aviso et al., 2019). Similarly, the negative emissions target and the resource constraints in NETs planning are subject to epistemic uncertainties. To illustrate, the modeled pathways to reach the 1.5 °C climate target require cumulative negative emissions ranges between 20 to 660 Gt CO_2 throughout the 21st century (IPCC, 2022). Resource constraints may be guided by the Planetary Boundaries framework that has zones of uncertainty (Steffen et al., 2015). Considering these uncertainties is critical in the design of a robust NETs portfolio.

Various approaches have been used to handle uncertainties in technology selection and planning. Post-optimization sensitivity analysis can be done to assess the imprecision in the input parameters of linear programming (LP) models (Carlsson and Korhonen, 1986). A study that optimized a NETs portfolio under resource constraints using an LP model performed sensitivity analysis by varying the negative emissions target

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and resource constraints and then observing the changes in the model output (Migo-Sumagang et al., 2021). Another post-optimization technique is by generating multiple solutions and subjecting the solutions to Monte Carlo simulation for robustness checking. This approach was demonstrated by a study using the Target-Oriented Robust Optimization (TORO) method and was demonstrated on emissions reduction technologies with uncertain performance and cost (Aviso et al., 2019). A novel approach called the Neutrosophic Data Envelopment Analysis (NDEA) was developed by Tapia (2021). The model incorporates risks and uncertainties and was demonstrated using NETs. The uncertain criteria weights in Multi-Criteria Decision Analysis (MCDA) was addressed by a method of tracing the rank invariance region in multi-criteria selection problems and has been demonstrated on NETs considering multiple environmental footprints (Tan et al., 2019).

An approach that incorporates the uncertainties during optimization is Fuzzy Mathematical Programming (FMP). FMP has been demonstrated in integrated negative emissions BC and EW networks using a fuzzy mixed-integer linear programming (FMILP) model to find the optimum source-sink matches while accounting for the uncertainties in CO_2 sequestration rate and BC contaminant limits (Belmonte et al., 2021). The model is based on the symmetric fuzzy formulation by Zimmermann (1978). A symmetric fuzzy model where the fuzzy membership function occurs only on one side of the constraint is widely used in sustainable energy applications (Arriola et al., 2020). However, this formulation may be insufficient when applied to NETs since these emerging technologies have plenty of uncertainties in their performance and costs. So far, no studies have been found using FMP to optimize an integrated NETs portfolio while simultaneously considering the uncertainties in the technologies and constraints.

To address this research gap, this work utilizes FMP to optimize a NETs portfolio considering parametric uncertainties in the environmental footprint and costs, and uncertainties in the target negative emissions and resource constraints. Accounting for these epistemic uncertainties is critical in planning emerging technologies like NETs. The rest of the paper is organized as follows. Section 2 presents the problem statement. Section 3 gives the optimization model. Section 4 demonstrates the model using two case studies. And section 5 discusses the conclusions of this study.

2. Problem statement

The problem is formally stated as follows. Considering a system with a set of m resources (land, water, energy, etc.) and a set of n NETs (BECCS, AR, DACCS, etc.). The NETs require resources and have associated costs to sequester a target amount of carbon dioxide. Each NET is depicted by its fuzzy environmental performance (footprint) based on its required resource and cost. Likewise, each resource is defined by its fuzzy resource constraint. The fuzzy linear programming method by Zimmermann (1978) is applied. The problem is to determine the best compromising solution in a NETs portfolio that maximizes the total negative emissions while conserving available resources. The final model must be able to meet the negative emissions target and resource constraints defined in fuzzy intervals.

3. Fuzzy optimization model

In the following equations and figures, the subscripts refer to indices and the superscripts refer to labels. The labels L and U refer to the lower and upper fuzzy limits.

Fuzzy sets are a class of objects with "grades of membership" characterized by a membership function (Bellman and Zadeh, 1970). The fuzzy set theory seeks the intersection between the fuzzy goals and fuzzy constraints (Bellman and Zadeh, 1970). The theory was used to formulate and solve fuzzy linear programming problems (Zimmermann, 1978). Carlsson and Korhonen (1986) applied fuzzy linear programming to develop an LP model with parametric uncertainties. These studies are the basis of the model formulation in this work. Each fuzzy constraint must be satisfied partially to a degree λ (Zimmermann, 1978). The value λ, is constrained between 0 and 1, where 0 represents the "least satisfaction," 1 represents the "most satisfaction," and any value that falls in between represents partial satisfaction (Zimmermann, 1978). The solution giving the highest degree of aggregate membership in the fuzzy targets and constraints is the optimum. There are various types of fuzzy membership functions namely trapezoidal, triangular, minimization, and maximization membership functions depending on the objective (Arriola et al., 2020). The functions represent the regions of acceptable, partially acceptable, and unacceptable values. In this study, the minimization and maximization membership functions are utilized. The minimization membership function is used when the objective calls for the lowest values (Arriola et al., 2020). For example, a conservative decision maker may opt to minimize the available resources as reflected in the resource constraints. The minimization membership function of the resource constraint is shown in Figure 1a. On the other hand, the maximization membership function is used when the objective calls for the highest values (Arriola et al., 2020). In this study, a conservative decision maker may opt to maximize the target negative emissions. A conservative decision-maker may also aim to maximize the environmental footprints and costs per unit of negative emissions the NETs deliver. The maximization membership functions of the negative emissions target and environmental footprint and cost are shown in Figures 1b and 1c.

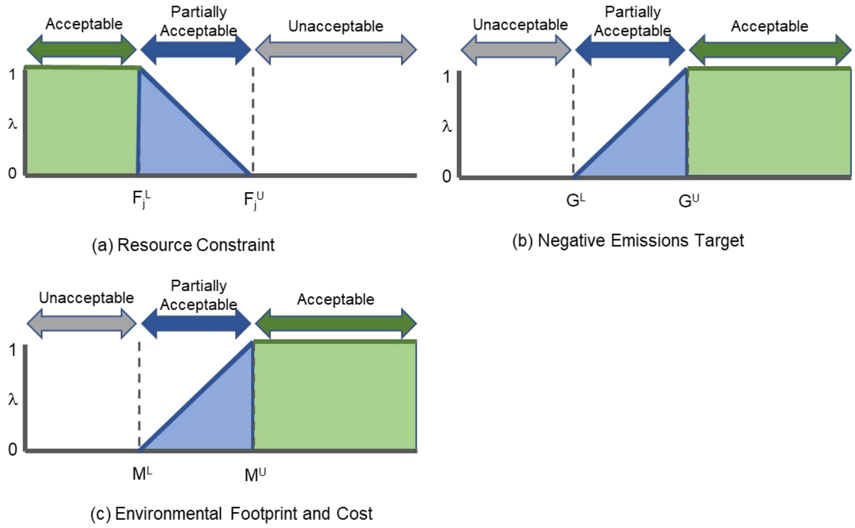

Figure 1: Fuzzy membership functions

In the model formulation, the objective function is to maximize the overall degree of satisfaction, λ as shown in Eq(1). The fuzzy negative emissions target is given by Eq(2). The continuous variable x_i in Eq(2), determines the negative emissions allocation for each NET i. The total negative emissions $\sum_i x_i$, approaches the upper negative emissions target G^U, as λ approaches 1, reflecting the maximization function in Figure 1b. The resource constraint is evaluated in Eq(3) using the fuzzy environmental footprint and cost M_{ij}, for each NET i for each resource j. The consumption of the resources will depend on the NETs environmental footprints and costs evaluated on the left side of Eq(3). The left side of the equation approaches the upper environmental footprint and cost limit $\sum_i x_i M_{ij}^U$, as λ approaches 1, reflecting the maximization function in Figure 1c. The right side of the equation approaches the lower resource limit F_j^L, as λ approaches 1, reflecting the minimization function in Figure 1a. This formulation gives rise to a quadratic programming (QP) model due to the multiplication of the variables x_i and λ in Eq(3). Linearization may be done using property operators in future models. Eq(1) to Eq(3) are useful in determining the negative emissions allocation of a NETs portfolio.
In cases where the negative emissions capacities are fixed, and the selection or non-selection of specific NETs is desired, the binary variable b_i may be introduced. The variable b_i represents the selection or non-selection of the NET in the portfolio such that if the value of b_i is 1, then the particular NET is selected in the portfolio, and if the value is 0, then it is not selected. The parameter Q_i, represents the fixed negative emissions capacity of the NET. The summation $\sum_i b_i Q_i$ in Eq(4) gives the total negative emissions of the portfolio. In Eq(2), the total negative emissions $\sum_i b_i Q_i$ approaches the upper negative emissions target G^U, as λ approaches 1. Eq(5) is a parallel version of Eq(3) where the binary variable b_i and fixed negative emissions capacity Q_i are introduced. Eq(6) limits the values of λ between 0 and 1, and Eq(7) limits the values of b_i to binary values. The formulation of the second case gives rise to a mixed-integer quadratic programming (MIQP) model.

$$\max \lambda \tag{1}$$

$$\sum_i x_i \geq G^L + \lambda(G^U - G^L) \tag{2}$$

$$\sum_i x_i \left[M_{ij}^L + \lambda\left(M_{ij}^U - M_{ij}^L\right)\right] \leq F_j^U + \lambda(F_j^L - F_j^U) \qquad \forall j \tag{3}$$

$$\sum_i b_i Q_i \geq G^L + \lambda(G^U - G^L) \tag{4}$$

$$\sum_i b_i Q_i \left[M_{ij}^L + \lambda\left(M_{ij}^U - M_{ij}^L\right)\right] \leq F_j^U + \lambda(F_j^L - F_j^U) \quad \forall i, j \tag{5}$$

$$0 \leq \lambda \leq 1 \tag{6}$$

$b_i \in \{0,1\}$ (7)

The current model does not consider the temporal aspects (start times, peak times, lifespans, permanence, and sink saturation). These aspects are also important in NETs planning.

4. Case studies

This section presents the two case studies demonstrating the performance of the model. Case study 1 demonstrates a QP model using Eq(1) to Eq(3) and Eq(6), where the continuous variable x_i for negative emissions allocation is determined. Case study 2 demonstrates a MIQP model using Eq(1), Eq(4) to Eq(7), where the binary variable b_i representing the selection or non-selection of NETs at fixed capacities is determined. Both nonlinear models were solved using the software LINGO 18.0 using a deterministic global solver (Gau and Schrage, 2004).

4.1 Case study 1

The case studies use the environmental performance and cost of NETs from literature as shown in Table 1. All costs were obtained from Fuss et al. (2018). The data for BECCS was derived from the study of Fajardy and Mac Dowell (2017) and the data for AR was based on the study of Smith and Torn (2013). The data for the land and water footprints of SCS and BC were obtained from Brack and King (2021), while the data for their nutrient footprints were obtained from Smith et al. (2016). The values in Table 1 indicate the lower (M_{ij}^L) and upper (M_{ij}^U) fuzzy environmental footprints and costs.

Table 1: Fuzzy environmental footprints and costs of NETs

NET	Land use (Mha/Gt CO_2)	Water use (G(m)^3/Gt CO_2)	Energy (EJ/Gt CO_2)	Nitrogen (Mt/Gt CO_2)	Phosphorus (Mt/Gt CO_2)	Cost (10^9 USD/Gt CO_2)
BECCS	30 - 197.7	300 - 1,300	-1.85-3.06	1.74 - 17.4	0 - 13.3	100 - 200
AR	1.8 - 4.1	950 - 2,200	Very low	0.025 - 0.20	0.055 - 0.21	5 - 50
SCS	0	0	0	22	5.5	0 - 100
BC	16 - 100	0	-50 - (-20)	8.2	2.7	30 - 120
DACCS	0.003 - 0.27	8.3×10^{-7} - 2.5×10^{-5}	6.7 - 22.6	0	0	100 - 300
EW	8.3 - 161	2.5×10^{-8}- 1.2×10^{-7}	2.7 - 10	0	0	50 - 200

The case study solves for the optimum NETs portfolio using global constraints. The cumulative negative emissions target is between 20 to 660 Gt CO_2 from 2020 to 2100 to meet the 1.5 °C climate goal (IPCC, 2022). An assumption that the negative emissions target is evenly distributed across 75 y (from 2025 to 2100) is made to determine the annual target of 0.27 to 8.8 Gt CO_2/y. These values indicate negative emissions targets G^L and G^U. The annual resource constraints for land, freshwater, and nutrients are based on the Planetary Boundaries by calculating the remaining resources (Steffen et al., 2015). The Planetary Boundary requires 54 to 75 % of the original forest cover to remain forested (Steffen et al., 2015), which is approximately 6 Gha 10,000 years ago (Ritchie, 2021). The current land-use change is at 62 % exceeding the lower boundary. Calculating for the remaining available land, it is 0 to 480 Mha. The annual freshwater use limit is between 4,000 to 6,000 G(m)^3/y and the current usage is 2,600 (Steffen et al., 2015). Calculating for the available freshwater, it is 1,400 to 3,400 G(m)^3/y. The nitrogen boundary is between 62 to 82 Mt/y but the current usage is 150 Mt/y, exceeding the boundaries (Steffen et al., 2015). A lower limit of 0 and an upper limit of 10 % of the lower boundary (6.2 Mt/y) is assumed, since the redistribution of nitrogen may be beneficial (Steffen et al., 2015). On the other hand, the phosphorous boundary is between 11 to 100 Mt/y and the current usage is 22 Mt/y, leading to an available phosphorous between 0 to 78 Mt/y. The global energy in 2050 is between 538 and 710 EJ, 55 to 86 % of which is projected to come from renewable energy (IRENA, 2020). The projected renewable energy consumption is between 25 to 66 % (IRENA, 2020). Calculating the renewable energy surplus, it is between 107.6 to 213 EJ. The available budget is based on the predicted climate change adaptation cost in 2050, between USD 280 x 10^9 and USD 500 x 10^9 (UNEP, 2016). It is assumed that the available suitable rock for EW is abundant (Strefler et al., 2018). The boundaries mentioned indicate the lower (F_j^L) and upper (F_j^U) fuzzy resource constraints.

Solving the model yields the optimum NETs portfolio in Table 2. AR, BC, DACCS, and EW are selected while BECCS and SCS are not selected. EW has the highest allocation (2.59 Gt CO_2/y), followed by AR (1.54 Gt CO_2/y), while the allocations for BC and DACCS are minimal. The total negative emissions potential of the portfolio (4.49 Gt CO_2/y) is within the fuzzy target, the total cost is USD 391x10^9/y, and all the fuzzy resource constraints are met. The overall degree of satisfaction (λ) is 0.49, indicating that the fuzzy constraints were satisfied to a degree of at least 49 %.

Table 2: Optimal NETs portfolio for case study 1 (λ = 0.49)

NET	Negative Emissions ($Gt\ CO_2/y$)	Land Use (Mha)	Water use $(G(m)^3/y)$	Energy input (EJ/y)	Nitrogen (Mt/y)	Phosphorus (Mt/y)	Cost (10^9 USD/y)
BECCS	0	0	0	0	0	0	0
AR	1.54	4.51	2,410.37	0	0.17	0.20	41.90
SCS	0	0	0	0	0	0	0
BC	0.36	20.78	0	-12.69	2.96	0.97	26.91
DACCS	0.003	0.0004	$3.84x10^{-8}$	0.043	0	0	0.60
EW	2.59	217.19	$1.86x10^{-7}$	16.35	0	0	321.73
Total	4.49	242.49	2,410.37	3.70	3.13	1.18	391.14

4.2 Case study 2

Case study 2 is the scenario where NETs have limited fixed capacities and the selection or non-selection of options is desired, like a knapsack problem. This type of selection will be more useful on smaller scales such as in corporate or country level scales, wherein pursuing a project entail committing to a certain NETs capacity. For demonstration purposes, the same global constraints in case study 1 are used. The average negative emissions capacities (Q_i) were obtained from the literature, amounting to 2.75, 2.05, 3.5, 1.25, 2.75, 3 Gt CO_2/y for BECCS, AR, SCS, BC, DACCS, and EW, respectively in 2050 (Fuss et al., 2018). Solving the model using the same data in case study 1 results in the selection of EW only. The total negative emissions potential of the portfolio (3 Gt CO_2/y) is within the fuzzy target, the total cost is USD $294x10^9$/y, and all the fuzzy resource constraints are met. The overall degree of satisfaction (λ) is 0.32, indicating that the fuzzy constraints were satisfied to a degree of at least 32 %.

Table 3: Optimal NETs portfolio for case study 2 (λ = 0.32)

NET	Negative Emissions ($Gt\ CO_2/y$)	Land Use (Mha)	Water use $(G(m)^3/y)$	Energy input (EJ/y)	Nitrogen (Mt/y)	Phosphorus (Mt/y)	Cost (10^9 USD/y)
EW	3	171.51	$1.66x10^{-7}$	15.11	0	0	294.02

The prioritization of EW in both case studies is similar to the results of Strefler et al. (2021) for Asia and Latin America using Integrated Assessment Models. The results of case study 1, which deprioritized BECCS, reflect the raised concern on the probable impact of BECCS on the resources (IPCC, 2022). Although AR is prioritized in case study 1, its water requirement is very significant (2,410.37 $G(m)^3/y$), and confirms the water security concern of the recent IPCC report (IPCC, 2022).

5. Conclusions

A fuzzy mathematical programming model has been developed for optimizing NETs portfolios. The model accounts for uncertainties in the environmental footprints and cost, which is a characteristic of emerging technologies such as NETs. The model gives the best compromising solution that maximizes the total negative emissions while minimizing resource consumption. Case studies demonstrate the two versions of the model. The QP model in case study 1 determines the optimal NETs allocation in a portfolio. Using the global constraints, the model has included AR, BC, DACCS, and EW with varying negative emissions allocation and excluded BECCS and SCS. The MIQP model in case study 2 selects the optimal NETs with fixed capacities in a portfolio. Demonstration using global constraints resulted in the selection of EW only. The current model can be extended in the future to consider temporal constraints and synergistic resource interactions. Implementing regional resource limits as opposed to global resource limits in case studies to address the risks and sustainability concerns is recommended. Corporate or country-level case studies wherein pursuing a project entail committing to a certain NETs capacity will benefit from the MIQP version of the model.

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