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Fuzzy Optimization Model for Biochar-based Carbon Management Networks

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Biochar application to soil is a promising carbon sequestration and soil amendment strategy due to its ability to store carbon for multiple centuries in soil and improve the fertility of the receiving agricultural lands. Other potential benefit includes co-production of renewable energy supply in gaseous (biogas) or liquid (bio-oil) form. Biochar can possess a range of properties that can alter the quality characteristics of the receiving soil such as pH, bioavailable nutrients, and cation exchange capacity. Different types of soil require suitable alkalinity and nutrient levels to increase crop productivity. It is difficult to estimate the precise characteristics of any potential application site since soil conditions (e.g., pH, moisture, baseline microbial profile, etc.) may vary across the whole area. Biochar application can also widely affect soil CH_4 and N_2O fluxes, which in turn makes it difficult to predict the exact amount of net CO_2 sequestration. It is necessary to apply appropriate methodologies to achieve the full sustainable potential of biochar in climate change mitigation and soil amendment. In this study, a fuzzy optimization model is developed to guide the implementation of industrial-scale biochar-based carbon management networks (BCMNs) in consideration of system uncertainties. The application of the model is illustrated via a case study which attains a degree of satisfaction value of 69.5 % (λ = 0.695) with a corresponding carbon sequestration (CS) potential amounting to 600 kt.

1. Introduction

Climate change has been a major focus of research due to the urgent need to significantly reduce global carbon dioxide emissions to maintain the average atmospheric temperature rise by 2,100 at below 2 °C. Switching to renewable energy sources and efficient energy systems can help mitigate climate change. However, in order to meet the target, there is a need to achieve net zero greenhouse gas (GHG) emissions by 2050, which in turn will require carbon capture and storage (CCS) and negative emissions technologies (NETs) (Haszeldine et al., 2018). NETs have received substantial attention and ample papers have been published since 2018 which provide qualitative and quantitative assessment of their potential in climate mitigation (Ng et al., 2020). NETs are technological options that can remove carbon dioxide from the atmosphere at various scales. Among the options are enhanced weathering (EW), direct air capture (DAC), bioenergy with carbon capture and storage (BECCS), ocean liming (OL), soil carbon sequestration (SCS), and biochar. Negative emissions from biochar application to land has fewer disadvantages compared to other NETs (Smith, 2016) and can potentially reduce emissions by 0.9–3.0 Gt CO_2/y (McLaren, 2012).

Biochar has caught the attention of the scientific community due to its potentially effective role in climate change mitigation. It can also significantly improve terrestrial ecosystem properties such as soil fertility, water and nutrient holding capacities, and soil carbon stocks (Cheng et al., 2020). There may be unexpected drawbacks such as release of potential contaminants present in biochar, oversupply of nutrients, and excessive increase in soil pH, which may cause harmful effects (Kuppusamy et al., 2016). Biochar may contain pollutants such as heavy metals which may cause adverse effects on plants in the soil. It can sustain the needed nutrients and alkalinity level of the soil; however, it is necessary to assess the appropriate supply rate to minimize any potential environmental impacts (i.e., degradation of surface water and ground water quality) and to prevent excessive

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soil alkalinity. A significant challenge exists in assessing the exact characteristics of the application site since the soil conditions may vary across the whole area (Tan, 2019), which in turn makes it difficult to determine the appropriate biochar application rate. These challenges can be potentially overcome with the aid of Process Systems Engineering (PSE) approaches such as mathematical programming.
A brief review by Tan (2019) provides clear research perspectives on the use of computer models in the planning of biochar-based carbon management network (BCMN). A bi-objective optimization model has been developed that controls the characteristics of biochar to make it suitable to the application sites (Belmonte et al., 2019). An optimization framework has been proposed that specifies a unique risk aversion parameter which is a measure that represents the preference of the decision-maker regarding the tolerable amount of a particular contaminant in every biochar sink (Belmonte, 2021). The paper addresses the challenge of determining the actual level of soil contamination that can be safely applied to the soil. A stochastic multi-objective optimization model has been proposed by Li et al. (2019) for the design of energy system with biochar production that achieves a carbon sequestration potential of 2.8 t CO_2/d.
This study develops a fuzzy mixed integer linear programming model (FMILP) to carefully plan BCMNs. An extended version of the previous optimization model (Belmonte et al., 2019) is employed in this work. The model incorporates fuzzy goal and fuzzy constraints to represent the salient features of biochar research. The FMILP model that is being proposed here can handle system uncertainties in terms of application rate limits for nutrients, alkalinity, and impurities in the soil to which biochar is applied. The remaining part of this paper is presented as follows. The formal problem statement is presented in the next section. The modifications of the previous model are also discussed. Afterwards, the applicability is depicted in the illustrative case study. Conclusions and future perspectives are given in the final section.

2. Problem statement

The problem that this work is addressing is presented formally in the following statements:

- Given a BCMN with m biochar sources and n biochar sinks operating at a given time frame;
- The sources are characterized by supply limits, and levels of alkalinity, impurity and nutrients;
- The sinks are characterized by storage limits, acceptance flowrates, fuzzy impurity limits, fuzzy alkalinity limits, and fuzzy nutrient limits;
- The carbon footprint is known for each source-sink connection;
- Given that the biochar has fuzzy CO_2 sequestration potential;

The problem is to find the optimal allocation of biochar to sinks which achieves the highest net carbon sequestration in consideration of uncertainties in system characteristics such as sequestration potential, and application limits in terms of impurities, alkalinity, and nutrients. The superstructure of the BCMN is represented in Figure 1.

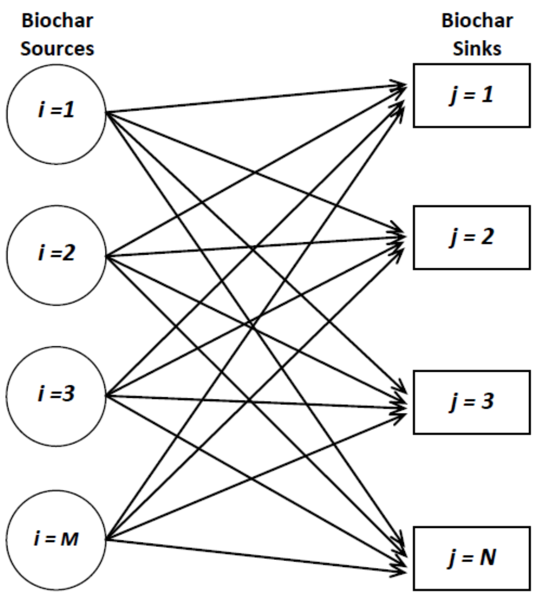

Figure 1: Source-sink superstructure for biochar network

3. Fuzzy MILP model

The model is formulated based on the previously developed model (Belmonte et al., 2019), but is modified and improved here to consider system uncertainties on nutrient limits, alkalinity limits, and tolerable impurity limits in the soil to which the biochar is added. It is difficult to assess the precise quality characteristics of the biochar application sites since the soil condition varies on all parts of the area (Tan, 2019). This in turn makes it challenging to predict the amount of nutrients, alkalinity, and impurities that can be applied to the soil to maximize the benefits (e.g., agricultural productivity) and minimize any potential adverse environmental impacts. Biochar application can also widely affect soil CH_4 and N_2O fluxes, which in turn makes it difficult to predict the exact amount of net CO_2 sequestration. The FMILP model developed here is based on fuzzy mathematical programming formulation by Zimmermann (1978). The importance of expressing parameters such as sequestration potential, and application limits in terms of impurities, nutrients, and alkalinity as fuzzy numbers is the provision of a versatile framework that is subjective while addressing uncertainty. The framework permits the uncertainties in key parameters to be represented and allows for simultaneous integration of fuzzy goals and fuzzy constraints in the mathematical model. This section only focuses on the modifications made and equations added in the previous formulation. The reader may refer to the previously written paper (Belmonte et al., 2019) for other specific information. The following equations depict the modifications and improvements made.

The goal is to maximize λ (the over-all level of satisfaction) as represented in Eq(1).

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

Figure 2 illustrates the fuzzy membership functions. Figure 2a shows that it is desired to maximize the CO_2 sequestration rate. Variable λ is increasing from zero (0) to one (1) as the carbon sequestration rate changes from the lower value (CS^L) to the upper value (CS^U). On the other hand, Figures 2b-2d show that it is desired to minimize the impurity concentration limit, nutrient application dosage, and alkalinity application dosage. This time, the value of λ decreases from 1 to 0 as these parameters change from the lower values to the upper values.

Eq(2) indicates the objective of minimizing the impurity limits, where x_{ijp} is the amount of biochar from the production site (i) to the designated application area (j) during the given time frame (p). The concentration of impurity k in biochar is given as Q_{ikp}. The maximum amount of impurity (k) in biochar that can be applied in the soil is Q^*_{jk} (subject to fuzzy application limits). The application limit to site j in period p is denoted by D_{jp}.

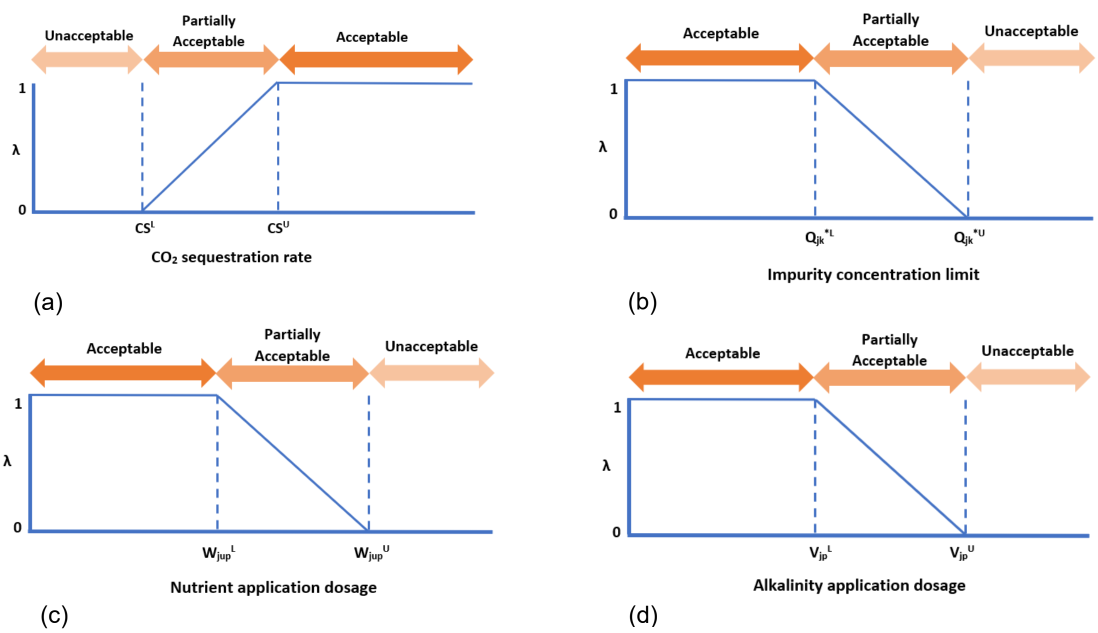

Figure 2: Graphical representation of fuzzy membership function: (a) CO_2 sequestration rate (b) impurity concentration (c) nutrient application dosage (d) alkalinity application dosage

$$\Sigma_i x_{ijp} Q_{ikp} \leq D_{jp}(Q^{*U}_{jk} - \lambda(Q^{*U}_{jk} - Q^{*L}_{jk})) \qquad \forall_{j,k,p} \qquad (2)$$

Eq(3) shows the objective of minimizing the nutrient application dosage (W_{jup}) to be supplied to the application sites which is subject to fuzzy limits. The parameter F_{iup} is the concentration of macronutrient u present in biochar.

$$\Sigma_i x_{ijp} F_{iup} \leq (W^U_{jup} - \lambda(W^U_{jup} - W^L_{jup})) \qquad \forall_{j,u,p} \qquad (3)$$

Eq(4) presents the objective of minimizing the alkalinity application dosage (V_{jp}) to be supplied to the application sites which is subject to fuzzy limits. The parameter Z_{ip} is the alkalinity concentration in biochar which represents base cation concentration (Fidel et al., 2017).

$$\Sigma_i x_{ijp} Z_{ip} \leq (V^U_{jp} - \lambda(V^U_{jp} - V^L_{jp})) \qquad \forall_{j,p} \qquad (4)$$

The net CO_2 sequestration (CS) of the BCMN is accounted by Eq(5) where A_{ij} is the sequestration factor for each possible source-sink connection within the network. The amount of carbon emissions by the system is given by the parameter B_{ij}. It is desired to achieve the maximum carbon sequestration, CS, as shown in Eq(6).

$$CS = \Sigma_i \Sigma_j \Sigma_p A_{ij} x_{ijp} - \Sigma_i \Sigma_j \Sigma_p B_{ij} x_{ijp} \qquad (5)$$

$$CS \leq CS^L + \lambda(CS^U - CS^L) \qquad (6)$$

4. Illustrative case study

This section illustrates a case study on BCMN that is characterized by three biochar sources, four biochar sinks, one impurity (Zn), one nutrient (P), alkalinity concentration (base cation), and a time frame of ten years. Sources 1 and 2 are operating within ten years while biochar source 3 begins operating in the 3rd year only. Table 1 gives the data for the sinks while Table 2 provides the data for the sources. The Zn, P, and alkalinity contents in biochar (see Table 2) assume the same data in the previous work (Belmonte et al., 2019). The fuzzy limits in each of the sinks in Table 1 are plausible values based on the range of application dosages in the literature for Zn (Belmonte et al., 2019), P (Leslie at al., 2017), and alkalinity (Hamza, 2008). Other data in Tables 1 and 2 are based from the previous study (Belmonte et al., 2018). Table 3 shows the CO_2 sequestration factors used in the case study (Belmonte et al., 2018). Other parameters such as carbon emission factors and distances used in the case study assume the same data in the previous work (Belmonte et al., 2018). CS is maximized employing the highest values of the impurity limit, nutrient limit, and alkalinity limit for the sinks to get its upper limit value. The lower limit value is zero which represents a scenario where the BCMN is not operational.

Table 1: Data used for the biochar sinks

`	Land Area (ha)	Dosage (t/ha)	Storage capacity, L_j(t)	Biochar flowrate, D_{jp}(t/y)	Fuzzy limits for Zn content, $Q^{*U}_{j1} - Q^{*L}_{j1}$ (kg/t)	Fuzzy limits for P content, $W^U_{j1p} - W^L_{j1p}$ (kg/y)	Fuzzy limits for Alkalinity content, $V^U_{jp} - V^L_{jp}$ (kg/y)
j = 1	1,922	35	67,270	6,727	0.125 - 0.050	11,532 - 769	384,400 - 28,830
j = 2	1,692	50	84,600	8,460	0.050 - 0.010	13,536 - 1,015	507,600 - 16,920
j = 3	10,750	20	215,000	21,500	0.020 - 0.010	43,000 - 2,150	3,225,000 - 107,500
j = 4	9,483	10	94,830	9,483	0.050 - 0.020	75,864 - 5,690	3,793,200 - 237,075

Table 2: Data used for the biochar sources

Source	Min. supply rate, S^L_{ip}(t/y)	Max. supply rate, S^U_{ip}(t/y)	Zn concentration, Q_{i1p} (kg/t)	P concentration, F_{i1p} (kg/t)	Alkalinity concentration, Z_{ip} (kg/t)
i = 1	6,000	8,000	0.104	2.355	52.872
i = 2	20,000	26,000	0.131	1.716	91.167
i = 3	10,000	13,000	0.030	1.400	34.030

The fuzzy optimization is performed and generated a degree of satisfaction value of 69.5 % (λ = 0.695) with a corresponding carbon sequestration (CS) potential amounting to 600 kt for the entire time frame of 10 y. Such optimal value is closer to the fuzzy upper limit (CS^U= 863,601 t). Table 4 shows the optimal values of impurity concentration limit (Zn), nutrient application dosage (P), and alkalinity application dosage utilized in the sinks. It can be seen that the optimal values are closer to the fuzzy lower limits.

Table 3: CO_2 sequestration factors, A_{ij}

Source	Sink			
	j = 1	j = 2	j = 3	j = 4
i = 1	3.86	4.29	4.72	5.15
i = 2	2.25	2.50	2.75	3.00
i = 3	3.66	4.06	4.47	4.88

Table 4: Optimal values of Zn, P, and alkalinity in the sinks

Sink	Zn (kg/t)	P (kg/y)	Alkalinity (kg/y)
j = 1	0.073	4,053.87	137,349.96
j = 2	0.022	4,836.41	166,675.54
j = 3	0.013	14,617.42	1,058,961
j = 4	0.029	27,107.10	1,322,404.35

Table 5 summarizes the result for the optimal BCMN. There are two values in each cell in Table 5. The first provides the allocation for the first 2 y, and the second provides the allocation for the last 8 y. It is evident that the maximum quantity of biochar from Source 1 is fully consumed during the first two years. The total supply of biochar for the entire network is fully coming from Source 3 when it starts operating from the third year onwards. The maximum available biochar from Source 3 is also completely utilized during the last eight years. Biochar from Source 2 is not used up during the ten-year operation. Sink 4 receives the highest supply of biochar amounting to 79,046.22 t throughout the ten-year period which utilizes 83.36 % of its storage capacity. The 93.27 % of such amount comes from Source 3 which in turn is equivalent to 70.89 % of the maximum production rate of Source 3.

The same case study is solved with additional constraint on network topology. It is assumed that a source can only be connected to a maximum of three sinks. The resulting optimal BCMN is presented in Table 6. It is interesting to note that this network achieves the same value of λ (0.695) and CS (600 kt) but offers a simpler configuration with the exclusion of Sink 1. This time, the model recommends blending of biochars at sink 2 during the last eight years of operation. Blending of biochars prevents the network from exceeding the quality requirements of the soil. Blending of 510.96 t biochar/y from Source 1 (containing 0.10 kg Zn/t biochar, 2.36 kg P/t biochar, 52.87 kg alkalinity/t biochar) with 783.85 t biochar/y from Source 3 (containing 0.03 kg Zn/t biochar, 1.40 kg P/t biochar, 34.03 kg alkalinity/t biochar) produces a mixture with 76.66 kg Zn/y, 2,300.70 kg P/y and 53,689.89 kg alkalinity/y which are less than the limits prescribed for Sink 2.

Table 5: Optimal BCMN (allocation, t/y)

Biochar	Biochar Sinks				
Sources	1	2	3	4	Total
1	836.74; 0	1,806.52; 0	2,698.24; 0	2,658.51; 0	8,000; 0
2					
3		0; 3,454.52	0; 329.33	0; 9,216.15	0; 13,000
Total	836.74; 0	1,806.52; 3,454.52	2,698.24; 329.33	2,658.51; 9,216.15	

Table 6: Optimal BCMN (allocation in t/y) with topological constraints

Biochar	Biochar Sinks				
Sources	1	2	3	4	Total
1		1,806.52; 510.96	2,698.24; 2,698.24	2,658.51; 0	7,163.27; 3,209.19
2					
3		0; 783.85		0; 9,216.15	0; 10,000
Total		1,806.52; 1,294.80	2,698.24; 2,698.24	2,658.51; 9,216.15	

5. Conclusion

A fuzzy optimization model is developed in this study for the planning of a BCMN. The FMILP model takes into account uncertainties in system characteristics for the determination of the optimal BCMN. The application of the model is illustrated via a case study which attains a degree of satisfaction value of 69.5 % (λ = 0.695) with a corresponding carbon sequestration (CS) potential amounting to 600 kt. The illustrative case study demonstrates two scenarios that can exist during the operation of BCMN. The fuzzy optimization approach has identified solutions that maximize carbon sequestration while minimizing the application limits in terms of impurities, alkalinity, and nutrients to meet the quality requirements of the soil. Incorporating additional constraint on network topology generates a solution that achieves the same amount of carbon sequestration but with a simpler configuration. The model provides useful insights that can guide the planning and implementation of large-sale BCMN in the future. Improvements can still be made to reflect other features of biochar research such as sustainability and economic feasibility. Future work can also focus on the possible integration of biochar with other NETs.

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