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Bi-Objective Mixed-Integer Linear Programming Model for High-Level Planning of Biochar-Based Carbon Management Networks

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Biochar is the stable, carbon-rich solid co-product of thermochemical biomass conversion. It has recently gained considerable interest, driven by the need to mitigate climate change through carbon sequestration in soil. During pyrolysis, much of the carbon in biomass is transformed into recalcitrant form, so that biochar applied to soils results in storage of carbon for hundreds of years and simultaneous improvement of soil fertility. Biochar can display a wide range of properties such as pH, cation exchange capacity (CEC) and elemental composition due to the assortment of raw materials and reaction conditions. The suitability of soil to biochar application depends on these properties. This has led to the “designer biochar” concept, wherein biochar could be tailored with relevant properties to address specific soil quality improvements. This aspect and the promising results of biochar application to soil can be potentially optimized through biochar-based carbon management networks (CMN) with the aid of mathematical programming. In this work, a bi-objective mixed-integer linear programming (MILP) model is developed for the high-level planning of biochar-based CMN. Additional parameters, variables and constraints are given to account for the incompatibilities of biochar sources and sinks. An illustrative case study is presented here to demonstrate the applicability of the developed model.

1. Introduction

Biochar is an emerging negative emission technology (NET) and process systems engineering (PSE) is duly positioned to respond to the challenges associated with its implementation on a globally significant level (Belmonte et al., 2017a). Quantitative models and decision-support tools can be developed to facilitate the careful planning and proper deployment of biochar-based systems in order to scale up the benefits of this technology, while minimizing the magnitude of unintended consequences.

Biochar is the stable, carbon-rich solid co-product of thermal degradation of organic material in a zero or low-oxygen environment which can sustainably sequester carbon and improve soil properties. During thermochemical conversion, much of the carbon in biomass is transformed into stable or recalcitrant carbon. Thus biochar application to soil results in carbon sequestration spanning hundreds of years. Other benefits of biochar application to soil include increased crop yield, reduction of the need for water and fertilizers, suppression of soil greenhouse gas fluxes, and the supply of green energy in the form of gaseous and liquid gasification/pyrolysis co-products.

Biochars can possess a wide range of physicochemical properties such as pH, cation exchange capacity (CEC), elemental composition, surface area and porosity due to a variety of biomass feedstocks and processing conditions. Biochar is generally alkaline, which can further affect its pH (Sun et al., 2018). Moreover, the type of feedstocks and pyrolysis temperature can significantly affect the alkalinity of biochar. Sun et al. (2018) asserted that biochar derived from agricultural residues appears to be alkaline while wood-derived biochar is acid at low pyrolysis temperatures. Consistently, increasing the pyrolysis temperature also increases the alkalinity of biochar (Yuan et al., 2011). Yuan and Su (2011) found a strong positive linear

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correlation between soil pH and biochar alkalinity. Thus, the alkalinity of biochar can strongly influence the liming effects on acid soils. Biochar can also serve as a good source of bioavailable nutrients for plants and microorganisms. The key factors that determine the amount of bioavailable nutrients in biochar are the type of feedstocks and pyrolysis conditions. Manure-derived biochar contains higher amounts of nutrients than the biochars produced from plants. On the other hand, Zhang et al. (2015) found that concentrations of P, K, Ca and Mg increased with rising pyrolysis temperature. The foregoing discussion implies that the physicochemical properties of biochar can be altered to cause favorable effects as a soil amendment. Furthermore, the suitability of soil to biochar amendment relies on these properties. Different soil types have certain pH and nutrient concentration requirements to increase crop productivity. This has led to the introduction of "designer biochar" concept wherein biochar could be customized in order to modify certain soil quality characteristics through selection of feedstock, pyrolysis conditions, and particle size (Novak et al., 2014). Developing specifically engineered biochar can also minimize the potential for adverse environmental effects.

The promising results of biochar application to soil can be potentially optimized through biochar-based carbon management networks (CMN). Tan (2016) developed a multi-period source-sink mixed-integer linear programming (MILP) model for the allocation of biochar for carbon sequestration. However, the formulation is too simplified and idealized, which led to the development of further extensions. Belmonte et al. (2017b) developed an extension by incorporating multiple contaminants that may be present in biochar as stream "quality" constraints. Furthermore, two-stage optimization was conducted to incorporate economic performance, an aspect that was not considered in the work of Tan (2016). The model was further modified by performing a bi-objective optimization of carbon sequestration and profitability and accounting for the dependence of total CO_2 sequestration on biochar-soil interactions (Belmonte et al., 2018).

This work advances from the previous papers by integrating modelling intervention to account for the incompatibilities of biochar sources and sinks. Additional parameters, variables and constraints are introduced to account for such interactions.

2. Formal problem statement

The given problem here can be formally stated as follows: The biochar-based carbon management network consists of a set of biomass processing plants chosen as sources $i \in I$ $(i = 1, 2, 3 \ldots M)$ supplying biochars to a set of agricultural lands specified as sinks $j \in J$ $(j = 1, 2, 3 \ldots N)$ during the given time frame comprised of time intervals $p \in P$ (periods, $p = 1, 2, 3 \ldots H$). Every source i is characterized by annual flowrate limits and levels of alkalinity, impurities $k \in K$ (contaminants, $k = 1, 2, 3 \ldots Q$), and macronutrients $u \in U$ (nutrients, $u = 1,2,3 \ldots G$) given as functions of pyrolysis temperature. Every sink j can only receive levels of alkalinity and nutrient u that are within the defined allowable range and accept up to a known maximum annual flowrate, maximum total storage capacity and maximum tolerable level of each impurity k. For each potential source-sink pair, the carbon footprint (i.e., from the handling, transportation and application) as well as the sequestration factor (i.e., direct and indirect benefits) per unit of biochar are known. The problem is formulated to determine the optimum allocation of biochar from source i to sink j in each time interval p whose objectives are to maximize both system-wide net CO_2 sequestration and profitability.

3. Mathematical model formulation

The previous MILP model developed for the optimization of biochar-based CMN is further modified here. In this section, the discussion will focus on the significant modifications made so the reader is likewise referred to the previous paper (Belmonte et al., 2018) for a more detailed discussion of the model. The planning problem deals with simultaneous optimization of two objective functions such as carbon sequestration and profitability. The improvements made are depicted by the following equations.

Eq(1) shows the source balance where x_{ijp} is the quantity of biochar allocated from source i to sink j in period p. The variable S_{ip} denotes total biochar production rate from source i in period p and is subject to lower and upper limits as shown in Eq(2). The binary variable b_{i} signifies the existence or non-existence of source i at any time within the given time frame. The lower ($\mathrm{S}_{\mathrm{ip}}^{\mathrm{L}}$) and upper ($\mathrm{S}_{\mathrm{ip}}^{\mathrm{U}}$) limits of biochar production rate are given by Eq(4) – (5) where $\mathrm{R}_{\mathrm{ip}}^{\mathrm{L}}$ and $\mathrm{R}_{\mathrm{ip}}^{\mathrm{U}}$ are the lower and upper limits, respectively, of biomass availability rate for source i. The quantity Y_{ip} is the biochar yield at source i in period p.

$$\Sigma_{\mathrm{j}} x_{\mathrm{ijp}} = S_{\mathrm{ip}} \qquad \forall \mathrm{i, p} \tag{1}$$

$$b_{\mathrm{i}} \mathrm{S}_{\mathrm{ip}}^{\mathrm{L}} \leq S_{\mathrm{ip}} \leq b_{\mathrm{i}} \mathrm{S}_{\mathrm{ip}}^{\mathrm{U}} \qquad \forall \mathrm{i, p} \tag{2}$$

$$b_{\mathrm{i}} \in \{0,1\} \qquad \forall \mathrm{i} \tag{3}$$

$$\mathrm{S}_{\mathrm{ip}}^{\mathrm{L}} = \mathrm{R}_{\mathrm{ip}}^{\mathrm{L}} \mathrm{Y}_{\mathrm{ip}} \qquad \forall \mathrm{i, p} \tag{4}$$

$$\mathrm{S_{ip}^{U}} = \mathrm{R_{ip}^{U}Y_{ip}} \qquad \forall \mathrm{i,p} \tag{5}$$

The biochar balances at the sinks are defined by the equations below:

$$\Sigma_{\mathrm{i}} x_{ijp} \mathrm{Q_{ikp}} \leq \mathrm{D_{jp}Q_{jk}^{*}}\psi \qquad \forall \mathrm{j,k,p} \tag{6}$$

$$\Sigma_{\mathrm{i}} x_{ijp} \mathrm{F_{iup}} = W_{\mathrm{jup}}\mathrm{C} \qquad \forall \mathrm{j,u,p} \tag{7}$$

$$\mathrm{W_{jup}^{L}} \leq W_{\mathrm{jup}} \leq \mathrm{W_{jup}^{U}} \qquad \forall \mathrm{j,u,p} \tag{8}$$

$$\Sigma_{\mathrm{i}} x_{ijp} \mathrm{Z_{ip}} = V_{\mathrm{jp}}\mathrm{C} \qquad \forall \mathrm{j,p} \tag{9}$$

$$\mathrm{V_{jp}^{L}} \leq V_{\mathrm{jp}} \leq \mathrm{V_{jp}^{U}} \qquad \forall \mathrm{j,p} \tag{10}$$

where $\mathrm{D_{jp}}$ is the limiting biochar application rate from sink j in period p (given in t/y), $\mathrm{Q_{ikp}}$ is the concentration of contaminant k present in biochar produced from source i in period p, $\mathrm{Q_{jk}^{*}}$ is the maximum tolerable level of contaminant k in the biochar that can be applied to the soil in sink j (levels of contaminant are expressed in ppm or g/t), and ψ is a dimensionless risk aversion parameter that can assume values from zero to one. The parameter ψ is a measure of the extent to which the decision-maker is willing to risk soil contamination (Belmonte et al., 2018).

The quantity $\mathrm{F_{iup}}$ is the concentration of nutrient u in biochar produced by source i in period p, W_{jup} is the application dosage for nutrient u to be applied to the soil in sink j during the period p which is subject to upper ($\mathrm{W_{jup}^{U}}$) and lower ($\mathrm{W_{jup}^{L}}$) limits, $\mathrm{Z_{ip}}$ is the concentration of alkalinity in the biochar from source i in period p, and V_{jp} is the alkalinity application dosage recommended for sink j in period p which is also subject to upper ($\mathrm{V_{jp}^{U}}$) and lower ($\mathrm{V_{jp}^{L}}$) limits. Nutrient and alkalinity concentrations are typically expressed in ppm or g/t while the corresponding application dosages are given in kg/y. However, the model can be adjusted with appropriate factors (C) for any set of units. In practice, W_{jup} and V_{jp} can be derived from agronomist recommendations and soil tests which will vary depending on the soil types and quality characteristics.

The quantities $\mathrm{Y_{ip}}$, $\mathrm{Q_{ikp}}, \mathrm{F_{iup}}$, and $\mathrm{Z_{ip}}$ are given here as functions of pyrolysis temperature. Pyrolysis temperature is the most critical parameter in the production of biochar as it significantly influences the yield and chemical properties of the resulting biochar. Therefore, the temperature can tailor biochar to possess certain characteristics suitable for the receiving soil. For this reason, pyrolysis temperature is incorporated in the model to determine its effect on CO_2 sequestration potential and profitability of a biochar-based carbon management network (CMN) while ensuring that the quality requirements of the soil (sink) are met. The succeeding section clearly illustrates the applicability of the improved MILP model in the high-level planning of biochar-based CMN.

4. Illustrative case study

The illustrative case study depicts three sources that supply different types of biochar produced from various biomass residues namely corn stover (CS), rice straw (RS) and sugar cane straw (SCS). The zinc (Zn), phosphorus (P) and potassium (K) contents of biochar as well as the alkalinity and yield (%) are given here as functions of pyrolysis temperature (T, °C). These equations (Table 1) were derived from the experimental data reported in the literature, which indicated significantly positive linear correlations between pyrolysis temperature and Zn, P, K and alkalinity concentrations of biochar produced from corn stover, rice straw and sugarcane straw. Strong negative linear correlations were also found between pyrolysis temperature and biochar yields across different feedstocks used in the case study. It may be assumed that each source, given fairly uniform biomass feedstock throughout the operational years, and without significant process retrofits, produces biochar with consistent yield (%) and quality levels of contaminant, nutrients and alkalinity; such that $Y_{i1} = Y_{i2} \ldots = Y_{iH}$, $Q_{ik1} = Q_{ik2} \ldots = Q_{ikH}$, $F_{iu1} = F_{iu2} \ldots = F_{iuH}$ and $Z_{i1} = Z_{i2} \ldots = Z_{iH}$. Zn is considered here as a potential toxic contaminant in biochar and may be of concern if used for soil amendment without considering its potential impact (Kuppusamy et al., 2016). The macronutrients consistently found in biochar can potentially supply the P and K macronutrient requirements of soil. However, there is a need to determine the application rate suitable for the soil and the corresponding crops to maximize productivity (Zhan et al., 2016) while minimizing environmental impacts. Excessive application of crop nutrients can potentially degrade groundwater (Novak et al., 2014) and surface water quality (Leslie et al., 2017). Alkalinity is one of the most influential biochar properties and meta-analysis showed general positive trend for crop productivity to increase with soil pH (Jeffery et al., 2011).Thus, biochar can be considered as a substitute for agricultural lime specifically in agricultural regions with acidic soils (Galinato et al., 2011). The alkalinity application rate must be properly chosen to prevent soils from being excessively alkaline (Novak et al., 2014). In this study, the biochar alkalinity represents base cation concentration which is a good predictor of total biochar alkalinity (Fidel et al., 2017).The model developed here incorporates the aforementioned aspects by introducing additional parameters for annual nutrient and alkalinity application dosage for each sink to address specific soil quality improvements and limitations. The characteristics of the four sinks are given in Table 2. The assumed maximum level of Zn in biochar that can be safely added to the soil is also given in Table 2.The recommended annual application dosage (Table 3) is based on the range of application rates used in the literature for P (Leslie et al., 2017), K (Zhan et al., 2016) and alkalinity (Hamza, 2008). It is assumed that the sinks with low, moderate and high level of P are agricultural lands that need a P supply of 0.6-8.0, 0.4-6.0 and 0.2-4.0 kg/ha/y respectively, to support plant growth and avoid adverse effects on soil quality. It is further assumed that the sinks with moderate and low level of K are farms whose soil quality characteristics are suitable for a K supply of 11.62 – 206.85 and 3.984 – 124.5 kg/ha/y, to maximize productivity and minimize environmental impact. The storage capacity of the sink is calculated based on the recommended biochar application dosage (Major, 2010) that can be incorporated to the soil until it is saturated. It is assumed that one-tenth (based on the 10-year planning horizon) of the storage capacity is the annual limit to the rate of biochar application. Sources 1 and 2 are operational throughout the 10-year time frame while Source 3 only starts to operate in the third year. The sequestration factors, transportation distance per source-sink pair and data used for cost calculations are based from the previous paper (Belmonte et al., 2018). The MILP model corresponding to this problem was implemented using the commercial optimization software LINGO 17.0 and solved with negligible CPU time using a laptop with 8.00GB RAM, i7-7500UCPU and a 64-bit operating system running on Windows 10 Home Single Language.

Table 1: Biochar source data for contaminant, nutrients and alkalinity levels

Source	Biochar Zn content, Qi1p (g/t)	Biochar P content, Fi1p (g/t)	Biochar K content, Fi2p (g/t)	Biochar alkalinity, Zip (g/t)
CS, i = 1	Q_{11p} = 0.1089T + 27.915	F_{11p} = 2.275T + 763	F_{12p} = 27.275T + 9,406	Z_{1p} = 55.074T + 14,320
RS, i = 2	Q_{21p} = 0.155T + 22.667	F_{21p} = 1.5T + 666.67	F_{22p} = 60T + 17,667	Z_{2p} = 97T + 23,267
SCS, i = 3	Q_{31p} = 0.024T + 13.8	F_{31p} = T + 700	F_{32p} = 20T + 7,500	Z_{3p} = 32.7T + 11,140

Table 2: Biochar sink data

Sink	Area (ha)	P level	K level	Soil pH	Application dosage (t/ha)	Storage capacity, Lj (t)	Limiting biochar flowrate, Djp (t/y)	Limiting biochar Zn content, Q*j1 (g/t)
j = 1	1,922	Moderate	Low	Slightly acidic (5.5-6.5)	35	67,270	6,727	20
j = 2	1,692	Low	Low	Slightly alkaline (7.0-7.5)	50	84,600	8,460	125
j = 3	10,750	High	Moderate	Slightly alkaline (7.0-7.5)	20	215,000	21,500	10
j = 4	9,483	Low	Moderate	Acidic (4.5 – 5.5)	10	94,830	9,483	50

Table 3: Additional biochar sink data

Sink	P application rate, (kg/ha/y)	Annual P application dosage, F^*_{j1p} (kg/y)	K application rate, (kg/ha/y)	Annual K application dosage, F^*_{j2p} (kg/y)	Alkalinity application rate, (kg/ha/y)	Annual Alkalinity application dosage, Z^*_{jp} (kg/y)
j = 1	0.4 – 6.0	768.80 – 11,532	11.62 – 206.85	22,334 – 397,566	15.0 - 200	28,830 – 384,400
j = 2	0.6 – 8.0	1015.20- 13,536	11.62 – 206.85	19,661 – 350,000	10.0 – 150	16,920 – 253,800
j = 3	0.2 – 4.0	2,150 – 43,000	3.984 – 124.5	42,828 – 1,338,375	10.0 – 150	107,500 – 1,612,500
j = 4	0.6 – 8.0	5689.80 – 75,864	3.984 – 124.5	37,780.3 – 1,180,634	25 – 300	237,075 – 2,844,900

5. Results and discussion

The bi-objective optimization is performed via the ε-constraint method (Haimes and Hall, 1974). Figure 1 shows the trade-off between CO_2 sequestration and profitability for the different values of pyrolysis temperature at $\psi = 1$. The best solution depends upon the preference of the decision-maker. The decision-maker can choose the most preferred solution (any point) from among these Pareto optimal sets. The mathematical model is solved for T = 700 °C, 600 °C, 500 °C, 400 °C and 300 °C. It can be seen in Figure 1 that as the temperature decreases, the system-wide net carbon sequestration and profitability increases. The effect of temperature is significant and greater increments of the values of the objective functions occur at T =

400 °C and 300 °C. CO_2 sequestration is 54.89 % and 86.44 % higher in solutions represented by points B and A respectively compared to the solution denoted by E. In addition, profitability is 85.5 % and 120 % higher in B and A respectively compared to E.

Each Pareto front (Figure 1) consists of solutions that each correspond to a particular biochar source-sink network. At T = 300 °C, the result of network A is shown in Table 4 as a representative example to give a clear understanding of the model's solution. Network A can sequester 1,007,187 t of CO_2 within the ten-year time frame and achieve a total profit of US$ 20,784,520. The table gives the optimum amount of biochar allocated for each sink coming from each source in the network. The first and second values in each cell show the biochar allocation during the first two years and last eight years of operation, respectively. The total amount of biochar produced by Source 1, 2 and 3 is 89,956.8 t (11,244.6 t/y x 8y), 39,750.3 t (19,875.15 t/y x 2y), and 116,400 t (14,550 t/y x 8y), respectively. Every sink has distinct soil quality characteristics and biochar can be customized in order to fit certain soil conditions. For instance, the amount of zinc, phosphorus, and potassium as well as the level of alkalinity in biochar can vary depending on the pyrolysis temperature in which the biochar is to be produced. At 300 °C, the allocated biochar to Sink 3 coming from Source 1 (3,418.4 t/y) contains 60.585 g Zn/t (0.1089 x 300 °C + 27.915) while the biochar from Source 3 coming to Sink 3 (376 t/y) contains 21 g Zn/t (0.024 x 300 °C + 13.8). Therefore, the amount of Zn contamination received by Sink 3 at 300 °C is 215,000 g/y during the last eight years of operation which is the limit prescribed for Zn at Sink 3. On the other hand, the biochar coming from Source 1 contains 1,445.5 g P/t (2.275 x 300 °C + 763) and 17,588.5 g K/t (27.275 x 300 °C + 9,406) while the biochar coming from Source 3 contains 1,000 g P/t (300 °C + 700) and 13,500 g K/t (20 x 300 °C + 7,500). Thus, the quantity of nutrients applied to Sink 3 at 300 °C are 5,317,300 g P/y ((1,445.5 g/t x 3,418.4 t/y) + (1,000 g/t x 376 t/y)) and 65,200,558 g K/y ((17,588.5 g/t x 3,418.4 t/y) + (13,500 g/t x 376 t/y)) during the final eight years of operation which are within the range of recommended application rate for Sink 3. Meanwhile, the alkalinity of the biochar produced at 300 °C is 30,842.2 g/t (55.074 x 300 °C + 14,320) from Source 1 and 20,950 g/t (32.7 x 300 °C + 11,140) from Source 3. This results to 113,308,300 g/y ((3,418.405 t/y x 30,842.2 g/t) + (376 t/y x 20,950 g/t)) of alkalinity applied to Sink 3 which is within the range of recommended alkalinity application rate for Sink 3.

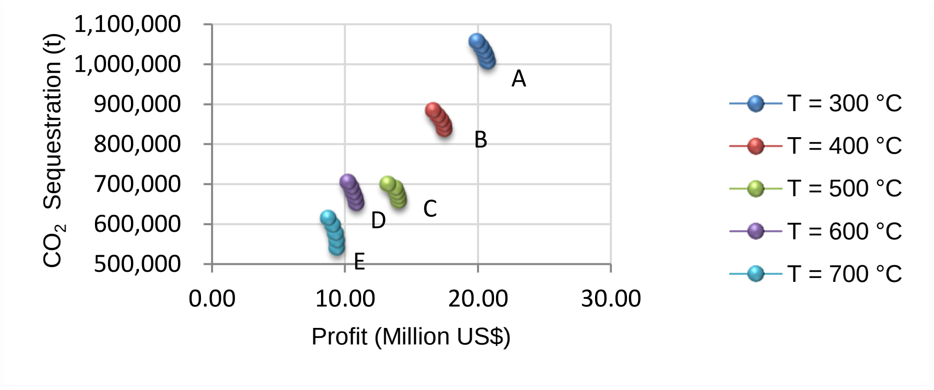

Figure 1: Comparison of Pareto optimal sets for each value of temperature (°C).

Table 4: Biochar source-sink network for T = 300 °C (biochar flowrates in t/y, the first and second values in each cell denote biochar allocation in first two years and last eight years of operation)

Source	Sink				
	1	2	3	4	Total
1			0; 3,418.41	0; 7,826.20	0; 11,244.6
2	1,945.15; 0	8,460; 0	3,108.42; 0	6,361.58; 0	19,875.15; 0
3	0; 6,406.67	0; 7,767.34	0; 376		0; 14,550
Total	1,945.15; 6,406.67	8,460; 7,767.34	3,108.42; 3,794.4	6,361.58; 7,826.20	

6. Conclusions

A bi-objective optimization for the high-level planning of biochar-based carbon management networks was proposed in this work. A MILP model was developed involving two objective functions namely maximizing system-wide net CO_2 sequestration and maximizing profitability. Compared to the previous model formulations, additional parameters, variables and constraints were introduced to account for more relevant and practical aspects. The model allows biochar to be customized by incorporating pyrolysis temperature as an important parameter in the mathematical formulation which can be varied to satisfy both objectives while ensuring that the sink's contaminant limit is not exceeded and the nutrients as well as the alkalinity requirements of the soil are met. Furthermore, the illustrative case study revealed that the pyrolysis temperature can significantly affect carbon sequestration and profitability of the biochar-based CMN. The model can further be extended in the future to handle uncertainties arising on the dependency of the model's solution on the values of the key parameters via fuzzy MILP, Monte Carlo, etc.

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