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Fuzzy Optimization of Direct and Indirect Biomass Co-Firing in Power Plants

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Co-firing of biomass in fossil fuel-fired power plants is a mature technology option for reducing greenhouse gas emissions. Up to 10 % of fossil fuel energy input can be displaced by biomass without the need for major retrofits. Co-firing may be done directly or indirectly. However, direct co-firing has the disadvantage of being less flexible with the use of different types of biomass. Indirect co-firing, on the other hand, overcomes this limitation by using a gasifier which converts the biomass into syngas and biochar. The syngas can then be used for co-firing, while biochar can be applied to soil as a form of carbon sequestration. This process stores the carbon initially fixed by biomass through photosynthesis in the soil, and results in the net transfer of part of the carbon in biomass from the atmosphere to the soil. Biochar thus acts as a negative emissions technology with potential for scale-up in the near future. The utilization of biomass for co-firing in a fleet of thermal power plants can be optimized as a carbon management network, subject to biomass availability and the presence of suitable biochar sinks. In this work, a fuzzy mixed integer linear programming model is developed to minimize net carbon emissions in such a system, taking into account parametric uncertainties in the storage capacities of the biochar sinks. It is assumed that there is the option to use direct, indirect or no co-firing in each power plant in the system. The model is illustrated using a case study.

1. Introduction

A mix of different strategies will be needed in order to meet the deep emissions cuts needed to stabilize climate. For example, widespread use of Process Integration (PI) tools such as Pinch Analysis (PA) can enhance energy efficiency of industrial plants (Klemeš et al., 2018), thus reducing fuel consumption, operating costs, and greenhouse gas (GHG) emissions. Tan and Foo (2018) recently proposed the term Carbon Management Network (CMN) to describe the use of PI tools specifically for mitigating GHG emissions. However, rapid reductions in emissions within the time frame of the Paris Agreement can only be met with the large-scale introduction of additional measures such as CO_2 capture and storage (CCS) and negative emissions technologies (NETs) (Haszeldine et al., 2018). NETs are different techniques which allow for reverse transfer of carbon from atmospheric CO_2 into various sequestered forms (McGlashan et al., 2012). Examples of NETs include bioenergy with CCS (BECCS), ocean liming, enhanced weathering, reforestation, soil carbon management, direct air capture (DAC), and biochar-based sequestration. The potential scale and technology maturity of different NET options was assessed by McLaren (2012). A more recent review by Minx et al. (2018) surveyed the global status of NETs research. Other aspects such as economics and risks were also discussed in a separate review (Fuss et al., 2018).

Biochar is the solid, carbon-rich product of thermochemical treatment (i.e., pyrolysis or gasification) of biomass. Biochar-based sequestration achieves negative emissions through the application of stable, carbonized biomass to soil (Woolf et al, 2010). Thus, carbon that has been previously fixed via photosynthesis during plant growth can be stored in the long term due to the resistance of biochar to decomposition. Much of its carbon content is thus retained in soil instead of returning to the carbon cycle, which would occur if biomass burns or decomposes (Smith, 2016). The principle underlying biochar as a NET is relatively simple, but its effective deployment on a large scale will require decision aids such as Process Systems Engineering (PSE) and PI tools (Belmonte et al., 2017). Secondary effects of biochar application to soil can also have positive or negative effects

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on background GHG emissions via changes in soil microbe profile, reduction of fertilizer and irrigation requirements in the case of agricultural soils, and co-production of energy or fuel outputs during biochar production (Woolf et al., 2010). Thus, data acquisition challenges are expected in conjunction with the use of PSE/PI models to optimize biochar use as a NET (Tan, 2019).

Mathematical Programming (MP) models have been developed in recent years to support the deployment of biochar-based CMNs. A mixed integer linear programming (MILP) model was developed by Tan (2016) to optimize sequestration of carbon using a two-echelon supply chain network, with pyrolysis plants as biochar sources and application sites (e.g., farms and plantations) as biochar sinks. An improved bi-objective MILP model was then proposed by Belmonte et al. (2017) to account for both GHG emissions and cost. Other approaches based on PA (Tan et al., 2018) and P-graph (Aviso et al., 2019) have also been proposed to plan biochar-based CMNs. One of the key considerations in such systems is the saturation of the receiving soil with biochar (Smith, 2016) or with biochar-borne contaminants such as dioxins, salts and heavy metals (Tan, 2016). The MILP model of Tan (2016) incorporates a parametric risk factor to account for this effect, but from an optimization standpoint is not entirely satisfactory. Such uncertainties can instead be dealt with using fuzzy set theory, which was proposed by Zadeh (1965) to allow partial membership of elements in sets and later on used for optimization in fuzzy MP models (Zimmermann,1978).

The prospect of achieving deep reductions in emissions of existing fossil-fuel fired power plants via indirect co-firing of biomass couple with biochar-based sequestration was first proposed by Dang et al. (2015). Such systems achieve GHG reduction emissions both via fossil fuel displacement and storage of carbon in soil, which is potentially greater than what can be achieved just from direct displacement of fossil energy (Fan et al., 2019). Co-firing can generally be used to displace up to 10 % of thermal energy input to a power plant with biomass (or its derivative) without requiring extensive and invasive modifications (Agbor et al., 2014). Widespread use of co-firing in a fleet of power plants can have a comparable effect as shutting down one-tenth of the existing plants and replacing the lost capacity with a purely biomass-fired facility. However, co-firing-based systems offer advantages with respect to flexibility due to the distributed nature of the biomass demand; as a result, practical implementation is much easier (Roni et al., 2017). Optimization of co-firing clearly needs to account for the spatial distribution of biomass sources and power plants (Mohd Idris et al., 2018). Co-firing can be done via combustion of solid biomass with fossil fuel (direct co-firing), or via co-combustion of syngas and bio-oil from biomass pyrolysis or gasification (indirect co-firing). In the latter case, significant amounts of biochar can be produced depending on process conditions; this solid by-product can then be used for carbon sequestration.

In this paper, a novel fuzzy MILP (FMILP) model is developed for optimizing three-echelon supply chain networks for biomass indirect co-firing coupled with biochar-based carbon sequestration. Unlike previous models developed (e.g., Tan, 2016), the model considers linkages between biomass sources and power plants in one layer; a second layer considers linkages from power plants to biochar application sites. Soil saturation limits at these sites are represented as fuzzy membership functions due to inherent uncertainties in estimating such constraints. The rest of the paper is organized as follows. Section 2 gives the formal problem statement. The model formulation is given in Section 3. Then, a case study is solved in Section 4 to illustrate the use of the FMILP model. Finally, Section 5 gives conclusions and prospects for future work.

2. Problem statement

The formal problem statement can be given as follows:

- There are M number of biomass sources (assumed here to be residual biomass) with known maximum availability, S_i;
- There are N number of powerplants which can consider bio-cofiring. Each powerplant has a determined percentage of thermal energy which will be replaced with biomass if a decision for co-firing is made;
- There are O number of co-firing technologies available for implementation. These are characterized by the amount of biomass needed if it is implemented, b_{jh}, and the biochar yield per unit of biomass fired, z_h;
- There are P number of biochar sinks which have a corresponding sequestration factor F_k and a fuzzy biochar limit, BC_k;
- The distances between the biomass sources and the powerplants are known and given by d_{ij};
- The distances between the power plants and the biochar sinks are known and given by r_{jk}

The problem is to determine the optimal allocation of biomass sources to powerplants (x_{ij}), to select which powerplant will implement biomass co-firing and to decide which biochar sink will receive the biochar generated (y_{jk}) to minimize the total carbon emission of the system, and without violating the fuzzy saturation limits of the biochar sinks. The problem superstructure is shown in Figure 1.

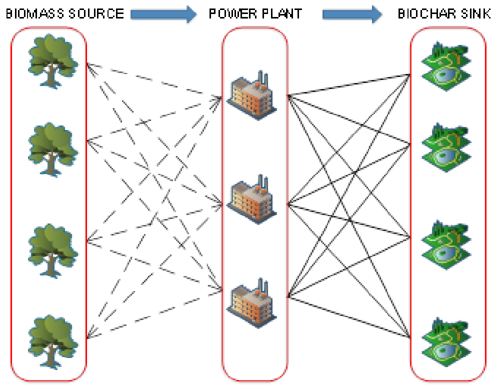

Figure 1. Problem superstructure

3. Model formulation

The carbon emission of the system is affected by the amount of coal which is replaced by biomass, the amount of carbon emissions generated from the transport of biomass to the powerplant and the transport of biochar from the powerplant to the biochar sinks, and the amount of CO_2 that is sequestered from the atmosphere as a result of biochar application to the soil. The total carbon emissions (CE) of the system can thus be calculated using Eq(1) where α is the carbon footprint associated with coal combustion, β is the carbon footprint associated with transport, b_{jh} is the amount of coal replaced with biomass in plant j using technology h and Q_{jh} is a binary variable which indicates whether co-firing technology h is implemented in powerplant j.

$$CE = \sum_{j}^{N}\left(-\sum_{h}^{V} \propto b_{jh}Q_{jh} + \sum_{i}^{M} \beta x_{ij}d_{ij} + \sum_{k}^{P} \beta y_{jk}r_{jk} - \sum_{k}^{P} y_{jk}F_{k}\right) \tag{1}$$

The total amount of biomass obtained from the source should not exceed the maximum available (Eq(2)) while the application of biochar should be within the fuzzy biochar limits allowable for any given sink (BC_k) as shown in Eq(3). Furthermore, the amount of biomass supplied to any powerplant j should be enough to meet the required coal replacement (Eq(4)). The binary variable Q_{jh} is activated (Q_{jh} = 1) only if technology h is implemented in plant j, otherwise it is not (Q_{jh} = 0) as indicated in Eq(5) and that only a maximum of one type of technology can be implemented for each powerplant if a decision to co-fire is made (Eq(6)). Eq(7) represents the biochar balance which indicates that all the biochar generated from the power plants should be allocated to the biochar sinks.

$$\sum_{j}^{N} x_{ij} \le S_i \qquad \forall i \in M \tag{2}$$

$$\sum_{j}^{N} y_{jk} \le BC_k \qquad \forall k \in P \tag{3}$$

$$\sum_{i}^{M} x_{ij} = \sum_{h}^{V} b_{jh}Q_{jh} \qquad \forall j \in N \tag{4}$$

$$Q_{jh} \in \{0,1\} \qquad \forall j \in N, \forall h \in V \tag{5}$$

$$\sum_{h}^{V} Q_{jh} \le 1 \qquad \forall h \in V \tag{6}$$

$$\sum_{k}^{P} y_{jk} = \sum_{h}^{V} b_{jh} Q_{jh} z_h \qquad \forall j \in N \qquad (7)$$

It is desired to minimize the total amount of carbon emissions, but this objective needs to be met while limiting fuzzy contamination limits at the application site. These two conditions will tend to contradict each other since maximizing the amount of sequestered biochar will further decrease the carbon emissions. To simultaneously take these two objectives into consideration, the objectives are calibrated to take a value between 0 and 1 based on the fuzzy membership functions. The objective function then is to maximize the aggregate degree of satisfaction as represented by Eq(8) subject to the satisfaction of the carbon emission objective and that of the satisfaction of biochar sink sequestration. The fuzzy membership function for the carbon emission is defined by Eq(9) while that of the biochar sink sequestration is defined by Eq(10) where CE^U and CE^L are the fuzzy limits for the carbon emissions while $BC^U{}_k$ and $BC^L{}_k$ are the fuzzy limits for the biochar sequestered at each sink k.

$$\max = \lambda \qquad (8)$$

$$CE \geq CE^U - \lambda(CE^U - CE^L) \qquad (9)$$

$$BC_k \geq BC_k^U - \lambda(BC_k^U - BC_k^L) \qquad \forall k \in P \qquad (10)$$

This FMILP formulation is computationally tractable and can be readily solved to global optimality with branch-and-bound solvers. In this work, the model is implemented using the commercial software LINGO 18.0, and the case study described below was solved with negligible CPU time using an Intel®Core™ i7-6500U CPU @ 2.50 GHz processor and 8 GB RAM.

4. Case study

The case study considered has 8 different biomass sources, 5 candidate powerplants for biomass co-firing and 4 available biochar sinks. The limiting data for the biomass sources and the distance from the powerplants are indicated in Table 1 while the limiting data for the powerplants together with the amount of biomass required for each co-firing technology are summarized in Table 2. Table 3 shows the fuzzy limit for the total amount of biochar sequestered by each sink as well as the distance of each biochar sink from the powerplants.
The lower fuzzy limit for the system's carbon emissions is obtained by setting the limit of the sequestered biochar to its upper fuzzy limit while the upper fuzzy limit for carbon emissions is obtained by setting the sequestered biochar to its lower fuzzy limit. The corresponding result shows that the upper CE limit (CE^U) is -1.96192 Mt/y while the lower CE limit is (CE^L) is -1.96594 Mt/y. The fuzzy optimal solution yields a degree of satisfaction, λ = 0.50, and the allocation of the biomass and biochar in Mt/y are shown in Table 4. In addition to the optimal solution, it is also possible to generate near-optimal solutions using integer cuts. Such near-optimal networks may be useful for practical problems by giving alternatives that are nearly as good as the optimum (Voll et al., 2015).

Table 1: Limiting data for biomass sources and distance from powerplants (d_{ij}) in km

Biomass Source (i)	Available Biomass (Mt/y) (S_i)	Powerplants (j)				
		P1	P2	P3	P4	P5
B1	0.10	60	120	160	220	240
B2	0.15	40	120	140	200	220
B3	0.10	30	90	140	200	220
B4	0.25	70	30	140	210	200
B5	0.10	40	40	60	140	130
B6	0.20	120	70	90	120	60
B7	0.12	80	140	80	120	160
B8	0.10	100	150	60	100	140

Table 2: Limiting data for powerplants

Powerplant (j)	Capacity of Powerplant (MW)	Baseline Coal Consumption (Mt/y)	Amount of Displaced Coal (Mt/y)	Biomass requirement for Direct Co-firing (Mt/y)	Biomass requirement for Indirect Co-firing (Mt/y)
P1	200	0.60	0.060	0.1200	0.1500
P2	250	0.75	0.075	0.1500	0.1875
P3	600	1.80	0.180	0.3600	0.4500
P4	500	1.50	0.150	0.3000	0.3750
P5	250	0.75	0.075	0.1500	0.1875

Table 3: Distance between powerplants and biochar sink (r_{jk}) in km

Biochar Sink (k)	Fuzzy limit for sequestered biochar (Mt/y)		Sequestration Factor (F_k)	Powerplants (j)				
	BC^L_k	BC^U_k	(Mt CO_2/Mt biochar)	P1	P2	P3	P4	P5
C1	0.04	0.06	3.20	100	140	70	100	140
C2	0.05	0.06	3.00	60	100	50	100	130
C3	1.00	1.08	2.60	100	30	50	110	80
C4	0.06	0.65	3.00	140	60	80	120	80

Table 4: Optimal biochar-based CMN for Case Study

Biomass Source (i)	Powerplants (j)				
	P1	P2	P3	P4	P5
B1	0	0	0	0.0900	0
B2	0	0	0.1500	0	0
B3	0	0	0.0475	0.0525	0
B4	0	0.1875	0.0625	0	0
B5	0	0	0.1000	0	0
B6	0	0	0	0.0125	0.1875
B7	0	0	0	0.1200	0
B8	0	0	0	0.1000	0
C1	0	0	0	0.0500	0
C2	0	0.01250	0	0.0250	0
C3	0	0	0	0	0
C4	0	0.02500	0	0	0.0375

5. Conclusions

A FMILP model has been developed in this work to optimize CMNs based on indirect biomass co-firing in power plants, coupled with biochar-based carbon sequestration. The model takes the form of a three-echelon supply chain network, with one layer linking biomass sources to power plants, and a second layer linking these powerplants to biochar application sites. The model also incorporates options for direct and indirect co-firing in the power plants, and uses a fuzzy limit to account for soil saturation with carbon or biochar-borne contaminants at the disposal sites. A case study was solved to illustrate the model. Future work can extend the model to account for scenario-based uncertainties, and can also integrate economic mechanisms such as carbon tax. Alternative solutions based on other PI tools such as PA or P-graph can also be explored.

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