CHEMICAL ENGINEERING TRANSACTIONS
VOL. 83, 2021

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.cetjournal.it

Guest Editors: Jeng Shiun Lim, Nor Alafiza Yunus, Jiří Jaromír Klemeš

ISBN 978-88-95608-81-5; **ISSN** 2283-9216

DOI: 10.3303/CET2183028

An Optimization Framework for Biochar-based Carbon Management Networks

Beatriz A. Belmonte

Research Center for the Natural and Applied Sciences, University of Santo Tomas, España Blvd., 1015 Manila, Philippines
babelmonte@ust.edu.ph

Biochar-based carbon management networks (BCMNs) are systems that are intended to strategically plan carbon sequestration via systematic production and allocation of biochars for long-term storage to agricultural lands and for simultaneous improvement of soil properties. Other significant potential benefit includes supply of clean energy in gaseous (biogas) or liquid (bio-oil) form. However, a challenge still exists in determining the levels of biochar contaminants that the soil can tolerate. This risk implies that adequate planning will be needed to ascertain the suitability of sinks to biochar application in order to lessen the potential for adverse effects on soil. To maximize the potential benefits of biochar, a modeling framework for BCMNs can be developed with the aid of Process Systems Engineering (PSE) techniques so as to ensure that the quality requirements set for the sinks are met. To fill this research gap in the global biochar literature, this work develops an optimization framework for BCMNs by accounting for the relevant and practical aspects of biochar research. Since the decision-maker can consider distinct degree of tolerance for every impurity and can have different preferences regarding the amount of contaminant that can be tolerated in each sink, a unique risk aversion parameter is assigned in each sink-contaminant pair. The parameter represents the extent to which the decision-maker can accept soil contamination level. To demonstrate the applicability of the framework, a representative network is explored, which attains a profit of USD 17,453,810 and a cumulative CO_2 sequestration of 876,961.4 t. The results show how the framework can be used to support decision-making for the proper deployment of BCMNs.

1. Introduction

Biochar has been a focus of ample research studies in recent years (Zhang et al., 2019). The basis for this considerable interest results from its direct link to climate change mitigation and indirect link to the water-energy-food nexus (Belmonte et al., 2017a). Numerous publications have heralded biochar as a potentially effective carbon sequestration tool due to its recalcitrant carbon fraction that can remain for a few centuries in soil (Aviso et al., 2018). Biochar has been constantly connected to food security due to its ability to sustain soil fertility which in turn results to agricultural productivity (Sri Shalini et al., 2020). Biochar production integrated with energy system was also designed to produce energy products with negative carbon footprint (Belmonte et al., 2019). Biochar can modify the water retention properties of soil (Tomczyk et al., 2020) leading to reduction of water footprint of crop production. Biochar application to soil has the potential to support the sustainable development goals designated by the United Nations (Kamali et al., 2020).

The Intergovernmental Panel on Climate Change (IPCC) projected that the atmospheric CO_2 concentration would rise to 590 ppm with an average global temperature of 1.9 °C towards the end of 2100 (Zhang et al., 2019). Some distinguished researchers believe that Negative Emissions Technologies (NETs) such as biochar, enhanced weathering, direct air capture (DAC), bioenergy with carbon capture and storage (BECCS), enhancing natural ocean dissolution and direct ocean injection can help achieve the targets of the Paris Agreement (Haszeldine et al., 2018). Biochar has potentially lower impact on land, water use, nutrients, albedo, energy requirement and cost than other NETs (Smith, 2016). Biochar was estimated to reduce emissions at a rate of 130 Gt CO_2 eq until 2100 (Woolf et al., 2010). McLaren (2012) estimated the emissions reduction potential of biochar-based Carbon Management Networks (BCMNs) to be 0.9–3.0 Gt-CO_2/y. Tan

Paper Received: 28/06/2002; Revised: 01/08/2020; Accepted: 10/08/2002
Please cite this article as: Belmonte B.A., 2021, An Optimization Framework for Biochar-based Carbon Management Networks, Chemical Engineering Transactions, 83, 163-168 DOI:10.3303/CET2183028

(2019) asserted that in order for BCMNs to become a globally significant solution to climate change, computer-aided planning is necessary to verify the actual climate change mitigation benefits.

Although biochar is hailed as potentially effective in reducing the CO_2 levels in the atmosphere, there is still a need to carefully plan biochar-based strategies to minimize any potential negative impacts on the environment. Biochar can contain contaminants such as heavy metals and PAHs because it is usually prepared from various feedstocks including waste materials. Biochar application to soils may pose a threat to plants and other organisms if no significant intervention is employed. Different types of soil possess unique quality characteristics and the tolerance level for contaminants present in biochar may differ for each type of soil. Soils are also exposed to several environmental factors that may strongly affect the maximum tolerable ecotoxicological risk for every contaminant (Ashraf et al., 2014). However, finding the levels of such contaminants that carry a maximum tolerable risk for the soil poses a significant challenge (Tan, 2016). This is due to the limited number of studies for single species and the laboratory conditions differ from the actual field conditions (Ashraf et al., 2014). This challenge can be addressed by appropriate modeling framework to carefully plan the proper deployment of BCMNs in order to lessen any adverse effects (Belmonte et al., 2018). The first mixed-integer linear programming model (MILP) for the optimal synthesis of BCMNs was formulated by Tan (2016). However, the model's applicability is limited due to its simplicity, that led to further improvements and extensions. A two-stage optimization model was developed by Belmonte et al. (2017b) to minimize total system cost which was not considered in the paper of Tan (2016). A modified version was further developed by conducting a bi-objective optimization involving carbon sequestration and profitability as the objective functions, and accounting for the dependence of CO_2 sequestration on complex interactions between the biochar and the soil (Belmonte et al., 2018). This study develops an extension of the previous models formulated for BCMNs. In the previous model, the decision-maker can only assign a single value for the soil contamination risk that is applicable for the entire BCMNs. Compared to the previous formulation, a unique risk aversion parameter is incorporated in the model for each sink-contaminant pair within the BCMNs to address the problem of determining the level of each contaminant that carries a maximum tolerable risk for the soil. This is in view of the fact that a particular contaminant may have distinct effect on each of the sinks to which the biochar is added. On the other hand, each of the contaminants present in biochar may have distinct impact on a particular type of receiving soil. A unique risk aversion parameter is necessary to properly assess the contamination risk for each sink-contaminant pair. This is the significant contribution of this work. The remainder of this paper is presented as follows. The succeeding section describes the problem statement. Then the modification made in the previous model formulation is discussed. A case study that presents four scenarios follows to clearly demonstrate the application of the extended model. Conclusions and potential future work are presented in the last section of this paper.

2. Problem statement

Figure 1 illustrates the superstructure for the biochar source-sink network. This section gives the formal problem statement: The biochar-based CMN is consisting of biochar production facilities specified as sources $i \in I\ (i = 1,2,3 \ldots M)$ and croplands specified as sinks $j \in J\ (j = 1,2,3 \ldots N)$. The biochars are to be produced from the sources and supplied annually to the sinks within the entire known time horizon divided into intervals of one-year periods $p \in P(p = 1,2,3 \ldots T)$. Each source i is set to have annual limits for the flowrate and levels of contaminants $k \in K\ (k = 1,2,3 \ldots Q)$. Every sink j is set to receive up to a maximum acceptable contaminant level, maximum annual biochar flowrate, and maximum storage capacity. The carbon footprint for each potential pair between a source and a sink is also known. The problem is to find the optimal biochar allocation from source i that is to be supplied to sink j for each time period p in order to maximize the profitability and CO_2 sequestration within the BCMN.

3. Modification of the model formulation

The discussion in this section focuses only on the relevant modification made in the mathematical model developed previously for the proper implementation of BCMNs. The complete formulation of the model can be found in the previous paper (Belmonte et al., 2018). The model is modified as Eq(1):

$$\Sigma_i x_{ijp} Q_{ikp} \leq D_{jp} Q^*_{jk} \psi_{jkp} \qquad \forall_{j,k,p} \tag{1}$$

Eq(1) shows the biochar balance at the sink. The variable x_{ijp}(t/y) is the amount of biochar that is to be produced from source i and supplied to sink j in period p. The parameter Q_{ikp} (g/t) is the concentration of impurity k in biochar supplied from source i in period p. The parameter D_{jp} (t/y) is the application dosage for biochar in sink j during the period p. The limit of concentration of impurity k in biochar used in sink j is given by Q^*_{jk} (g/t). A unique risk aversion parameter ψ_{jkp} is specified for each sink-contaminant pair in period p to consider the technical challenge of determining the actual tolerance limit of the soil for a particular impurity. It is incorporated in the formulation to measure how much contamination in the soil the decision-maker can allow. A value of zero represents the unwillingness of the decision-maker to take any potential risk and a value of one signifies the decision-maker's readiness to accept contamination up to the prescribed physical limit. The succeeding illustrative case study demonstrates how the modified model is applied for the planning and implementation of BCMNs.

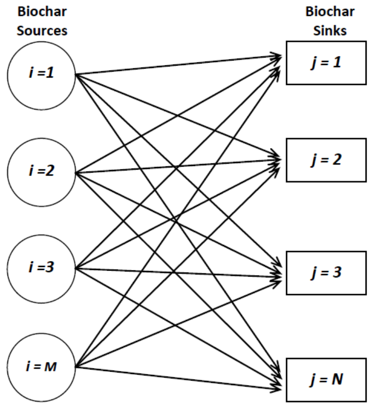

Figure 1: Source-sink superstructure for biochar network

4. Illustrative case study

The case study is adapted from the previous paper (Belmonte et al., 2018) and modified in this study. It represents a network having three biochar sources, four biochar sinks, three metal impurities (Na, Mg, Ca) and a planning horizon of 10 y. These metals can form salts that can negatively affect plant growth when they reach an excessive amount in soil (Abdul Qados, 2011). Tables 1 and 2 show the data for the biochar sources and sinks . The maximum levels of impurities in biochar that can be added to the soil safely are provided in the last three columns of Table 2. The data from these tables are based from the previous paper (Belmonte et al., 2018). The reader is encouraged to refer to the previous paper for the detailed discussions of the complete data used in this work.

Table 1: Data for the sources

Source	Minimum production rate, S_{ip}^{L} (t/y)	Maximum production rate, S_{ip}^{U} (t/y)	Biochar Na content, Q_{i1p} (g/t)	Biochar Mg content, Q_{i2p} (g/t)	Biochar Ca content, Q_{i3p} (g/t)	Years of operation
Coconut shell, $i = 1$	6,000	8,000	80	150	4,600	1-10
Rice husk, $i = 2$	20,000	26,000	2,900	10,400	5,000	1-10
Bagasse, $i = 3$	10,000	13,000	300	1,300	2,600	3-10

Table 2: Data for the sinks

Sink	Area (ha)	Dosage of biochar application (t/ha)	Storage capacity, L_j (t)	Limiting biochar flowrate, D_{jp} (t/y)	Limiting biochar Na content, Q_{j1}^{*} (g/t)	Limiting biochar Mg content, Q_{j2}^{*} (g/t)	Limiting biochar Ca content, Q_{j3}^{*} (g/t)
$j = 1$	1,922	35	67,270	6,727	750	2,600	1,250
$j = 2$	1,692	50	84,600	8,460	7,250	26,000	12,500
$j = 3$	10,750	20	215,000	21,500	1,500	5,200	2,500
$j = 4$	9,483	10	94,830	9,483	2,900	10,400	5,000

Every type of soil can possess unique quality characteristics. Therefore, a particular contaminant may have varied effects on the receiving soils. On the other hand, different contaminants may have distinct effects on a particular soil type. Determining the safe accurate level of contaminants that can be applied to the soil where the biochar is added poses a significant challenge (Tan, 2016). To account for this uncertainty, a unique risk aversion parameter is specified to each sink-contaminant pair. Since the decision-maker can consider distinct degree of tolerance for every impurity and can have different preferences regarding the amount of contaminant that can be tolerated in each sink, a unique risk aversion parameter can be assigned in each sink-contaminant pair. There are four situations that can exist during the implementation of the BCMNs. First, the sinks can accept different levels of soil contamination risk for the same contaminant (i.e., $\psi_{111} \neq \psi_{211} \neq \psi_{311} \neq \psi_{411}$). For example, the decision-maker can assign different levels of risk aversion parameter for Na in sinks 1,2,3,4. Second, a sink can accept different levels of soil contamination risk for the different contaminants (i.e., $\psi_{111} \neq \psi_{121} \neq \psi_{131}$). For instance, the decision-maker can specify different values of risk aversion parameter for Na in sink 1, Mg in sink 1 and Ca in sink 1. Third, the sinks can tolerate the same levels of soil contamination risk for the same contaminant (i.e., $\psi_{111} = \psi_{211} = \psi_{311} = \psi_{411}$). Correspondingly, the decision maker can designate the same level of risk aversion parameter for Na in sinks 1,2,3,4. This may happen in cases where the soils in different locations possess the same quality characteristics. Fourth, a sink can tolerate the same levels of soil contamination risk for the different contaminants (i.e., $\psi_{111} = \psi_{121} = \psi_{131}$). In this situation, the decision maker can set the same values of risk aversion parameter for Na in sink 1, Mg in sink 1, and Ca in sink 1. This may happen in cases where the different contaminants have the same impact on a particular soil. It is important to note that two situations may occur simultaneously during the implementation of the BCMNs. Table 3 below shows the combination of situations (termed here as Scenarios 1,2,3,4) that can happen within the BCMNs. For simplicity, the value of the risk aversion parameter assigned per sink-contaminant pair in each year is assumed to be constant throughout the 10 y planning horizon.

Table 3: Scenarios in the case study

Scenario 1	The sinks can accept different levels of soil contamination risk for the same contaminant (i.e., $\psi_{111} \neq \psi_{211} \neq \psi_{311} \neq \psi_{411}$). A sink can also accept different levels of soil contamination risk for the different contaminants (i.e., $\psi_{111} \neq \psi_{121} \neq \psi_{131}$).
Scenario 2	The sinks can accept different levels of soil contamination risk for the same contaminant (i.e., $\psi_{111} \neq \psi_{211} \neq \psi_{311} \neq \psi_{411}$). A sink can also tolerate the same levels of soil contamination risk for the different contaminants (i.e., $\psi_{111} = \psi_{121} = \psi_{131}$).
Scenario 3	A sink can accept different levels of soil contamination risk for the different contaminants (i.e., $\psi_{111} \neq \psi_{121} \neq \psi_{131}$). The sinks can also tolerate the same levels of soil contamination risk for the same contaminant (i.e., $\psi_{111} = \psi_{211} = \psi_{311} = \psi_{411}$).
Scenario 4	The sinks can tolerate the same levels of soil contamination risk for the same contaminant (i.e., $\psi_{111} = \psi_{211} = \psi_{311} = \psi_{411}$). A sink can also tolerate the same levels of soil contamination risk for the different contaminants (i.e., $\psi_{111} = \psi_{121} = \psi_{131}$).

5. Results and discussion

Four scenarios are considered in this work as depicted in Table 3. Table 4 is given here as a representative example to give a clear demonstration of how the risk aversion parameter is assigned to each sink-contaminant pair within the BCMN. The model is employed in each scenario and Figure 2 shows the trade-off between profitability and carbon sequestration for the four scenarios considered in this study. Any point in each Pareto optimal set represents a possible solution to the problem. The increments of the objective function values in Scenario 4 are substantially higher compared to Scenarios 1, 2 and 3. A significant increase in carbon sequestration is depicted in Scenario 4. As can be seen, the highest values in profit and carbon sequestration are obtained in Scenario 4. It can also be observed that the points are near to each other for Scenarios 1,2 and 3 implying that the values of the objective functions are close to each other. Evidently, the carbon sequestration potential and profitability of the BCMN largely depends on the degree by which the decision maker is ready to risk soil contamination.

Table 4: Risk aversion parameter per sink-contaminant pair used in the case study (Scenario 3)

Contaminant	Risk aversion parameter, ψ_{jkp}			
	Sink			
	$j = 1$	$j = 2$	$j = 3$	$j = 4$
Na, $k = 1$	1	1	1	1
Mg, $k = 2$	0.3	0.3	0.3	0.3
Ca, $k = 3$	0.7	0.7	0.7	0.7

Any point in the Pareto front represents a specific biochar-based network. In order to clearly demonstrate the result of the model's solution, a representative network (Table 5) is explored. Table 5 gives the characteristics of Network A (see Figure 2). It attains a profit of USD 17,453,810 and a cumulative CO_2 sequestration of 876,961.4 t. The optimal amounts of biochar received by each sink as supplied by each source in the network are shown. The optimum supply of biochar for the first 2 y of implementation is provided in the first cell of Table 5. The values in the second cell show the optimum supply during the last 8 y. The model does not allocate biochar for Sinks 1 and 2 during the entire ten-year period. On the other hand, the model suggests blending of biochars at Sinks 3 and 4 from the 3rd up to the 10th year of implementation. Blending hinders the system from exceeding the contamination limit set for Sinks 3 and 4. For example, combining 3,732.65 t/y of biochar from Source 1 (with 80 g Na/t, 150 g Mg/t and 4,600 g Ca/t) with 7,784.35 t/y of biochar from Source 3 (with 300 g Na/t, 1,300 g Mg/t, 2,600 g Ca/t) results to 11,517 t/y of biochar at Sink 3 for the last 8 y of implementation (with 228.70 g Na/t, 927.29 g Mg/t, 3,248.20 g Ca/t). The contamination limits for Na, Mg and Ca are set at 32,250,000 g/y (21,500*1500*1), 33,540,000 g/y (21,500*5,200*0.3) and 37,625,000 g/y (21,500*2,500*0.7) at Sink 3. It can be computed from Table 5 that the total quantities of biochar supplied by the sources are 80,000 t (8,000 t/y * 2 y + 8,000 t/y * 8 y) from Source 1 and 104,000 t (13,000 t/y * 8 y) from Source 3.

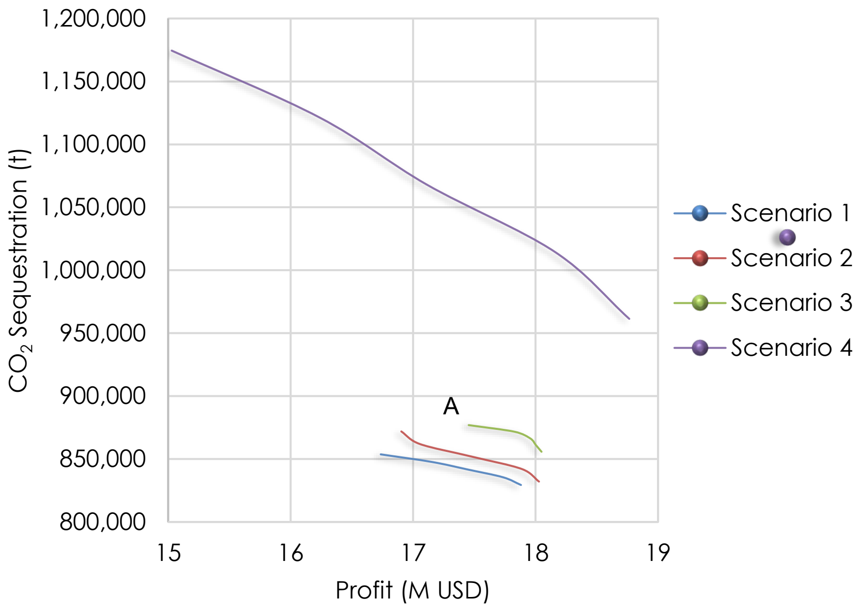

Figure 2: Pareto-optimal sets for each scenario in the case study

Table 5: BCMN for scenario 3, net CO_2 sequestration = 876,961.4 t, profit = 17,453,810 USD (biochar flowrates in t/y)

Source	Sink				
	1	2	3	4	Total
1	0; 0	0; 0	784.67; 3,732.65	7,215.33; 4,267.35	8,000; 8,000
2	0; 0	0; 0	0; 0	0; 0	0; 0
3	0; 0	0; 0	0; 7,784.35	0; 5,215.65	0; 13,000
Total	0; 0	0; 0	784.67; 11,517	7,215.33; 9,483	8,000; 21,000

6. Conclusions

A bi-objective optimization is employed for the proper implementation of BCMNs. The model maximizes CO_2 sequestration and profitability of the BCMNs. The modeling framework recommends blending of biochars from different sources to ensure that the contamination limits set for the sinks will not be exceeded. In comparison to the previous work, a unique risk aversion parameter is specified to represent the measure by which the decision maker can accept soil contamination risk per sink-contaminant pair. The result of this work shows that the degree by which the decision maker is willing to risk soil contamination can significantly affect the CO_2

sequestration potential and profitability of the BCMNs. The model proposed here can provide useful insights for policy makers in formulating policies that can accelerate the commercial deployment of BCMNs. Government can use the model as a decision-support tool to initiate actions that can benefit the biochar producers (investors) and consumers (farmers). Future works can focus on exploring the variations of other model parameters to determine their impact to the environmental and economic aspects of the BCMNs.

Acknowledgment

The funding from the Research Center for the Natural and Applied Sciences of the University of Santo Tomas (UST-RCNAS) is gratefully acknowledged.

References

Abdul Qados A.M.S., 2011, Effect of salt stress on plant growth and metabolism of bean plant Vicia faba (L.), Journal of the Saudi Society of Agricultural Sciences, 10(1), 7–15.

Ashraf M.A., Maah M.J., Yusoff I., 2014, Soil contamination, risk assessment and remediation, Chapter In: M.C.H. Soriano (Ed.), Environmental risk assessment of soil contamination, IntechOpen Limited, London, UK, 3-56.

Aviso K.B., Ismael J., Arogo A., Louis A., Coronel O., Janairo M.J., Foo D.C.Y., Tan R.R., 2018, P-Graph approach to planning biochar-based Carbon Management Networks, Chemical Engineering Transactions, 70, 37-42.

Belmonte B.A., Benjamin M.F.D., Tan R.R., 2017a, Biochar systems in the water-energy-food nexus: the emerging role of process systems engineering, Current Opinion in Chemical Engineering, 18, 32-37.

Belmonte B.A., Benjamin, M.F.D., Tan R.R., 2017b, A two-stage optimization model for the synthesis of biochar-based carbon management networks, Chemical Engineering Transactions, 61, 379-384.

Belmonte B.A., Benjamin M.F.D., Tan R.R., 2018, Bi-objective optimization of biochar-based carbon management networks, Journal of Cleaner Production, 188, 911–920.

Belmonte B.A., Benjamin M.F.D., Tan R.R., 2019, Optimization-based decision support methodology for the synthesis of negative-emissions biochar systems, Sustainable Production and Consumption, 19, 105–116.

Haszeldine R.S., Flude S., Johnson G., Scott V., 2018, Negative emissions technologies and carbon capture and storage to achieve the Paris Agreement commitments, Philosophical Transactions Royal Society A, 376:20160447.

Kamali M., Jahaninafard D., Mostafaie A., Davarazar M., Paula A., Gomes D., Tarelho L., Dewil R., Aminabhavi T.M., 2020, Scientometric analysis and scientific trends on biochar application as soil amendment, Chemical Engineering Journal, 395, 125128.

McLaren D., 2012, A comparative global assessment of potential negative emissions technologies, Process Safety and Environmental Protection, 90(6), 489–500.

Smith P., 2016, Soil carbon sequestration and biochar as negative emission technologies, Global Change Biology, 22, 1315–1324.

Sri Shalini S., Palanivelu K., Ramachandran A., Raghavan V., 2020, Biochar from biomass waste as a renewable carbon material for climate change mitigation in reducing greenhouse gas emissions — a review, Biomass Conversion and Biorefinery, 280.

Tan R.R., 2016, A multi-period source-sink mixed integer linear programming model for biochar-based carbon sequestration systems, Sustainable Production and Consumption, 8, 57–63.

Tan R.R., 2019, Data challenges in optimizing biochar-based carbon sequestration, Renewable and Sustainable Energy Reviews, 104, 174–177.

Tomczyk A., Sokolowska Z., Boguta P., 2020, Biochar physicochemical properties : pyrolysis temperature and feedstock kind effects, Reviews in Environmental Science and Biotechnology, 19(1), 191–215.

Woolf D., Amonette J.E., Street-Perrott F.A., Lehmann J., Joseph S., 2010, Sustainable biochar to mitigate global climate change, Nature Communications, 1, 56.

Zhang C., Zeng G., Huang D., Lai C., Chen M., Cheng M., Tang W., Tang L., Dong H., Huang B., Tan X., Wang, R., 2019, Biochar for environmental management: Mitigating greenhouse gas emissions, contaminant treatment, and potential negative impacts, Chemical Engineering Journal, 373, 902–922.