Multi-objective Robust Optimization for the Design of Biomass Co-firing Networks

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Abstract

Biomass co-firing in coal power plants is an immediate and practical approach to reduce coal usage and pollutant emissions because only minor modifications are required. With direct co-firing, biomass can be used directly as secondary fuel in power plants to partially displace coal. Although it requires minimal investments, it can lead to equipment corrosion from unconventional fuel properties of the biomass-coal blend. With indirect co-firing, the risk of damage is minimized by separately processing biomass. The solid biochar by-product can be used as soil fertilizer to achieve further reductions in GHG emissions through carbon sequestration. However, as this calls for a separate biomass energy conversion plant, its investment cost is higher. Moreover, this system faces uncertainties from the inherent variability in biomass quality. This must be accounted for because mixing fuels results in the blending of their properties. In this work, a robust optimization model is proposed to design cost and environmentally effective biomass co-firing networks that decides on appropriate co-firing configurations and fuel blends. A case study is solved to demonstrate validity. Results of Monte Carlo simulation show that the robust optimal network configuration is relatively immune to uncertainty realizations as compared with the optimum identified with deterministic models.

Keywords
Multi-objective optimization, Robust optimization, Biomass co-firing

1. Introduction

The means of producing energy using fossil fuels (e.g. coal) are unsustainable. They have been tied to health and environmental issues, including climate change, caused by hazardous greenhouse gas (GHG) emissions (Ramos et al., 2018), which can lead to disastrous environmental events. Hence, policymakers encourage minimizing the causes of global warming and climate change (Dundar et al. 2016), such as by using biomass as a renewable energy source, which is considered to be carbon neutral (U.S. EPA 2018). Co-firing biomass with coal in existing power plants is an immediate and practical approach to reduce coal usage and pollutant emissions with only relatively minor modifications (Madanayake et al. 2017). The management of biomass supply chains is challenging because of its seasonal and widely geographically dispersed availability and uncertain quality (Zandi Atashbar et al. 2016). Consequently, ensuring that a continuous supply is available will require biomass residue to be collected from several sources, introducing biomass quality variability into the system (Shabani and Sowlati 2013). In co-firing systems, feedstock composition must be considered because blending fuels results in the blending of their properties (Veijonen et al. 2003). Existing handling equipment are not designed to handle significantly different biomass properties.

Biomass is typically characterized by high moisture content and low lower heating value (LHV), which can significantly impact conversion yield and supply chain management decisions (Pérez-Fortes et al. 2014). High moisture content decreases LHV or the amount of energy that may be generated from the combustion of the feedstock (Boundy et al. 2011). Additionally, the high alkalinity of the ash content of biomass leads to deposit formation in the conversion equipment, particularly slagging and fouling, which warrants the need for displacement limits. Not considering feedstock quality may artificially lower costs and emissions during planning, and cause the system to incur dramatically more costs and environmental impact to adjust their initial plans and designs. Significant financial losses and environmental emissions will ensue when two batches of feedstock yield considerably different amount of energy (Castillo-Villar et al. 2017). Moreover, biomass properties are inherently plagued with uncertainties, significantly influenced by external factors, such as climate, weather, and cultivation and harvesting approaches; the effect of these separately and their interactions are difficult to predict and measure (Ghaderi et al., 2016).

Three possible configurations may be implemented in co-firing systems, particularly direct, indirect and parallel co-firing. Under direct co-firing systems, biomass can be used directly as secondary fuel in power plants to partially displace coal; a single common boiler is used to burn a mix of biomass and coal. This configuration is the most used because it is relatively simpler and cheaper. However, there is a higher risk for corrosion of the equipment because of unconventional fuel composition. To deal with this, only low co-firing rates or displacement limits are set. This risk is minimized with indirect co-firing because biomass is separately processed from coal; and thus, allows for higher co-firing rates. Biomass is first converted into syngas through gasification or into bio-oil and syngas through pyrolysis, which are used as secondary fuel in direct co-firing systems. The solid biochar by-product from the thermal conversion of the biomass can be used as soil fertilizer, which can reduce GHG emissions through carbon sequestration. Thus, adopting this can potentially realize negative emissions for the biomass fraction of the power plant feedstock. Investment costs for indirect co-firing is relatively more expensive than direct co-firing because it requires a separate biomass energy conversion plant. Parallel co-firing systems burn coal and biomass in separate boilers that feed into a common turbine (Agbor et al. 2014). The tradeoffs between the three schemes reiterate the importance of considering conflicting economic and environmental objectives.

The application of biochar to soil leads to the permanent sequestration of recalcitrant carbon (Woolf et al. 2010). Biochar-based systems are natural extensions of biomass-based energy systems (He et al. 2017). Biochar streams have different quality levels based on the feedstock used and the process conditions undergone by the feedstock. These must be matched with biochar sinks, such as agricultural lands, that have various contaminant tolerance limits to control and avoid the risks of biochar application to soil (Belmonte et al. 2017), and to maximize its capability and residency of storing carbon in the long term.

The outline of the rest of the paper is as follows. The next section presents a literature review. Section 3 describes the MINLP model formulation. A case study is solved and discussed in Section 4 to demonstrate model validity and capabilities. Finally, conclusions and recommendations for future work are provided in Section 5.

2. Literature Review

The planning and management of biomass supply chains have primarily been modelled mathematically using either simulation or optimization models. Although, simulation modelling has several strengths, including high flexibility, and the ease of dealing with stochastic, large, and complex supply chains, it is criticized for its inability to optimally design large-scale supply chains considering multiple conflicting objectives, which is inherent in biomass co-firing supply chains. Hence, several studies have opted to use optimization models to represent, design, and plan biomass co-firing supply chains (Ba et al., 2016).

Despite the importance of feedstock quality and its significant impact on conversion efficiency, no study has properly captured it in optimization models. The models proposed by Mohd Idris et al. (2018) and Dundar et al. (2016) decided on the optimal blending ratios for biomass and coal to satisfy a minimum biomass percentage regulation; however, they did not give any consideration for biomass properties. Pérez-Fortes et al. (2014) considered biomass composition in equipment requirements, but properties were modelled as deterministic parameters with no impact on conversion efficiency and equipment degradation.

Quantitative approaches can support the optimal synthesis of such systems to capture economic and environmental benefits, costs, and challenges, such that unacceptable compromises are minimized (Otte and Vik 2017). Tan (2016) was the first to propose an optimization model for the design of biochar carbon management networks which allocated biochar with different contaminant levels to sinks with predefined storage capacities and contaminant level limits. Belmonte et al. (2017) and Belmonte et al. (2018) extended this with a two-stage and a bi-objective optimization model respectively that minimized costs and maximized carbon sequestration. Noticeably, studies considering the optimal design of biochar-based carbon management networks integrated with biomass or biomass co-firing networks remain limited. In addition, existing models assume a predefined co-firing scheme for the biomass co-firing network. However, this forces the model to establish a network relying on what the specific co-firing scheme requires; optimal solutions obtained in exclusive setups may not be the global optimal for the given problem.

Integrating uncertainty is needed because deterministic parameters are difficult to estimate in practical situations (Amin and Zhang 2013). Even a small level of uncertainty could result in a meaningless optimal solution (Ben-Tal and Nemirovski 1999), especially for a system that involves investment decisions that are difficult and costly to reverse. Biomass networks typically experience uncertainties in biomass composition, but existing studies are not able to properly consider this. Optimization models for biomass co-firing applications that incorporate uncertainties are still limited (Ghaderi et al. 2016). Stochastic optimization is the most commonly used approach. Castillo-Villar et al. (2017) considered biomass feedstock composition, specifically moisture and ash content, as uncertain parameters in a stochastic programming model but only additional costs to handle and treat the excess moisture and ash were captured. Similarly, Gonela et al. (2015) considered uncertain energy demand, energy selling price, and biomass supply using fuzzy numbers.

However, there are three major weaknesses to the stochastic approach, (1) most real-world cases have insufficient access to historical data needed to establish probability distributions for the uncertain parameters, (2) the optimal solution is usually infeasible for most realizations of uncertainty, and (3) uncertainty is usually modelled through scenario-based stochastic programming, which can develop into large-sized, complex, and computationally challenging or intractable problems. Robust optimization is a suitable alternative to this because it can provide optimal solutions impervious to any realization of the uncertainty in a specified bounded set (Pishvaee et al. 2011). Nonetheless, it has received significantly less attention in supply chain network design (Govindan et al. 2017).

To date, no other study has been made that simultaneously consider economic and environmental objectives while incorporating the impact of uncertain feedstock properties on conversion performance, and other relevant decisions. The robust optimization model proposed in this study will decide whether each existing coal power plant must be retrofitted for co-firing, which would require capital investments that must be justified by the supply of biomass. For plants that are chosen for this investment, the periods the co-firing option will be used, where and how much biomass must be sourced for each plant, the biomass co-firing rate, as well as the optimal biochar allocation.

3. Model Formulation

A mixed integer nonlinear programming model was developed for the biomass co-firing network described, which makes investment and operational decisions that considers overall costs and environmental emissions while satisfying supply and demand constraints. The model also considers fuel properties as uncertain parameters that impact the efficiency of conversion processes. Table 1 presents the indices while Table 2 defines the parameters and decision variables used in the following model formulation.

Table 1: Indices

Notation	**Definition**
i	Biomass source
j	Coal power plants
k	Biochar sinks
l	Biochar contaminant types
n	Co-firing schemes
t	Time period

Table 2: Parameters and decision variables

Notation	**Definition**
D_t	Energy demand on period *t*
s_{it}	Available biomass at source *i* on period *t*
L_{jn}^u	Upper displacement limit of power plant *j* for co-firing scheme *n*
L_{jn}^l	Lower displacement limit of power plant *j* for co-firing scheme *n*
q^c	LHV of coal
g	Higher heating value of biomass
W_j	Baseline coal usage in power plant *j*
f_{jl}	Concentration of contaminant *l* in the biochar produced in power plant *j*
f_{lk}^*	Maximum allowable concentration of contaminant *l* in biochar sink *k*

T_k	Total biochar storage capacity in sink *k*
d_{ij}	Distance from biomass source *i* to power plant *j*
r_{jk}	Distance from power plant *j* to biochar sink *k*
ic_{jn}	Cost to retrofit power plant *j* for co-firing scheme *n*
a_{jt}	Biomass combustion cost in power plant *j* on period *t*
p_{it}	Cost of biomass from source *i* on period *t*
h	Transportation cost
γ	Emissions due to coal combustion
e	Transportation emissions
z_n	Biochar yield from co-firing scheme *n*
P	Biochar application cost
G_k	Sequestration factor of biochar sink *k*
ψ	Allowable soil contaminant tolerance factor
v_{it}	LHV of biomass in power plant *j* on period *t*
x_{ijt}	Amount of biomass from source *i* to power plant *j* on period *t*
y_{jkt}	Amount of biochar generated from power plant *j* and sequestered in sink *k* on period *t*
q_{jt}	LHV of feedstock in power plant *j* on period *t*
u_{ijt}	Co-firing rate of biomass from source *i* in power plant *j* on period *t* (mass basis)
R_{jn}	Binary variable, 1 if power plant *j* is retrofitted for co-firing scheme *n*
O_{jnt}	Binary variable, 1 if biomass option of power plant *j* retrofitted to co-firing scheme *n* is used on period *t*

$$Max\ Env = \sum_j \sum_t \gamma W_j u_{jt} + \sum_j \sum_k \sum_t G_k\, y_{jkt} - \sum_i \sum_j \sum_k \sum_t e\big(d_{ij} x_{ijt} + r_{jk} y_{jkt}\big) \quad (1)$$

$$Min\ Cost = \sum_j \sum_n ic_{jn} R_{jn} + \sum_j \sum_k \sum_t P\, y_{jkt} + \sum_i \sum_j \sum_k \sum_t h\big(d_{ij} x_{ijt} + r_{jk} y_{jkt}\big) + \sum_i \sum_j \sum_t (a_{jt} + p_{it}) x_{ijt} \quad (2)$$

The objective functions of the biomass co-firing network are to maximize environmental emissions reductions (1) and to minimize additional costs (2). Emissions reduction is equated to the sum of combustion emissions of displaced coal and biochar-based carbon sequestration less the emissions from transporting biomass to coal power plants and biochar to biochar sinks. On the other hand, additional costs are incurred from retrofitting, biochar application, transportation, and biomass purchase and combustion costs.

$$\sum_j q_{jt} W_j \geq D_t \quad \forall t \quad (3)$$

$$\sum_j x_{ijt} \leq s_{it} \quad \forall it \quad (4)$$

$$R_{jn} \geq O_{jnt} \quad \forall jnt \quad (5)$$

$$\sum_n R_{jn} \leq 1 \quad \forall j \quad (6)$$

$$\sum_n L^l_{jn} O_{jnt} \leq \sum_i u_{ijt} \leq \sum_n L^u_{jn} O_{jnt} \quad \forall jt \quad (7)$$

$$\sum_n x_{ijt} O_{jnt} (1 - z_n) = W_j u_{ijt} \quad \forall ijt \quad (8)$$

$$q_{jt} = \sum_i \big(v_{it} u_{ijt} + q^c (1 - u_{ijt})\big) \quad \forall jt \quad (9)$$

$$\sum_k y_{jkt} = \sum_i \sum_n x_{ijt} O_{jnt} z_n \quad \forall jt \quad (10)$$

$$\sum_j y_{jkt} \leq T_k \quad \forall kt \quad (11)$$

$$\sum_j \sum_n y_{jkt} f_{jl} O_{jnt} \leq \sum_j \psi y_{jkt} f^*_{lk} \quad \forall ktl \quad (12)$$

$$x_{ijt}, y_{jkt}, q_{jt}, u_{jt} \geq 0 \quad R_{jn}, O_{jnt} \in \{0,1\} \quad (13)$$

The model constraints include demand satisfaction as defined in (3), which is dependent on the LHV of the mixed fuel feedstock and the amount of feedstock handled by the conversion equipment. Equation (4) limits the amount of biomass that can be purchased and transported from each source location to the source's available supply each period. Equation (5) ensures that co-firing may only be used if the power plant has been retrofitted for co-firing, while (6) defines the co-firing schemes as mutually exclusive options. Equation (7) sets upper and lower coal displacement limits to the biomass and coal blends that will be used in each power plant and period depending on the co-firing scheme implemented. The total biomass to undergo conversion in modified coal power plants is described in (8) as the product between the baseline coal usage of the power plant and co-firing rate. Equation (9) computes for the LHV of the mixed feedstock fuel from the sum-product of the mass percent based on the co-firing share of each of the material and their LHVs. The amount of biochar that may transported from coal power plants is shown in (10) as a function of the biomass processed and the fraction biochar yield of the co-firing scheme selected. Equation (11) limits the amount of biochar allocated to each sink by the storage capacity of the sink, while (12) ensures that the contaminant levels of the biochar allocated to each sink does not exceed the allowable contaminant levels. Equations (1)-(13) show the optimization model for the co-firing network without the consideration of uncertainties.

However, there is a need to consider uncertainties in the design and management of biomass co-firing networks, which may arise from variability in biomass quality, particularly in its LHV. Realizations of this uncertainty can significantly affect the feasibility and performance of the network decisions. Thus, it is important that the optimal solution obtained remains feasible despite the occurrence of the highest possible degree of uncertainty. With this, the deterministic optimization model is modified to account for uncertainties in biomass LHV (v_{it}). This affects the demand (3) and LHV (9) constraints in the above formulation. The revised formulation for these constraints is given in (14) and (15), where the tilde '~' accent represents uncertainty in the parameter.

$$\sum_j \tilde{q}_{jt} W_j \geq D_t \quad \forall t \tag{14}$$

$$\tilde{q}_{jt} = \sum_i \left(\tilde{v}_{it} u_{ijt} + q^c (1 - u_{ijt})\right) \qquad \forall jt \tag{15}$$

This uncertainty is incorporated through the Target-Oriented Robust Optimization (TORO) approach proposed by Ng and Sy (2014). With TORO, the original objectives of additional costs minimization and emissions reduction maximization are translated into targets that consider the different scenarios that result from biomass LHV uncertainty. This procedure allows the decision maker to select among non-dominated solutions based on how much risk or uncertainty they are willing to tolerate. Equation (16) shows the modified objective function, which now maximizes the robustness index ($\theta \in [0,1]$), which is the degree of uncertainty that can be tolerated by a solution before it becomes infeasible. A higher value of θ implies a larger degree of perturbation for the biomass LHV; thus, a more risk-averse decision maker would prefer a higher θ because it is more robust. This replaces and is subject to the previously shown objective functions, which are translated into costs increase (τ_{cost}) and emissions reductions (τ_{env}) targets shown in (17) and (18). The bisection search algorithm is used to maximize θ.

$$max\ \theta \tag{16}$$

$$\sum_j \sum_n ic_{jn} R_{jn} + \sum_i \sum_j \sum_k \sum_t h\left(d_{ij} x_{ijt} + r_{jk} y_{jkt}\right) + \sum_j \sum_k \sum_t P\, y_{jkt} + \sum_i \sum_j \sum_t (a_{jt} + p_{it}) x_{ijt} \leq \tau_{cost} \tag{17}$$

$$\sum_j \sum_t \gamma W_j u_{jt} + \sum_j \sum_k \sum_t G_k\, y_{jkt} - \sum_i \sum_j \sum_k \sum_t e\left(d_{ij} x_{ijt} + r_{jk} y_{jkt}\right) \geq \tau_{env} \tag{18}$$

4. Model Validation

The model was validated through CPLEX, a linear solver, in MATLAB. To facilitate these, nonlinear equations were linearized. The network considered includes 6 potential locations for biomass sources, 4 existing coal power plant, and 3 potential biochar sinks. Hypothetical values were used for the validation, the parameters used are summarized in the appendices. Biomass LHVs are uncertain in nature and could assume values bounded within predefined maximum and minimum values.

Targets are set using the equations shown in (19) and (20), which can be used by decision makers as a guide when setting their targets. Establishing targets that are too optimistic leads to risks of not being able to meet these targets, while setting too conservative targets limits the results of the model, which could result in significant opportunity losses for the decision maker.

$$\tau_{cost} = \alpha \tau_{cost(1)} + (1 - \alpha) \tau_{cost(0)} \tag{19}$$

$$\tau_{env} = \alpha\tau_{env(1)} + (1-\alpha)\tau_{env(0)} \tag{20}$$

Equations (19) and (20) can be used to identify a range of targets through the parameter $\alpha \in [0,1]$ for both costs and emissions reductions. In the two equations, $\tau_{cost(0)}$ and $\tau_{env(0)}$ reflect the costs and emissions reductions under the most optimistic conditions where $\alpha = 0$, while $\tau_{cost(1)}$ and $\tau_{env(1)}$ represent the most pessimistic conditions where $\alpha = 1$. Eleven values of $\alpha \in [0,1]$ were considered in increments of 0.1, providing 11 targets for each costs and environmental emissions. Then, a solution is obtained for each of the targets through a bisection search maximizing the robustness index θ.

The result of the model validation which compares the trend of additional costs and environmental emissions reductions are shown in Fig. 1. It can be observed that as the robustness index θ increases, both additional costs and environmental emissions reduction decreases. With risk-averse behavior, θ approaching 1, less biomass feedstock would be used for co-firing and biochar soil amendment by the network. This is to minimize the risk of using biomass feedstock that has lower LHV values which could result in not being able to satisfy demand requirements. Thus, less additional costs would be incurred by the supply chain as costs to purchase and transport biomass, and to transport and apply biochar to soil sinks are reduced. On the other hand, a risk-seeking decision maker would choose to implement co-firing more, especially indirect co-firing to reach the highest possible reduction on environmental stress. This explains why higher costs would have to be paid as the robustness index decreases. However, having significantly lower robustness indices will reflect on the network's capability to handle uncertainty realizations. Particularly, significantly worse performance on the emissions reductions may occur, as well as shortcomings in reaching demand especially if biomass LHV is lower than expected.

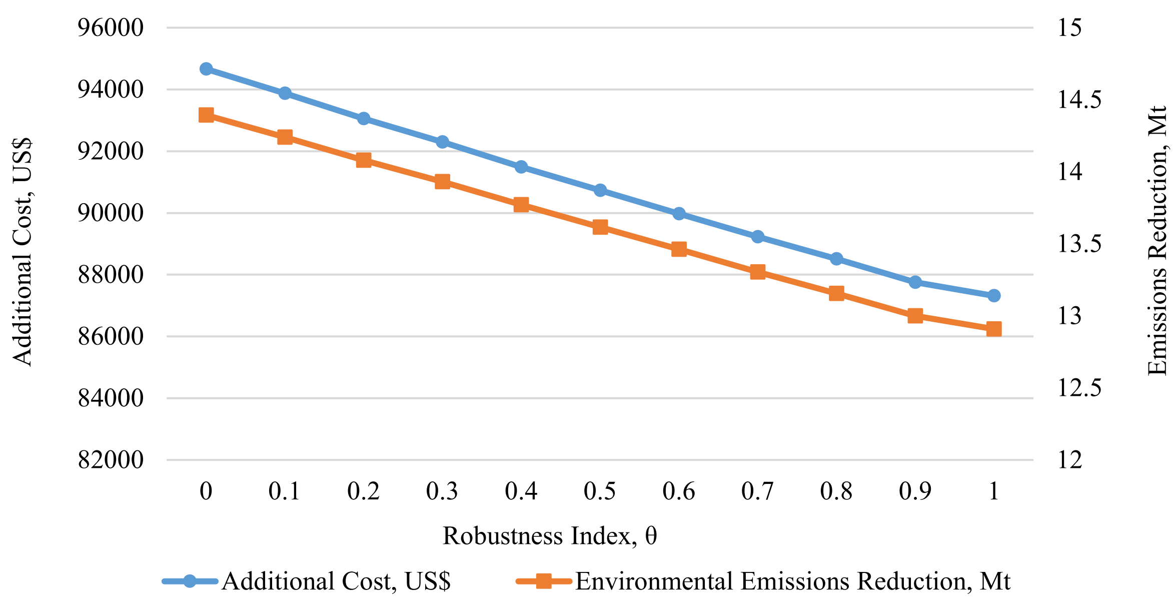

Figure 1: Comparison of Cost and Environmental Emissions Reduction Trend.

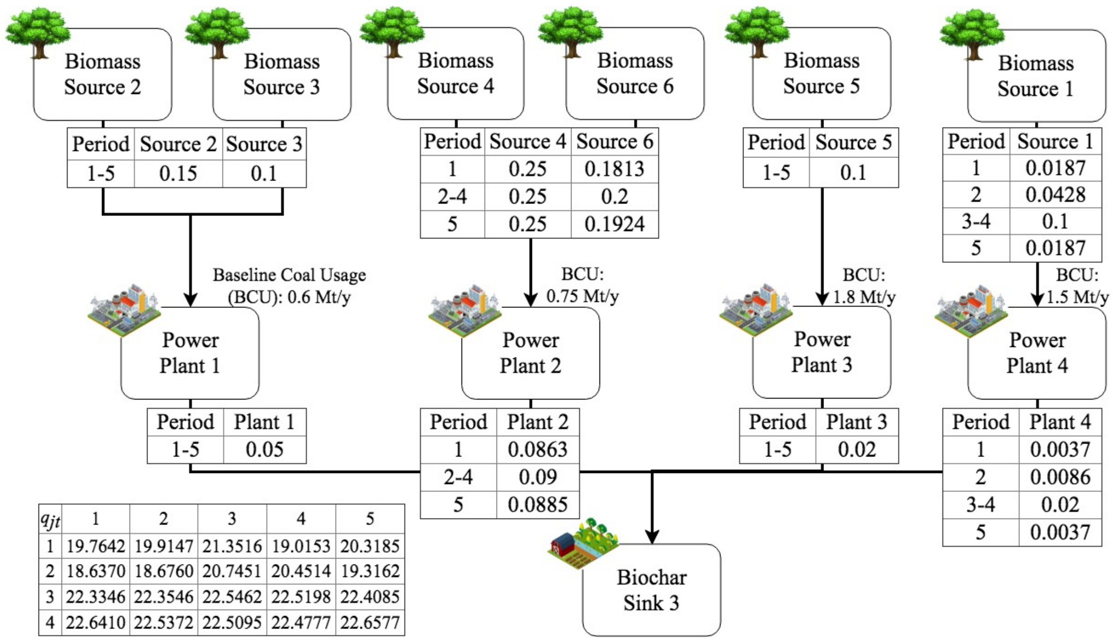

Figure 2: Optimal biomass co-firing network with robustness index θ=0.50.

The optimal biomass co-firing supply chain network at robustness index $\theta = 0.50$ is shown in Fig. 2. In this scenario, it can be observed that all existing power plants were chosen to be retrofitted for indirect co-firing because it allows for higher coal displacement and biochar application to soil which would increase reductions in environmental emissions. Power plants are supplied biomass from the sources closest to them every period to minimize environmental emissions contributions from transportation. Similarly, all power plants bring biochar to a single sink to avoid emitting GHG emissions from transporting to several sinks. Furthermore, the model does not choose to maximize the allowable coal displacement limits. The LHV of the mixed fuel processed by the power plants in each period shown in the lower left-hand corner of Fig. 2 show that LHV decreases as more biomass is processed by the conversion equipment because of relatively low biomass LHV. As a result, only a limited amount of biomass can undergo conversion to electricity in the power plants to ensure that the demand each period can be satisfied, while maximizing the reductions in environmental emissions. On the other hand, when biomass LHV is less uncertain, for example at $\theta = 0.00$, the more biomass is used by the system, and more biochar are applied to soil to maximize carbon sequestration.

5. Conclusions and Recommendations

A multi-objective robust optimization model for the design of biomass co-firing networks considering uncertain biomass quality has been developed and proposed in this study. The model considers both additional costs and reductions in environmental emissions during optimization, while ensuring that a robust solution that is relatively immune to changes in uncertain parameters is identified depending on the risk-appetite of the decision maker. This can guide decision-makers, such as network owners and managers, to commit to a final design. Compared to existing multi-objective optimization models which assume deterministic scenarios, uncertainty biomass quality is captured. Furthermore, the scope of the supply chain is extended to consider biochar-based carbon sequestration and selection between co-firing technologies which has not been addressed in existing literature. The model is validated through solving a hypothetical case study. The results of Monte Carlo simulation ($p = 0.02$) demonstrated that the robust model is more effective than its deterministic counterpart, as it is able to provide network configurations that are relatively more immune to realizations of uncertainty in biomass quality.

The environmental impacts of biomass co-firing systems and the application of biochar as soil amendment are not limited to only carbon or GHG emissions. Hence, future work can explore other aspects of the supply chain's environmental impact. For example, other potential categories of environmental impacts not captured in this study include acidification, human toxicity, and eutrophication potential. In addition, other entities involved in the network may be integrated, such as pretreatment and storage facilities. Pretreatment may be used to improve the quality of biomass before it is converted to energy in power plants. This way, the allowable co-firing limits and energy yield for the biomass fraction of the feedstock are increased. Keeping biomass and coal in inventory across periods can ensure that the proper amounts of feedstock with desirable properties are available for combustion to satisfy demand every period. The proposed modelling framework may be useful in selecting between available pretreatment technology options, and production and inventory planning. Lastly, the model may be applied to solve real-world problems.

References

Agbor, E., Zhang, X., and Kumar, A, A review of biomass co-firing in North America. *Renewable and Sustainable Energy Reviews*, vol. 40, pp. 930-943, 2014.

Amin, S. H., and Zhang, G., A multi-objective facility location model for closed-loop supply chain network under uncertain demand and return. *Applied Mathematical Modelling*, vol. 37, no. 6, pp. 4165-4176, 2013.

Ba, B. H., Prins, C. and Prodhon, C., Models for optimization and performance evaluation of biomass supply chains: An Operations Research perspective. *Renewable Energy*, vol. 87, pp. 977-989, 2016.

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

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

Ben-Tal, A., and Nemirovski, A., Robust solutions of uncertain linear programs. *Operations Research Letters*, vol. 25, no. 1, pp. 1-13, 1999.

Boundy, B., Diegel, S. W., Wright, L., and Davis, S. C., Biomass energy data book. Oak Ridge: U.S. Department of Energy, 2011.

Castillo-Villar, K. K., Eksioglu, S., and Taherkhorsandi, M., Integrating biomass quality variability in stochastic supply chain modeling and optimization for large-scale biofuel production. Journal of Cleaner Production, vol. 149, pp. 904-918, 2017.

Dundar, B., McGarvey, R. G., and Aguilar, F. X., Identifying optimal multi-state collaborations for reducing CO2 emissions by co-firing biomass in coal-burning power plants. *Computers & Industrial Engineering*, vol. 101, pp. 403-415, 2016.

Ghaderi, H., Pishvaee, M. S., and Moini, A., Biomass supply chain network design: An optimization-oriented review and analysis. *Industrial Crops and Products*, vol. 94, pp. 972-1000, 2016.

Gonela, V., Zhang, J., Osmani, A., and Onyeaghala, R., Stochastic optimization of sustainable hybrid generation bioethanol supply chains. *Transportation Research Part E: Logistics and Transportation Review*, vol. 77, pp. 1-28, 2015.

Govindan, K., Fattahi, M., and Keyvanshokooh, E. Supply chain network design under uncertainty: A comprehensive review and future research directions. *European Journal of Operations Research*, vol. 263, pp. 108-141, 2017.

He, Y., Zhou, X., Jiang, L., Li, M., Du, Z., Zhou, G., Xu, C. Effects of biochar application on soil greenhouse gas fluxes: a meta-analysis. *GCB Bioenergy*, vol. 9, pp. 743-755, 2017.

Madanayake, B. N., Gan, S., Eastwick, C., and Ng, H. K., Biomass as an energy source in coal co-firing and its feasibility enhancement via pre-treatment techniques. *Fuel Processing Technology*, vol. 159, pp. 287-305, 2017.

Mohd Idris, M. N., Hashim, H., and Razak, N. H., Spatial optimisation of oil palm biomass co-firing for emissions reduction in coal-fired power plant. *Journal of Cleaner Production*, vol. 172, pp. 3428-3447, 2018.

Ng, T. S., and Sy, C. L., A resilience optimization approach for work-force inventory control dynamics under uncertainty. *Journal of Scheduling*, vol, 17, pp. 427-444, 2014.

Otte, P. P., and Vik, J., Biochar systems: Developing a socio-technical system framework for biochar production in Norway. *Technology in Society*, vol. 51, pp. 34-45, 2017.

Pérez-Fortes, M., Laínez-Aguirre, J. M., Bojarski, A. D., and Puigjaner, L., Optimization of pre-treatment selection for the use of woody waste in co-combustion plants. *Chemical Engineering Research and Design*, vol 92, no. 8, pp. 1539-1562, 2014.

Pishvaee, M. S., Rabbani, M., and Torabi, S. A., A robust optimization approach to closed-loop supply chain network design under uncertainty. *Applied Mathematical Modelling*, vol. 35, pp. 637-649, 2011.

Ramos, A., Monteiro, E., Silva, V., and Rouboa, A., Co-gasification and recent developments on waste-to-energy conversion: A review. *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 380-398, 2018.

Shabani, N., and Sowlati, T., A mixed integer non-linear programming model for tactical value chain optimization of a wood biomass power plant. *Applied Energy*, vol. 103, pp. 353-361, 2013.
Tan, R. R., A multi-period source–sink mixed integer linear programming model for biochar-based carbon sequestration systems. *Sustainable Production and Consumption*, vol. 8, pp. 57-63, 2016.
U.S. EPA, EPA's Treatment of Biogenic Carbon Dioxide (CO2) Emissions from Stationary Sources that Use Forest Biomass for Energy Production. Policy Statement, 2018.
Veijonen, K., Vainikka, P., Järvinen, T., Alakangas, E., and VTT Processes, Biomass Co-firing: An Efficient Way to Reduce Greenhouse Gas Emissions. Retrieved from European Bioenergy Networks, 2013.
Woolf, D., Amonette, J. E., Street-Perrott, F., Lehmann, J., and Joseph, S., Sustainable biochar to mitigate global climate change. *Nature Communications*, vol. 1, pp. 1-9, 2010.
Zandi Atashbar, N., Labadie, N., and Prins, C., Modeling and optimization of biomass supply chains: A review and a critical look. *IFAC-PapersOnLine*, vol. 49, no. 12, pp. 604-615, 2016.

Appendices

Appendix A: Biomass Data.

Biomass Source	Supply (Mt/y)	LHV (Low, High) (GJ/t-y)				
		1	2	3	4	5
1	0.10	7, 15	10.5, 20	13, 17.2	9, 17.86	7.5, 18.8
2	0.15	12, 15	9, 13	10, 17.1	12.5, 21.5	9.2, 17.8
3	0.10	18, 21	11, 16	12, 16.5	17.5, 22.8	11.5, 19.37
4	0.25	10, 18	13, 19	11.56, 18.3	18, 18	10.35, 16
5	0.10	13, 18	14.2, 18.5	12.5, 14.8	15, 17.5	14, 18
6	0.20	9.5, 17	15, 21	11, 18	10.3, 16	15, 15

Appendix B: Co-firing Scheme Parameters.

Co-firing Scheme	Displacement Limits	Biochar Yield	Power Plant Retrofitting Costs (US$)			
			1	2	3	4
1	0, 0.2	0.0	3000	3000	2500	2500
2	0, 0.5	0.2	8000	9000	7500	7200

Appendix C: Power Plant Data.

Power Plant	Baseline Coal Usage (Mt/y)	Biochar quality (t/Mt)		
		PAH	PAH	PAH
1	0.60	10	20	2
2	0.75	2	2	1
3	1.80	1	0.8	3
4	1.50	2	3	4

Appendix D: Biochar Sink Data.

Biochar Sink	Capacity (Mt)	Sequestration Factor (Mt CO_2/Mt)	Biochar quality limit (t/Mt)		
			PAH	Zn	Pb
1	0.06	3.52	55	50	34
2	0.05	2.58	40	125	33
3	1.00	3.56	25	30	12

Appendix E: Other Relevant Parameters.

Coal LHV	22.73 GJ/t
Biomass combustion cost	\$5000/Mt
Biomass purchase cost	\$2000/Mt
Transportation cost	\$200/km
Biochar application cost	\$5000/Mt
Coal combustion emissions	3.16 Mt CO_2/Mt
Transportation emissions	0.0001 Mt CO_2/km
Demand	100 GJ/y

Biographies

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Charlle Sy is an Associate Professor in the Department of Industrial Engineering at De La Salle University, Manila, Philippines. She earned her B.S. and M.S. in Industrial Engineering from the same university. Meanwhile, she obtained her PhD in Industrial and Systems Engineering in the National University of Singapore, Singapore. She has published in Scopus-indexed journals and conference papers and had completed research projects in the energy, service and semiconductor industries. Her research interests include optimization under uncertainty, energy networks, supply chains, and system dynamics.