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Fuzzy optimization of carbon management networks based on direct and indirect biomass co-firing

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ABSTRACT

A drastic reduction in greenhouse gas emissions from electricity generation will be needed to mitigate climate change to a safe level. Residual biomass from agriculture is an underutilized energy source that can contribute to the needed emissions cut, but its geographic dispersion presents logistical problems. Direct and indirect co-firing of biomass in existing power plants presents a flexible means of utilizing this resource. Indirect co-firing of biomass with biochar co-production can even give greater reduction in greenhouse gas emissions if the biochar is applied to soil as a form of carbon sequestration. In this paper, a fuzzy linear programming model is developed for optimizing a carbon management network based on direct and indirect biomass co-firing, coupled with biochar application to soil for the latter case. The model can match biomass sources to power plants; the power plants that use indirect co-firing are also matched to biochar application sites. The model is illustrated using a case study representative of a developing country with an agriculture-intensive economy. Results show that not all powerplants need to implement co-firing to reach a balance between reducing GHG emissions and the risk of introducing contaminants in soil. The model provides effective decision support for decarbonizing power generation, particularly in developing countries that still make use of coal-fired power plants and which have abundant biomass resources in the form of agricultural waste.

1. Introduction

Removal of atmospheric CO_2 at the scale of multiple Gt/y is potentially possible through widespread biomass cultivation. As far back as the 1970s, Dyson [1] provided early estimates of the potential of such biomass growth as a means to avert a climate crisis through large-scale CO_2 fixation. More recently, it has been argued that CO_2 removal or negative emissions technologies (NETs) will be needed in order to reach a target of net zero emissions by 2050, which is necessary to limit temperature rise by 2100 to well below 2 °C [2]. The NETs will play the role of offsetting positive emissions that will continue to occur elsewhere (e.g., from aviation or maritime transport). For example, Alcalde et al. [3] estimate that it is possible to achieve net zero greenhouse gas (GHG) emissions in Scotland by optimally deploying land resources for NETs. The term NET applies to a range of carbon management technologies that achieve net removal of CO_2 from the atmosphere through various physical and chemical pathways. Examples of NETs include direct air capture, enhanced weathering, ocean fertilization, soil carbon management (SCM), and biochar application to soil, among others. McLaren [4] provides an assessment of the scalability and technological maturity of major NETs. More recent surveys of NETs have also been published, focusing on the research landscape [5], potential positive and negative effects of use [6], and policy framework requirements [7].

Terrestrial systems play a critical role in global carbon management [8]. In particular, the management of soil carbon can maximize the role of this compartment in retaining a large proportion of the world's

Abbreviations: AI, Artificial Intelligence; CCS, Carbon Capture and Storage; CFB, Circulating Fluidized Bed; CFD, Computational Fluid Dynamics; CMN, Carbon Management Network; EFB, Empty Fruit Bunch; GHG, Greenhouse Gas; GIS, Geographic Information Systems; IGCC, Integrated Gasification Combined Cycle; LCA, Life Cycle Assessment; LCOE, Levelized Cost of Electricity; MILP, Mixed Integer Linear Program; MP, Mathematical Programming; MSW, Municipal Solid Waste; NET, Negative Emissions Technology; NGCC, Natural Gas Combined Cycle; PA, Pinch Analysis; PC, Pulverized Coal; PI, Process Integration; PKS, Palm Kernel Shell; ROI, Return on Investment.

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carbon stock [9]. Smith [10] discusses the role of optimizing natural soil carbon stock, as well as enhancement of carbon content through application of biochar, as potentially scalable NETs. Biochar can be broadly defined as carbonized biomass which is applied to soil to improve soil properties, to sequester carbon, or both. Unlike raw, untreated biomass, biochar is relatively chemically stable, and thus provides a means to fix recalcitrant carbon in soil over timescales that are relevant to climate change mitigation. As the carbon content in biomass (and hence the thermochemically derived biochar) was originally removed from the atmosphere via photosynthesis, sequestration of this carbon in soil results in negative net emissions at the system level. In addition to the direct sequestration of carbon, secondary effects may also occur through modification of background soil greenhouse gas (GHG) emissions (e.g., reduction of soil CH_4 or N_2O flux) or reduction in the need for synthetic fertilizers in the case of agricultural land [11]. However, such effects are highly dependent on specific interactions between the biochar and the soil, and are generally difficult to predict [12].

The use of biochar as both soil amendment and a NET can be cast within a more general framework for sustainable biomass utilization [13]. In particular, the dilemma of whether to use biomass as an energy source to displace fossil fuels, or as a feedstock for biochar production, has been studied via life cycle assessment (LCA) [14]. The optimal choice depends strongly on case specific assumptions, such as the carbon intensity of the system's background energy mix. Fan et al. [15] recently developed a systematic graphical procedure for carbon break-even analysis. The methodology allows for effective visualization and sensitivity analysis for decision support. In addition to alternative uses of biomass, another critical issue in the scale-up of biochar as well as other NETs is the efficient use of limited resources – especially land area which may be required for other purposes [16]. Process integration (PI) via Mathematical Programming (MP) and Pinch Analysis (PA) techniques can potentially provide a valuable contribution to the planning of future large-scale NET systems [17].

Application of biochar to soil may pose the risk of introducing trace contaminants to soil [18]. Potentially hazardous contaminants include naturally occurring components originally present in biomass (e.g., salts or heavy metals) or those formed from undesirable side reactions during thermochemical processing (e.g., dioxins and furans). In addition, introduction of carbon load to soil can result in reaction of soil microbes known as "priming" [19]. The variability of such reactions can have different effects on soil fertility and net carbon sequestration benefit [20]. In principle, the biochar can be customized to create specific effects; for example, Mašek et al. [21] recently reported the beneficial agronomic impact of doping biochar with potassium.

NETs in general, and biochar in particular, can be useful to help both developed and developing countries achieve their commitments to the Paris Agreement. However, in the case of many developing countries, the commitments are conditional on provision of aid and technology transfer to help achieve low-carbon growth trajectories [22]. Biochar is thus a particularly attractive option in countries with agriculture-intensive economies, where crop residues are an abundant and often underutilized energy resource [23]. As byproducts, these crop residues can be used as feedstock for biochar production without incurring incremental emissions that would result from dedicated energy crops. In addition, carbon sequestration using biochar can be scaled up using existing infrastructure (e.g., roads and railways) and technologies (e.g., farm equipment) unlike CO_2 capture and storage (CCS), and is also less likely to have social acceptability issues due to perceived risks. Biomass pyrolysis for co-production of biochar with liquid (bio-oil) and gaseous (syngas) products can serve as a core platform for negative emissions systems. The bio-oil and syngas fractions can be used to provide electricity in polygeneration plants [24] and biorefineries [25]. Such systems can be designed to account for the effects of variations in biomass properties as in the case of flexible feedstock plants [26].

Belmonte et al. [27] discussed the important role of Process Systems Engineering (PSE), and specifically PI tools such MP and PA, in planning large-scale Carbon Management Networks (CMNs) based on biochar. The earliest work in this sub-area developed a supply chain-like MP model formulated as a mixed integer linear program (MILP) [28]. In the latter work, the objective function is to maximize the amount of carbon sequestered; a key feature is the use of trace contaminants in biochar as a constraint to application to agricultural land. An improved bi-objective model was later developed, taking into account economic goals [29]. A unified MILP model that includes both pyrolysis conditions and CMN planning was then developed, with the intent of tuning process parameters to match the sink requirements [30]. In addition to MP models, other methods such as PA [31] and P-graph [32] have been demonstrated for planning of biochar-based CMNs. These models rely on the assumption that key system parameters are known *a priori*. As pointed out by Tan [33], in future large-scale CMNs, data acquisition for use in such models may present significant practical challenges. Use of Artificial Intelligence (AI) [34], remote sensing, and Geographic Information Systems (GIS) offer potential solutions to the data acquisition problems [35]. The strategic roadmap for the development of gigaton-scale biochar-based CMN that incorporates smart planning, operations, monitoring, and feedback is given in a recent perspective paper [33].

Dang et al. [36] first proposed the concept of indirect biomass co-firing in coal-fired power plants coupled with biochar-based carbon sequestration to achieve very low GHG emissions. Direct biomass co-firing is a well-known approach for reducing GHG emissions of coal-fired power plants through partial fossil energy displacement. The effect can be further amplified if only the bio-oil and syngas fractions from pyrolysis are used as fuel, while the biochar fraction is used for carbon sequestration. Aviso et al. [37] developed a MILP model for planning biochar co-firing networks that optimally match biomass sources with power plants; the model also introduces the option of using direct and indirect co-firing options in each plant. However, the model fails to take into account the potential uncertainties in the risk resulting from applying biochar to soil over extended periods of time [18]. Previously developed models have proposed the use of a "risk aversion factor" to provide such a safety margin against soil contamination from biochar-borne substances [28]. Thus, while indirect biomass co-firing with biochar-based carbon sequestration is an attractive decarbonization technique for power plants, there remains a clear gap in the literature on how to account for uncertainties in soil contamination risk at the biochar application sites.

In this paper, a novel fuzzy MILP model is developed to optimize biomass co-firing networks with consideration of the inherent uncertainties in soil contamination risk. This model is based on the earlier deterministic formulation by Aviso et al. [37]. The main advantage of fuzzy optimization is that it allows fuzzy objectives (or goals) and fuzzy constraints to be integrated within the same mathematical model [38]. Multiple objectives can be considered, along with constraints for which partial violation is allowed. Furthermore, this formulation addresses the limitation of the previous formulation through the use of fuzzy set theory [39] to handle system uncertainties which are likely to be significant in real systems [32]. These features allow for the simultaneous consideration of achieving the model objectives and accounting for uncertainties that occur in real engineering problems to be dealt with. This improvement allows the model to find more robust solutions that is not possible with conventional deterministic models. The current work focuses on environmental issues; economic aspects will be dealt with in a subsequent paper.

The rest of this paper is organized as follows. Section 2 provides an extensive survey of state-of-the-art literature on biomass co-firing. Section 3 gives a description of the fuzzy MILP model, which is then used on a Philippine case study in Section 4. An analysis of the general implications of indirect co-firing with biochar-based carbon sequestration is then given in Section 5. Finally, Section 6 gives conclusions and prospects for future work. The over-all organization and flow of the study is illustrated in Fig. 1.

2. Literature review: biomass co-firing

Coal remains to be a major source of electricity globally, despite adverse effects in the environment such as the release of greenhouse gases (GHG). The global production of electrical power from coal accounts to about 38.5% of the energy mix [40]. Coal-fired power plants also account for 30% of the global energy-related emissions. Coal use is used extensively in developing countries in Asia, with 170 GW capacity under construction; 90% of the constructed coal-fired capacity for the past 20 years have been in this region [41]. With the projected increase of the demand for energy in Association of Southeast Asian Nations (ASEAN), the electricity production in the existing coal-fired power plants in the region can impede global efforts to limit warming to safe levels [42]. To reconcile the need to meet rising demand of electrical power and to mitigate the GHG emissions, there are three alternatives available for coal-fired power plants based on International Energy Agency [41]. The first option is the incorporation of CCS through retrofitting. The second option is reducing the operations to only provide back-up power. The third option is to reduce coal use through biomass co-firing. The net GHG reduction benefit of co-firing is proportional to the amount of coal displaced by the biomass fuel. In practice, the proportion of coal that can be displaced is limited since the power plants are designed and optimized to burn coal. Introduction of a second fuel can be done to a limited extent, but once the biomass ratio reaches a critical value, technical problems can arise. In particular, fouling and slagging problems in boilers can result from excess biomass use. Changes in flame characteristics from burning biomass with coal also alter heat transfer and can degrade thermal efficiency. Depending on feedstock properties, an increase in NOx emissions may occur and thus lead to increased eutrophication impact [43]. A recent study proposes the production of synthetic "bio-coal" from biomass which can potentially match coal properties sufficiently so as to allow higher substitution rates during co-firing [44].

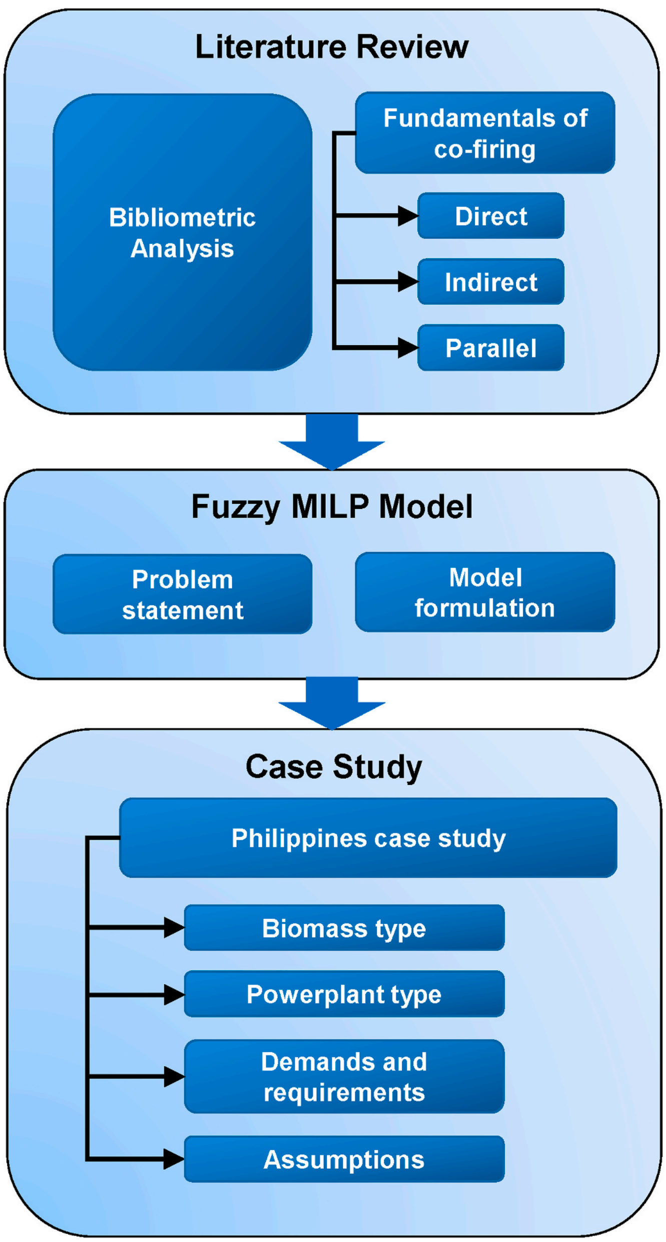


Fig. 1. Organization and flow of the study.

Biomass co-firing in coal-fired power plants provides negative carbon dioxide (CO_2) emission when combined with CCS [45]. According to Verma et al. [46], biomass co-firing in coal-fired power plants is an easy way to increase renewable energy generation without building new power plants. The retrofitting of a coal-fired power plant to accommodate biomass co-firing is economically practical, with relatively low investment cost and risk compared to building equivalent capacity in the form of dedicated biomass-fired plants. Fuel flexibility can be achieved by using various types of biomass feedstock with coal. In addition, the biomass co-firing promotes energy security as it consumes a locally available and renewable fuel. Distributed use of this biomass resource also reduces supply chain risks that may result from variations in availability or quality. For example, in the Philippines, the use of agricultural and agro-industrial crop residues for energy production can provide 350 PJ of energy annually [47]. This can substantially reduce GHG emissions from fossil fuels while providing electricity for rural areas.

Previous review papers on biomass co-firing have focused on different aspects of this technology. Roni et al. [48] reviewed the policy initiatives globally to promote biomass co-firing for power generation. They summarized statistics of the various biomass resources around the world, the existing biomass co-firing plants, and different technologies used. They also proposed the design of the biomass supply-chain network which can potentially replace significant amounts of coal in the United States (US). Agbor et al. [49] reviewed the various biomass co-firing plants in North America, including environmental, technological, and logistical concerns. Al-Mansour and Zuwala [50] introduced an evaluation methodology which consisted of a technology score sheet to assess the different biomass co-firing plants in Europe. Meanwhile, Agbor et al. [51] conducted an integrated environmental and techno-economic analysis for sixty scenarios of biomass co-firing in a coal- and natural gas-fired power plant, assuming different biomass types. Their results show that the use of forest residues as biomass feedstock for co-firing in a fully paid-off coal-fired power plant is the most attractive in terms of both CO_2 abatement cost and levelized cost of electricity (LCOE). Dzikuć and Piwowar [52] performed life-cycle assessment (LCA) of power generation from biomass co-firing with lignite and coal in Poland. One of the key findings of the study is that the delivery of biomass to small co-firing plants compared to the delivery to large power plants is more environmentally viable. Madanayake et al. [53] summarized the various biomass characterization, technologies, and pre-treatment processes for co-firing in coal power plants that have been performed. In addition, their assessment included energy, cost and CO_2 avoidance for the different pre-treatment processes (e.g., leaching, torrefaction, mechanical treatment, and biological treatment). Torrefaction has shown to be an effective pre-treatment method to improve the fuel properties of biomass to make it comparable with coal. Malico et al. [54] focused on reviewing the status and future directions of solid biomass for energy production in Europe. According to their study, biomass co-firing with coal can significantly reduce the environmental impacts of energy generation. Niu et al. [55] reviewed the ash-related concerns during biomass co-combustion with coal, which limits the potential to displace coal. Later on, Niu et al. [56] outlined the different torrefaction studies conducted which emphasized the properties, challenges, and economy of torrefaction for the pre-treatment of biomass for co-firing in coal power plants. In addition, Nunes et al. [57] reviewed the torrefaction process and its beneficial effects to biomass co-firing with coal. Rehfeldt et al. [58] summarized the different technologies for fuel switching and highlighted that biomass co-firing in coal-fired power plants emerged as one of the solutions to meet the emission reduction target for the 1.5 °C global warming scenarios. Tabet and Gökalp [59] reviewed the different computational fluid dynamics (CFD) studies conducted to determine the optimal co-firing percentage, injection location, load swings, fuel staging, projected heat release, and predicted emissions. Verma et al. [46] outlined the different drying technologies and approaches performed prior to biomass co-firing in a coal-fired power plant. As the inherent moisture content of fresh biomass makes its heating value lower, drying is an essential step prior combustion. Bhuiyan et al. [60] reviewed the thermo-chemical characteristics of various biomass types for co-firing with coal in an industrial furnace. Various experimental studies were categorized, reviewed, and analyzed which consisted of small-scale, laboratory-scale, and industrial scale based on technology, emissions, burnout performance, ash analysis, and co-firing blends. Their study also summarized the emerging trends in biomass co-firing in a coal-fired power plant. Lee et al. [61] summarized various works on the energy and environmental assessment of converting biomass residues to biochar as fuel. The results of the review show some challenges of biomass co-firing, such as elevated acidification, ozone depletion, terrestrial ecotoxicity, and land use. Their study also highlights the use of biogas or bio-oil for co-firing with coal. The biogas/bio-oil used for the co-firing come from the gasification of biomass, while the biochar product can be used for potential carbon sequestration. Recently, Clark et al. [42] reviewed the coal-fired power plant capacity, attrition rate, and plant lifespan in the different ASEAN countries. They pointed out that the shift to renewable energy production, including biomass co-firing, can help reduce GHG emissions generated in the region.

The performance evaluation of biomass co-firing has been recently studied by the following works. Andrić et al. [62] performed an environmental performance evaluation in retrofitting a coal-fired power plant to a biomass co-firing coal-fired power plant. The assessment includes the determination of the maximum distance of the biomass source from the power plant which makes it environmentally viable compared to the combustion of 100% coal. The results have shown that a 20% biomass ratio results in 11–25% reduction in the carbon footprint and 8–15% reduction in the emergy flow. In addition, the biomass supply distance was suggested to be shorter by 49–62% compared to the supply distance of coal. Bertrand et al. [63] analyzed the potential of biomass co-firing in the 27 countries of European Union (EU) in terms of its demand, CO_2 abatement, and breakeven prices of electricity generation. The results revealed that the demand for biomass-based electricity can be stimulated by a carbon tax. In addition, the high demand for the biomass-based electricity can translate to high biomass prices, which may lead to increased competition for biomass resources with other downstream uses. Kebede et al. [64] did an economic impact assessment of biomass co-firing in coal-fired plants in West and South Alabama in the US. The study employed a regional input-output model which considered three sizes of wood pellet plants. The results show beneficial multiplier effects on other sectors of the economy. In particular, the use of biomass co-firing has shown to create economic activities for the rural communities. Khorshidi et al. [65] performed a techno-economic analysis to evaluate the co-firing of biomass gas with natural gas in an existing natural gas combined cycle (NGCC) plant. The carbon capture capabilities of the proposed setup was also analyzed. Miedema et al. [66] evaluated various configurations of the biomass supply chain with different blends of biomass co-combusted with coal in a coal-fired power plant. The assessment covered GHG emissions, renewable energy production, energy consumption, and energy efficiency for the various biomass co-firing rates. The 60% biomass co-firing blend was estimated to give a reduction in the GHG emissions of 48%. The co-firing of torrefied and pelletized biomass with coal was the optimum choice. Mun et al. [67] evaluated the performance of a 500 MW coal-fired power plant in Korea which utilized five types of biomass feedstock for co-firing, namely, wood pellet, empty fruit bunch (EFB) pellet, palm kernel shell (PKS), walnut shell, and torrefied biomass. Their results show a decline in the plant efficiency with the use of biomass co-firing. Torrefied biomass was found to be better than the other four types of biomass feedstock. Royo et al. [68] proposed a methodology to analyze the implementation of biomass co-firing in a coal-fired power plant in Spain. The study evaluated both agricultural and forest residues as biomass feedstock within 100 km radius of the coal-fired power plants using LCA. The results estimate the reduction in the annual GHG emissions of Spain to be 3.4 $MtCO_{2eq}$/y. Schakel et al. [69] employed LCA to assess the environmental impact of biomass co-firing in a coal-fired power plant with CCS. Two types of coal-fired power plants were compared: integrated gasification combined cycle (IGCC) plant and the supercritical pulverized coal (PC) power plant. The biomass co-firing of 30% yielded a negative CO_2 emissions of 67–85 g/kWh. Smith et al. [70] developed a decision support tool for the energy industry for the development of biomass co-firing projects in existing coal-fired power plants in the US. The tool considers the economic, environmental, and social impacts of biomass co-firing. The most economical scenario was observed for the 5% biomass co-firing over a 20-year project life. Tokarski et al. [71] performed a comparative analysis to assess the energy and environmental performance of biomass co-firing and combustion for different technologies. A performance indicator was developed based on the electricity consumed to generate the fuel. The lowest energy consumption was observed for biomass co-firing using a fluidized bed combustion plant, but the highest efficiency was achieved through biomass co-firing in a PC plant.

Mohd Idris et al. [72] proposed a spatial optimization approach which employs an integration of the geographic information system (GIS) with a MILP model for the oil palm biomass co-firing in coal-fired power plant to minimize the CO_2 emissions. The model considers the biomass supply chain and logistics. The use of oil palm biomass co-firing in coal-fired power plants is estimated to reduce CO_2 emissions by up to 46%. Truong et al. [73] developed an explicit optimization model to assess the costs of co-firing of rice residues in a coal-fired power plant in Vietnam. The cost of CO_2 emissions was found to be the main driver for the co-firing technology used. The implementation of biomass co-firing using rice straw and husk resulted in 8% reduction in CO_2 emissions an abatement cost of US$ 137 million. Wang et al. [74] proposed a hybrid LCA method to evaluate the environmental and economic costs of biomass- and coal-fired electricity generation in China. Their results show that the use of wood residue-fired electricity can lower the power costs by 2–14% compared to the baseline. Yang et al. [75] employed ten LCA models based using GaBi software and the Integrated Environmental Control Model to evaluate different coal-fired power plants implementing biomass co-firing with CCS. Zero emissions were achieved using 25% biomass co-firing, while a negative emissions level of 877 kg CO_{2eq}/MWh was reached at 100% biomass use.

In summary, state-of-the-art literature shows that there is great potential in reducing the GHG emissions by using different co-firing technologies to retrofit existing coal-fired power plants. It is thus important that the model considers how these aspects can influence the selection of the optimal solution.

2.1. Bibliometric analysis

A bibliometric analysis was performed using Scopus search to assess the research trends in the optimization of biomass co-firing in coal-fired power plants. Two keyword search scenarios were considered. The first scenario (scenario 1) utilized a Scopus keyword search combination of 'biomass co-firing' and 'coal fired power plant' and yielded 205 documents (195 articles and 10 reviews). The second scenario (scenario 2) using the keyword combination of 'biomass co-firing' and 'coal fired power plant' and 'optimization' resulted in 17 documents (all 17 of which are articles).

Using CorTexT Manager [76] (http://manager.cortext.net/), the corpus text data files for the two scenarios of the Scopus database were analyzed. The contingency matrices for scenarios 1 and 2 are shown in Figs. 2 and 3, respectively; where the keywords in the articles are cross-referenced with the journal articles. The heat-map scale indicates the co-occurrence of the keywords in papers. Positive and negative values indicate higher and lower co-occurrences, respectively.

An inter-temporal network stream was obtained using CorTexT Manager for scenario 1 where the keywords were cross referenced with the keywords from scenario 1 as shown in Fig. 4. Since scenario 2 has only 17 papers, no inter-temporal network stream could be generated. This indicates that the application of optimization to biomass co-firing in coal fired power plants is still very limited. The keyword stream is represented by a Sankey diagram of the keyword-to-keyword matches shown in Fig. 2. The evolution of the keywords from 2002 to 2018 which is divided into 4 periods is illustrated in Fig. 4. The Sankey diagram shows the dynamic evolution of the relationships in terminology over time. Darker colors indicate more links between keywords, while tube width signifies co-occurrences of the keywords.

The geographic distribution of the publications in both scenarios was also examined. Most of the works for scenario 1 are performed in the USA and Europe, as shown in Fig. 5. China and South Korea are the only Asian countries with significant presence. For scenario 2 where optimization studies were performed, countries such as Malaysia, Canada, Australia, and Denmark are also included, as shown in Fig. 6.

This bibliometric analysis reveals important temporal, geographic, and topical trends in publications on biomass co-firing. The analysis also identifies a notable research gap. Despite the large number of papers, only a small minority focus on indirect co-firing with biochar-based carbon sequestration.

2.2. Fundamentals of co-firing

This section discusses the basic principles of different biomass co-firing techniques, which can be incorporated as alternatives within the model developed in this paper. The benefits of co-firing result directly from partially replacing thermal energy from coal with an equivalent amount of thermal energy from biomass. Three known methods in utilizing biomass for co-combustion with coal through co-firing are the direct co-firing, indirect co-firing, and parallel co-firing [45]. A brief discussion of each option is given here.

2.2.1. Direct co-firing

The concurrent burning of biomass and coal is known as direct co-firing. The fuels can either be pre-mixed prior combustion in the furnace, or directly injected separately into the furnace. In the case of pre-mixed coal and biomass, the two fuels are combined before or after the milling process. In the case of direct injection, both fuels are fired either by combined burners or separated burners. Direct co-firing requires the least investment cost. However, direct co-firing is highly susceptible to the variations in fuel quality, and may result in problems such as corrosion and ash deposition. Thus, the blending of biomass for direct co-firing is limited. About 3–5% blend of biomass with coal for co-firing have shown good results without the need for retrofitting the coal-fired power plant. With the addition of cyclone boilers, the percentage of biomass for co-firing can be increased to 20% [77]. Direct co-firing is suitable for PC plants. A typical blend of direct co-firing is around 10% of the thermal energy input from biomass for co-firing with coal due to techno-economic limitations [78].

Recent studies on direct co-firing in coal fired power plants are as follows. Woytiuk et al. [79] performed LCA of torrefied and raw coppice willow co-firing with lignite in a PC plant. Their results have shown a GHG reduction of 34% for the torrefied biomass and 31% for the raw coppice. In order to eliminate the black smoke generated during direct co-firing of palm fiber and palm kernel shell biomass with coal, Abdullah et al. [80] proposed the use of proportional integral derivative (PID) controllers to monitor and control the biogas input to the boiler. Fogarasi and Cormos [81] evaluated an oxy-fuel co-firing of sawdust and

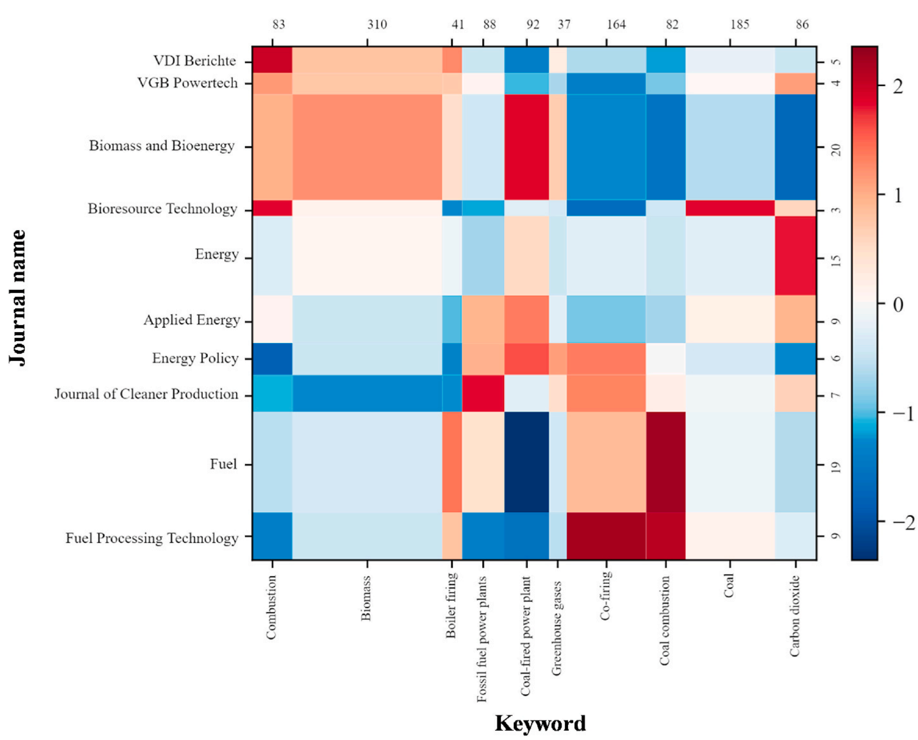


Fig. 2. The contingency matrices for the Scopus keyword search on scenario 1.

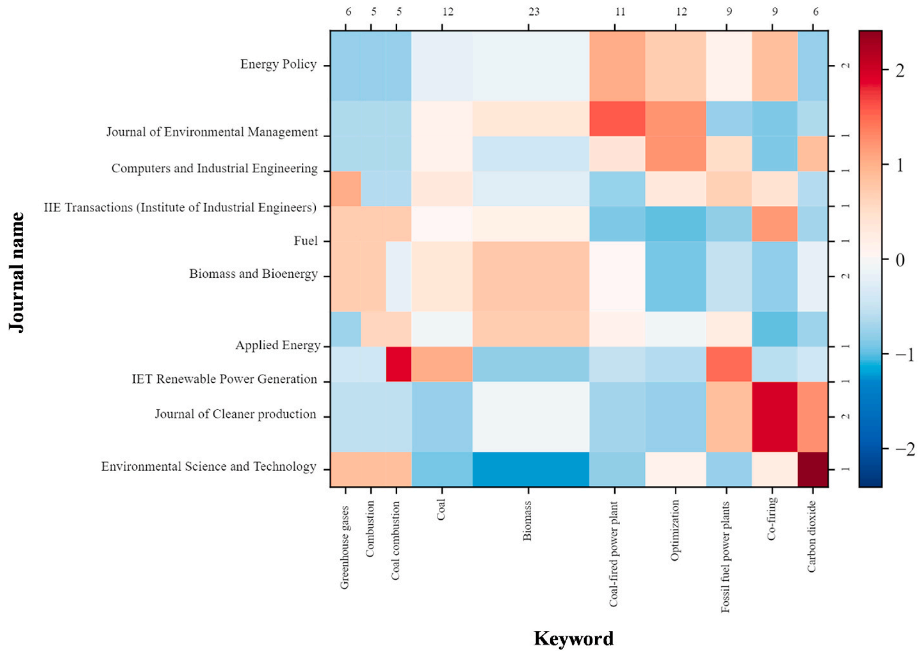


Fig. 3. The contingency matrices for the Scopus keyword search on scenario 2.

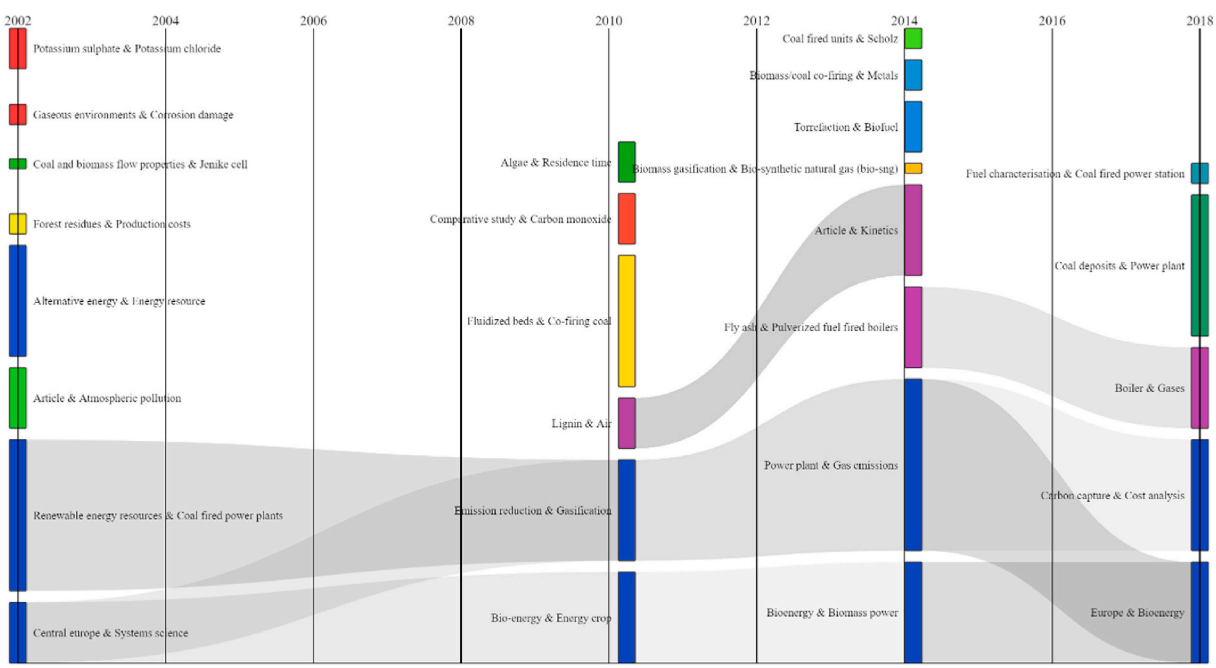


Fig. 4. The Sankey diagram of the keywords for the semantic network.

coal with CCS. Their findings revealed that the increase of biomass usage resulted to a gradual reduction of the performance indicators of the power plant. Alobaid et al. [82] performed an evaluation of the direct co-firing of torrefied biomass with coal in a 1 MW coal-fired power plant. Their results show no significant deviation in the char burnout and flue gas emissions when compared with the 100% coal. However, higher oxygen demand was observed. Milićević et al. [83] used CFD with MP to optimize lignite and wheat straw co-firing with coal. Their results have shown that a 10% thermal ratio of wheat straw biomass yielded an elevated gas temperature with lesser NOx emissions compared with the combustion of pure lignite. Zhang et al. [84] conducted a comparative operational simulation of direct co-firing and indirect co-firing of straw biomass in terms of efficiency and emissions using Aspen Plus. The simulation results show comparable results for direct and indirect co-firing of straw biomass.

2.2.2. Indirect co-firing

Indirect co-firing requires the separate firing of biomass and coal on different furnaces. The indirect co-firing of biomass can be performed in three different ways. First, the biomass can be burned in a different furnace from which the combustion gases generated are then injected into the coal boiler. Second, the biomass and coal can be burned in different furnaces after which their combustion gases are combined and fed to the boiler. Third, the biomass can first be pre-processed through

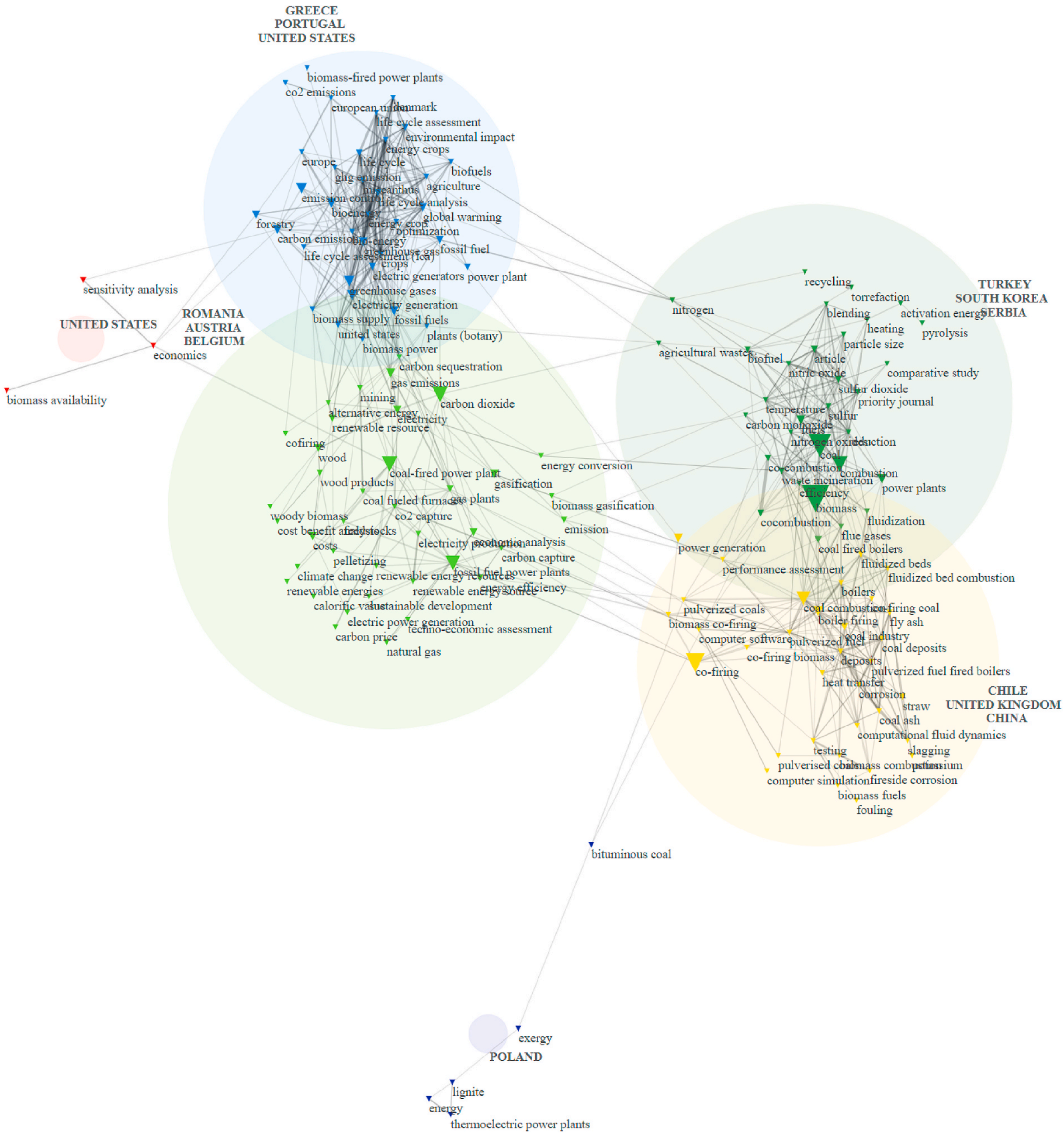


Fig. 5. The network map of cited journals cross referenced with the cited journals for scenario 1.

gasification, with the syngas and bio-oil fractions being used as fuel. Since biomass is not directly fed with coal in the furnace, issues such as fouling/slagging and corrosion are reduced compared to direct co-firing. Higher co-firing rates are thus possible, and can potentially approach 100% via the bio-coal route [44]. Indirect co-firing can also generate biochar which presents an alternative opportunity to achieve negative emissions via soil carbon sequestration. The schematic configuration of the concept of indirect co-firing is shown in Fig. 7.

Studies performed recently on indirect co-firing are as follows. Ostrowski et al. [85] performed tests to evaluate the viability of the syngas co-firing produced from biomass low-temperature gasification in a rotary reactor. The objective of the laboratory experiment was to determine the suitable biomass feedstock for indirect co-firing in power boilers using an industrial scale gasification unit operating at a temperature of 400 °C. Hurskainen and Vainikka [86] reported 20–40% indirect co-firing in a PC plant in Finland. Karampinis et al. [78] summarized different technology schemes, impacts, and future perspective for biomass indirect co-firing in a coal-fired power plant compared with other co-firing schemes. Basu et al. [77] analyzed the indirect biomass co-firing in a coal fired power plant in Canada and compared it with direct co-firing setup. Their results show direct co-firing had better return on investment (ROI) compared to indirect co-firing, but also suffered from fouling, corrosion, and mill breakdown issues. Kalisz et al. [87] focused on the indirect co-firing of biodegradable wastes in coal-fired power plants. Co-firing rates of 10, 20, and 40% were evaluated. Their results show a minimal deviation of the boiler operation even when using at higher co-firing rates, thus highlighting the advantage of indirect co-firing for decarbnonization. Drosatos et al. [88] proposed an indirect biomass co-firing strategy using cardoon (*Cynara cardunculus*) biomass at 35% co-firing rate. The indirect co-firing of biomass was numerically simulated using ANSYS Fluent. The results were compared with a previous work which utilized the Macro

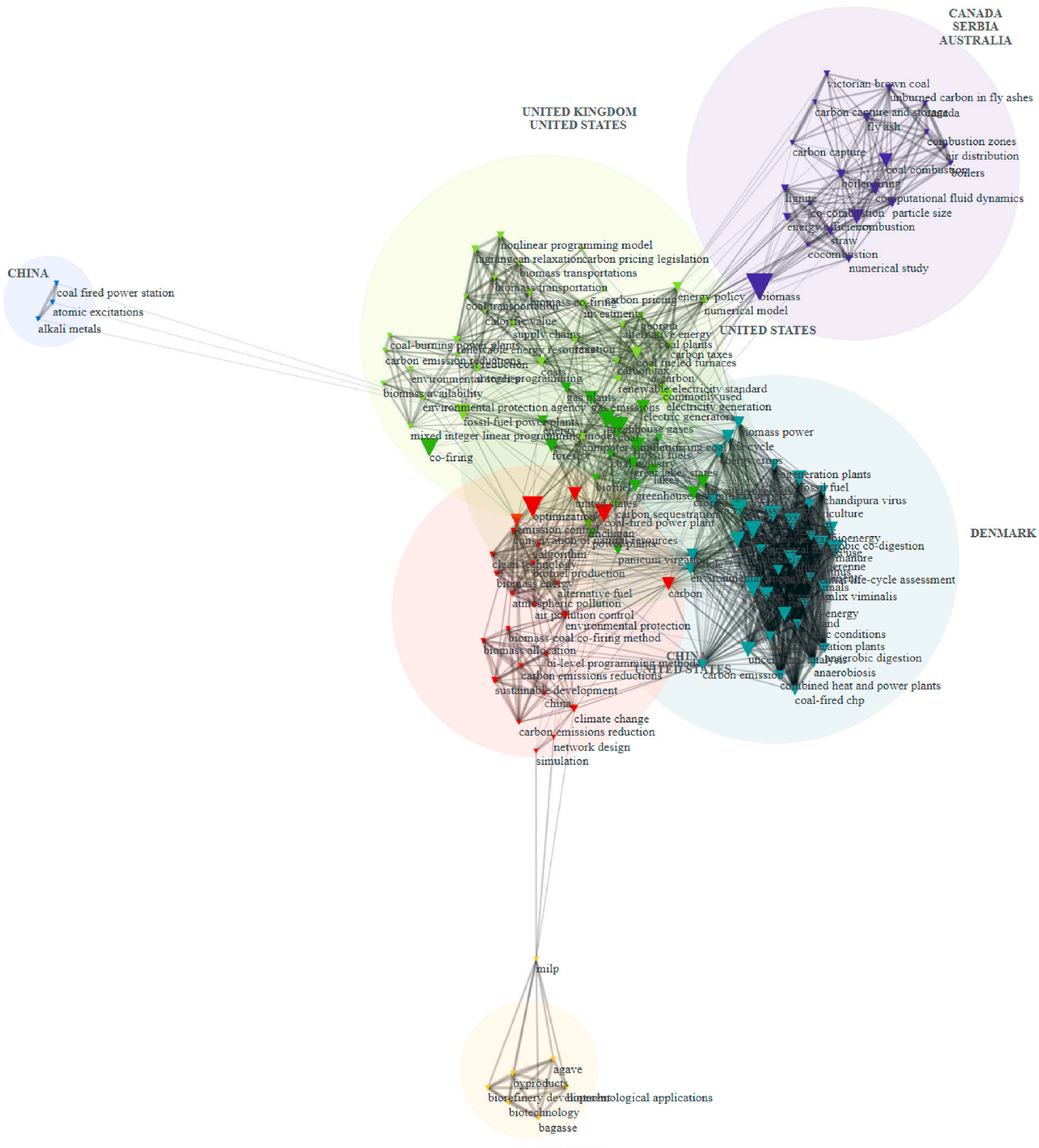


Fig. 6. The network map of cited journals cross referenced with the cited journals for scenario 2.

Heat Exchanger Model of ANSYS Fluent yielded good agreement with the previous model.

2.2.3. Parallel co-firing

Parallel co-firing utilizes separate dedicated furnaces and boilers for the biomass and coal fuels. The steam generated from the boilers are then delivered into the power plant system Having an independent system for using the biomass to generate steam allows relatively higher amounts of biomass to be utilized but also entails more investment and retrofit [89]. In addition, biomass ash is separated from coal ash which allows the use of a wide variety of biomass types with ease in management of the ash content.

Previous studies on the development of parallel co-firing in coal fired power plants are as follows. McPhail et al. [90] performed an economic, energy, and environmental assessment of utilizing municipal solid waste (MSW) biomass for co-firing in a coal-fired power plant. Their results show that the flue gas quality is highly dependent on the moisture content and composition of the MSW. The use of MSW for co-firing also reduces CH_4 emissions from MSW disposal in landfills. Ruhul Kabir and Kumar [91] compared the environmental and energy performance of the parallel co-firing with the direct co-firing technology using wood, forest residues, and agricultural residues. The results showed that the torrefied and pelletized biomass have higher energy and environmental benefits. Forest residues also gave lower environmental impacts compared with the agricultural residues and wood. A feasibility study was conducted by Amirabedin and McIlveen-Wright [92] on the parallel and direct co-firing of biomass with lignite using the exergy analysis methodology. Their results show better environmental performance achieved with

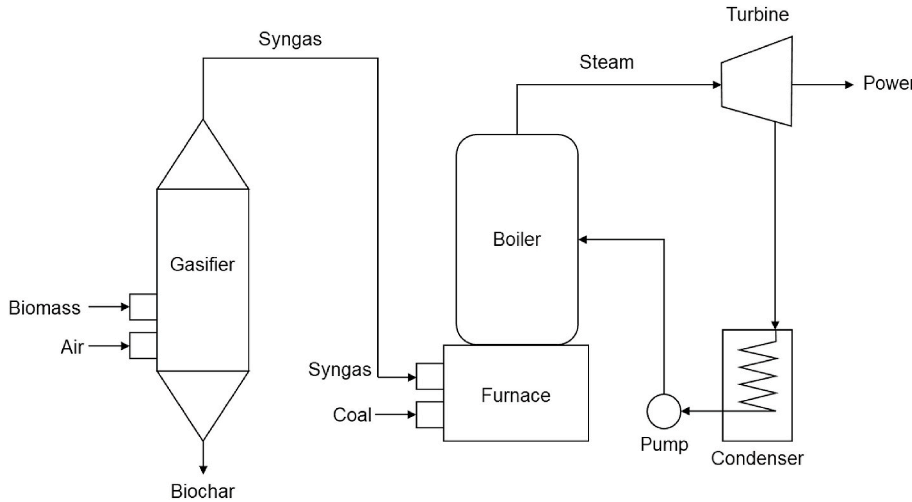


Fig. 7. The schematic configuration of indirect co-firing adapted from Loha et al. [45].

parallel co-firing. Kotowicz and Bartela [93] evaluated the adaptation of two configurations of biomass parallel co-firing into a supercritical PC power plant. They quantified the minimum amount of biomass needed to run the parallel co-firing scheme.

2.3. Fuzzy MILP model

This section describes a novel MP model to optimize biomass co-firing networks that incorporate biochar-based carbon sequestration. This formulation is based on a previously developed deterministic model [37], but considers uncertainties in biochar storage capacities at the application sites [32]. Zimmermann's symmetric fuzzy MP is used as basis to develop the extended model, as this framework allows uncertain constraints to be considered concurrently with fuzzy goals and has the advantage of integrating both objectives and constraints into a single mathematical model [38]. Such models are formulated so that the satisfaction of fuzzy constraints can range from 0 (violated) to 1 (fully satisfied), with partial satisfaction being signified by fractional values. The same scale is also applied to fuzzy goals. In addition, this new model also explicitly considers biomass type, a feature not available previously [37].

2.4. Formal problem statement

The formal problem statement can be stated as follows. Given the following:

- The availability of *U* types of biomass which can be obtained from *M* number of sources;
- *N* power plants of known capacity which can adopt co-firing technologies;
- *C* co-firing technologies which can accommodate *S* levels of biomass co-firing to be implemented, and known biochar yields based on biomass type and co-firing technology;
- *P* biochar sinks with known sequestration factor and fuzzy limits for biochar application;
- The distances between biomass sources and operating power plants;
- The distances between power plants and the biochar application sites or sinks;

The problem is to determine the optimal allocation and selection of biomass type and source, co-firing technology, biomass co-firing rate, and biochar sink application rate which will minimize the total carbon emitted by the supply chain, without violating the site-specific limits for biochar application.

2.5. Model nomenclature

Sets.

C Set of co-firing technologies
M Set of biomass sources
N Set of operational power plants
P Set of biochar sinks
S Set of levels for co-firing substitution
U Set of biomass types

Indices.

h Index for co-firing technology
i Index for biomass source
j Index for power plant
k Index for biochar sink
l Index for co-firing rate
t Index for biomass type

Parameters.

α Carbon footprint of coal combustion (Mt CO_2/Mt coal)
β Carbon footprint for transport (Mt CO_2/Mt/km)
$B_{j,l,h,t}$ Amount of biomass needed for co-firing in plant *j* using substitution level *l*, co-firing technology *h* and biomass type *t*
CAP_j Capacity of power plant *j*
CF^L Fuzzy lower limit for carbon footprint of the system
CF^U Fuzzy lower limit for carbon footprint of the system
$D_{i,j}$ Distance between biomass source *i* and power plant *j*
F_k Sequestration factor for biochar sink *k*
$R_{j,k}$ Distance between power plant *j* and biochar sink *k*
$S_{i,t}$ Indicates the supply of biomass type *t* from biomass source *i*
SEQ_k^L Lower fuzzy limit for biochar application in biochar sink *k*
SEQ_k^U Upper fuzzy limit for biochar application in biochar sink *k*
Continuous Variables
λ Over-all degree of satisfaction obtained by the system
λ_k^A Degree of satisfaction for biochar application in biochar sink *k*
λ^B Degree of satisfaction for carbon footprint achieved by the system
CF Carbon footprint of supply chain network
SEQ_k Amount of biochar sequestered in sink *k*
$x_{i,j,t}$ Amount of biomass type *t* from biomass source *i* delivered to power plant *j*
$y_{j,k}$ Amount of biochar from power plant *j* applied to sink *k*

Binary Variables

$bq_{j,t}$ Binary variable which indicates if biomass type t is used for power plant j

$q_{j,l,h,t}$ Binary variable which indicates the selection of technology h for power plant j using biomass type t at a co-firing rate l

2.6. Model formulation

This fuzzy MILP model is an extension of a previously developed deterministic MILP model [37] where the option of biomass type has been included and multiple objectives integrated to identify the optimal network. The superstructure of the system being solved can be visualized as shown in Fig. 8. The carbon footprint of the entire supply chain, *CF*, can be obtained using Eq. (1). The first term, accounts for the avoided carbon emissions resulting from biomass co-firing where α is the carbon footprint associated with coal combustion. The level of substitution is indicated by $\mathrm{B_{j,l,h,t}}$ and will depend on the type of biomass selected, the level of substitution and the type of co-firing technology implemented. The binary variable $q_{j,l,h,t}$ takes a value of 1 to indicate which combination of biomass type, substitution level and technology is implemented, otherwise $q_{j,l,h,t} = 0$. The second term in Eq. (1) accounts for the emissions arising from the transport of biomass from its source to the powerplant where β is the carbon footprint for transport, $\mathrm{D_{i,j}}$, is the distance from source to the powerplant and $x_{i,j,t}$ is the amount of biomass type t transported from source i to power plant j. The third term in Eq. (1) accounts for the emission from the transport of biochar from the power plant to the biochar sink, where $\mathrm{R_{j,k}}$ is the distance between powerplant j and sink k and $y_{j,k}$ is the amount of biochar transported. The last term in Eq. (1) accounts for the sequestered carbon due to biochar application where $\mathrm{F_k}$ is the sequestration factor.

$$CF = -\alpha\sum_{j=1}^{N}\sum_{l=1}^{S}\sum_{h=1}^{C}\sum_{t=1}^{U}\mathrm{B_{j,l,h,t}}q_{j,l,h,t} + \beta\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{U}\mathrm{D_{i,j}}x_{i,j,t} + \beta\sum_{j=1}^{N} \times \sum_{k=1}^{P}\mathrm{R_{j,k}}y_{j,k} - \sum_{j=1}^{N}\sum_{k=1}^{P}\mathrm{F_k}y_{j,k} \tag{1}$$

Eq. (2) accounts for the material balance of the biomass source. Indicating that for any biomass type from each biomass source, the total amount delivered to all power plants should not exceed the available supply, $\mathrm{S_{i,t}}$.

$$\sum_{j=1}^{N}x_{i,j,t} \le \mathrm{S_{i,t}} \qquad \forall\, i,t \tag{2}$$

Similarly, each power plant should receive the required amount of biomass needed for the chosen co-firing substitution level, using the chosen biomass type and co-firing technology, as given by Eq. (3).

$$\sum_{i=1}^{M}\sum_{t=1}^{U}x_{i,j,t} = \sum_{l=1}^{S}\sum_{h=1}^{C}\sum_{t=1}^{U}\mathrm{B_{j,l,h,t}}q_{j,l,h,t} \qquad \forall\, j \tag{3}$$

A co-firing technology in power plant j using type t is activated if at least one co-firing technology operating at a co-firing rate h is selected, as specified by Eq. (4). Eq. (5) indicates whether biomass type t is used in power plant j with the binary variable $bq_{j,t}$, while Eq. (6) ensures that only one type of biomass is utilized in any powerplant if a co-firing technology will be implemented.

$$\sum_{l=1}^{S}\sum_{h=1}^{C}q_{j,l,h,t} = bq_{j,t} \qquad \forall\, j,t \tag{4}$$

$$x_{i,j,t} \le \mathrm{M}bq_{j,t} \qquad \forall\, j,t \tag{5}$$

$$\sum_{t=1}^{U}bq_{j,t} \le 1 \qquad \forall\, j \tag{6}$$

All biochar generated from the power plants should be applied to the biochar sinks as indicated in Eq. (7). The total amount of biochar applied in each sink, SEQ_k, is given by Eq. (8) and should be within the fuzzy biochar applications limits of the sink as shown in Eq. (9).

$$\sum_{k=1}^{P}y_{j,k} = \sum_{l=1}^{S}\sum_{h=1}^{C}\sum_{t=1}^{U}\mathrm{B_{j,l,h,t}Z_{h,t}}q_{j,l,h,t} \qquad \forall\, j \tag{7}$$

$$\sum_{j=1}^{N}y_{j,k} = SEQ_k \qquad \forall\, k \tag{8}$$

$$\mathrm{SEQ_k^L} \le SEQ_k \le \mathrm{SEQ_k^U} \qquad \forall\, k \tag{9}$$

Finally, Eqs. (10) and (11) define the binary variables.

$$q_{j,l,h,t} \in \{0,1\} \qquad \forall\, j,l,h,t \tag{10}$$

$$bq_{j,t} \in \{0,1\} \qquad \forall\, j,t \tag{11}$$

However, the intention is to simultaneously minimize the carbon emission of the supply chain and minimize the amount of sequestered biochar to reduce the potential harmful impacts of biochar soil application. In this regard, the model is modified into a fuzzy optimization model where the objective function is to maximize the degree of

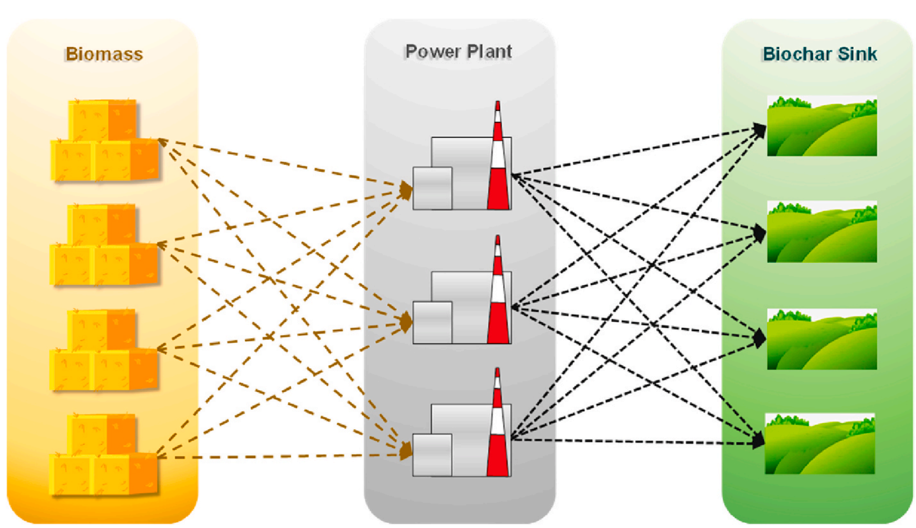


Fig. 8. CMN superstructure [36].

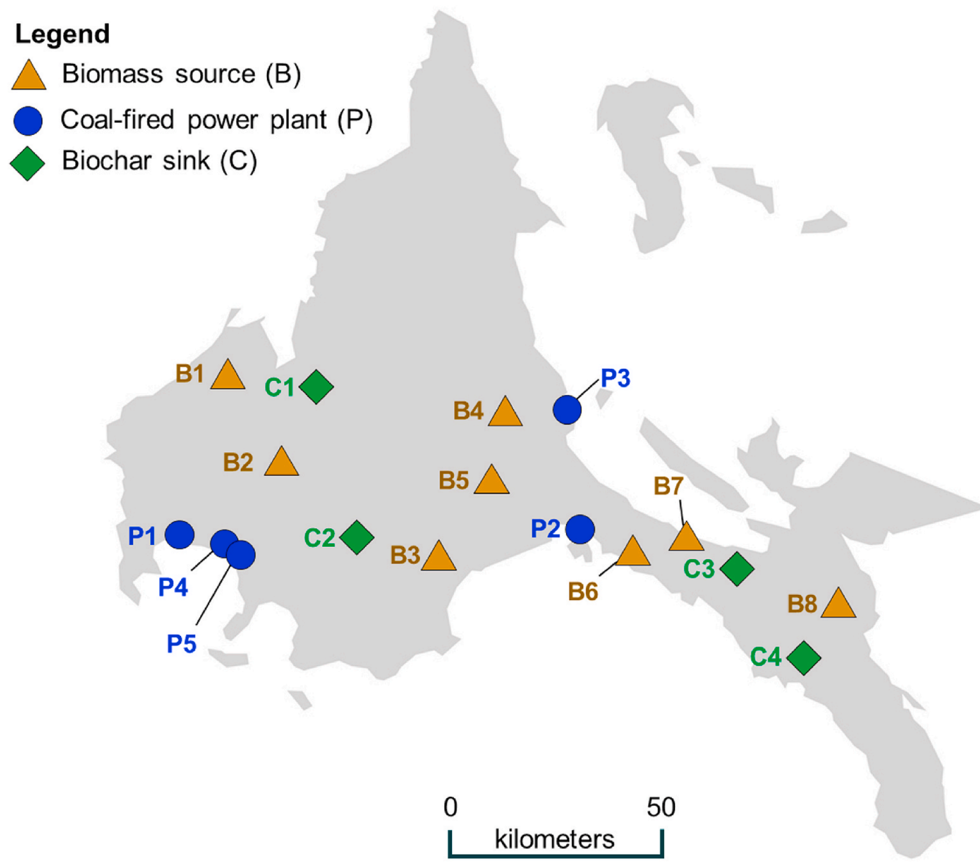


Fig. 9. Map of calabarzon region.

satisfaction as defined by Eq. (12). This adapts the improved fuzzy MP formulation of Javadian et al. [94] to ensure that the resulting solution is Pareto optimal. The overall degree of satisfaction should be less than any of the individual degrees of satisfaction (λ_k^A, λ^B) as given by Eqs. (13) and (14). The degree of satisfaction for the biochar sequestration is given by Eq. (15) while the degree of satisfaction for the carbon footprint of the supply chain is given by Eq. (16).

$$\max = \lambda + \frac{1}{1000}\left(\sum_{k=1}^{P} \lambda_k^A + \lambda^B\right) \quad (12)$$

$$\lambda \leq \lambda_k^A \quad (13)$$

$$\lambda \leq \lambda^B \quad (14)$$

$$SEQ_k = \mathrm{SEQ}_k^U - \lambda_k^A\left(\mathrm{SEQ}_k^U - \mathrm{SEQ}_k^L\right) \qquad \forall\, k \quad (15)$$

$$CF = \mathrm{CF}^U - \lambda^B\left(\mathrm{CF}^U - \mathrm{CF}^L\right) \quad (16)$$

The optimal solution of this fuzzy MILP model can be determined without significant difficulty using the branch-and-bound algorithm, which is widely available in commercial optimization software. Use of the model is illustrated in the next section with a case study.

3. Case study

In the Philippines, coconut plantations are a major potential source of waste biomass. In 2018, the country produced 14.7 Mt of coconut, 11% of which was produced from the Calabarzon region of the country, immediately south of the capital region of Metro Manila [95]. Based on this production share, the regional availability of residual biomass can be estimated from the national totals reported by Go et al. [47]. The main products of the coconut industry include coconut oil and the residual copra meal, which is used as livestock feed. Cellulosic residue in the form of coconut husk or shell is generated and separated from the main product in plantations. The fibrous coconut husk typically comprises about 35% of the total weight of a coconut, while the hard, woody coconut shell makes up 12% of its weight. This case study considers eight different sources of coconut residue, which includes both coconut

Table 1
Available biomass from different sources in Mt/y [adapted from 47].

Source	Biomass Type	
	Coconut Shell (A)	Coconut Husk (B)
B1	0.020	0.049
B2	0.044	0.109
B3	0.007	0.017
B4	0.007	0.017
B5	0.001	0.003
B6	0.004	0.010
B7	0.026	0.065
B8	0.027	0.067

Table 2
Powerplant characteristics [96].

Power plant	Capacity (MW)	Plant type	Baseline coal consumption (Mt/y)	Displaced coal (Mt/y)	
				5%	10%
P1	600	PC	1.80	0.0900	0.1800
P2	1184	PC	3.55	0.1775	0.3550
P3	511	PC	1.53	0.0765	0.1530
P4	300	CFB	0.90	0.0450	0.0900
P5	270	CFB	0.81	0.0405	0.0810

Table 3
Required biomass for direct co-firing.

Power plant	5% substitution		10% substitution	
	Coconut Shell	Coconut Husk	Coconut Shell	Coconut Husk
P1	0.1125	0.1125	0.2250	0.2250
P2	0.2219	0.2219	0.4438	0.4438
P3	0.0956	0.0956	0.1913	0.1913
P4	0.0563	0.0563	0.1125	0.1125
P5	0.0506	0.0506	0.1013	0.1013

Table 4
Biomass requirement for indirect co-firing.

Power plant	5% substitution		10% substitution	
	Coconut Shell	Coconut Husk	Coconut Shell	Coconut Husk
P1	0.1442	0.1372	0.2885	0.2744
P2	0.2845	0.2706	0.5689	0.5412
P3	0.1226	0.1166	0.2452	0.2332
P4	0.0721	0.0686	0.1442	0.1372
P5	0.0649	0.0617	0.1298	0.1235

Table 5
Distances between biomass sources and power plants (km).

	P1	P2	P3	P4	P5
B1	65	204	211	60	62
B2	54	198	202	48	50
B3	78	123	133	75	73
B4	172	118	52	178	176
B5	167	68	61	171	169
B6	225	38	78	233	231
B7	247	47	85	258	256
B8	312	79	128	349	347

shell and the coconut husk that are assumed to be collected and stored at these centralized staging points. The biomass can potentially be used in five different power plants which are considering to implement co-firing technology by substituting coal with coconut residue in two different levels (e.g. 5% and 10% substitution). The power plant specifications are based on the list of the Philippine Department of Energy [96]. The first three are PC plants, while the last two are circulating fluidized bed (CFB) plants. All of the power plants except P3 are multi-unit plants. Furthermore, the power plants can either implement direct or indirect co-firing. Indirect co-firing generates biochar, which can then be used for soil application in four different biochar sinks. The Calabarzon region is illustrated in Fig. 9 along with relevant features. The amount of biomass available in the different sources by type is summarized in Table 1 while the power plant characteristics are summarized in Table 2. A parameter value of $\alpha = 3.16$ Mt CO_2/Mt coal is used in this paper, representing the typical emissions rate from coal use.

Co-firing may be done directly or indirectly. Indirect co-firing will generate biochar and will require more biomass for substitution to meet the equivalent thermal energy requirement. The biomass requirements for direct and indirect co-firing are given in Table 3 and 4, respectively based on 5% and 10% substitution rates.

The distances between the biomass sources and power plants are given in Table 5, while the distances between power plants and biochar sinks are shown in Table 6. The distances have been estimated from Google Maps. A land transportation carbon footprint parameter value of $\beta = 0.0001$ $MtCO_2$/Mt/km is used here based on [28].

The biochar generated from the co-firing technologies depending on the type of biomass used are shown in Table 7. The biochar sink characteristics are summarized in Table 8.

It is assumed that the carbon emission upper limit is 0 while the carbon emission lower limit was determined by minimizing the carbon footprint of the entire supply chain using Eq. (1) as the objective function and Eqs. (2)–(11) as constraints. The model was coded and

Table 6
Distances between power plants and biochar sinks (km).

	C1	C2	C3	C4
P1	60	90	261	300
P2	195	120	57	75
P3	200	115	80	110
P4	55	70	210	310
P5	62	75	233	330

Table 7
Biochar yields for co-firing technology [96].

	Direct co-firing	Indirect co-firing	
		Coconut shell	Coconut husk
Biochar yield (kg/kg)	0	0.22	0.18

Table 8
Biochar sink characteristics.

Biochar sink	Fuzzy biochar limit (Mt/y)		Sequestration factor
	Lower limit	Upper limit	(Mt CO_2/Mt of biochar)
C1	0.01	0.02	3.20
C2	0.02	0.03	3.00
C3	0.03	0.04	2.60
C4	0.01	0.02	3.00

implemented using the optimization software LINGO 18.0 [97] operated in a laptop running on Windows 10 using the Intel® Core™ i7-6500 CPU Processor at 2.50 GHz. For this case study, the minimum carbon footprint, which was determined in 4 s computational time, to be −1.701 Mt CO_2/y.

Optimizing the model using the objective function in Eq. (12), with Eqs. (2)–(11) and Eqs. (13)–(16) as constraints, results in a degree of satisfaction of $\lambda = 0.941$, with a system carbon footprint of −1.600 Mt CO_2/y. The optimal solution was obtained in 2 s computational time and indicates that power plants P3, P4 and P5 should implement co-firing rates of 10%. P3 selects direct co-firing while P4 and P5 select indirect co-firing. P3 and P4 utilize the coconut husk, while P5 uses the coconut shell. The summary of the optimal network is shown in Table 9. The optimal CMN for power plants P3, P4, and P5 are shown in Figs. 10–12, respectively. It can be seen that even though C3 has the highest limit for biochar application, it was not considered as the first option for storage because of its distance from P4 and P5. Thus, the benefits of CO_2 sequestration from biochar application will be reduced by the carbon footprint generated if the biochar is transported from P4 and P5 to C3. Furthermore, C3 has a relatively lower sequestration factor in comparison to the other biochar sinks. This characteristic means that secondary benefits of biochar application (e.g., soil GHG reduction) at this location are not as large as they are at other sites. The sinks with favorable responses to biochar application may be favored by the model in spite of transportation penalties. For example, P4 prefers to deliver its biochar to C4 even if C4 is almost 50% farther away than C3. The results illustrate that there is no one solution towards reducing the carbon footprint of the system and that the consideration of different technology options and biomass types for co-firing identifies an optimal solution which efficiently manages the constraints of local conditions. In this case study for example, it was not necessary to implement co-firing technology for all power plants to achieve carbon emission reductions. Furthermore, both biomass types were utilized as fuel in at least one of the powerplants selected to implement the co-firing technology.

In practice, it is also useful to examine near-optimal solutions whose performance may approach that of the global optimum [98]. Such alternative solutions can be generated by adding integer-cut constraints

Table 9
Optimal allocation of biomass and biochar in Mt/y.

	P1	P2	P3	P4	P5
B1	0	0	0.0123	0.0282	0.0200
B2	0	0	0	0.1090	0.0440
B3	0	0	0.0170	0	0.0070
B4	0	0	0.0170	0	0.0070
B5	0	0	0.0030	0	0.0010
B6	0	0	0.0100	0	0.0040
B7	0	0	0.0650	0	0.0260
B8	0	0	0.0670	0	0.0208
C1	0	0	0	0.0026	0.0080
C2	0	0	0	0	0.0206
C3	0	0	0	0.1150	0
C4	0	0	0	0.0106	0

to the original fuzzy MILP; some software such as LINGO can generate these solutions automatically. The top 10 solutions and their performance levels are summarized in Table 10. Note that the magnitude of carbon sequestration of the tenth best solution is 96.6% of the optimal level. The allocation for some of these near optimal solutions are further shown in Table 11 (Solution 6) and Table 12 (Solution 10); due to space constraints, the details of the other solutions are not included here. Solution 6 converts three of the power plants for co-firing, with P2 and P4 implementing direct co-firing and P5 using indirect co-firing. P5 utilizes coconut shell at 10% co-firing rate, P2 utilizes the coconut husk at 5% co-firing rate, and P4 uses coconut husk at 10% co-firing rate. Only two biochar sinks were used (i.e. C1 and C2). Solution 10, on the other hand, converts four power plants, with P3 implementing direct co-firing, and P1, P4 and P5 using indirect co-firing technology. P5 uses coconut shell at 10% co-firing rate, while P1, P3 and P4 make use of the coconut husk at 5% co-firing rate. Furthermore, all biochar sinks were used with the highest level of application of 0.0229 Mt/y in C3.

To illustrate which connections between biomass sources and power plants as well as power plants to biochar sinks appear most frequently in the top 10 solutions, a summary is provided in Table 13, where a darker shade of gray indicates a higher number of occurrences of the 10 networks considered. The most frequent connections occurred between B1 – P1, B2 – P4, B2 – P5 and B3 – P5 (7 times in 10 solutions) presented and between P5 – C2 (9 times in 10 solutions presented). In contrast, the connection between B2 – P2 only occurred once in the 10 solutions while connections between P2 – C1, P3 – C1, P3 – C2, and P5 – C4 were not activated at all in any of the 10 solutions examined. This was primarily due to the relatively high distance between the power plants and the biochar sinks in the chosen power plant to biochar sink pair. Such analysis of these optimal and near-optimal solutions may give important insights for decision-makers, who may not necessarily be convinced of the model outputs alone [98]. For instance, the final network design should prioritize connections which occurred most frequently when alternative network designs were examined.

4. General implications for decarbonization efforts

Efforts to shift the global energy mix away from coal towards renewables are not being pursued uniformly in different parts of the world. While serious measures are being taken to phase out coal-fired power plants in developed countries, in the developing world, coal is usually seen as a low-cost option (not considering externalities) for meeting growing energy demand that comes with increased electricity access, population growth and economic progress. There remains the common notion that electricity from coal helps in reducing energy poverty in the Third World, although recent detailed analysis shows that rural electrification can be decoupled from coal use [99]. For example, analysis of the ASEAN in particular reveals lack of political will to decarbonize the power mix, which potentially endangers the capability of ASEAN countries to meet their commitments to the Paris Agreement [42]. The ASEAN region is also sufficiently large as an economic bloc to affect global GHG emissions cuts needed to meet the 2 °C temperature rise target.

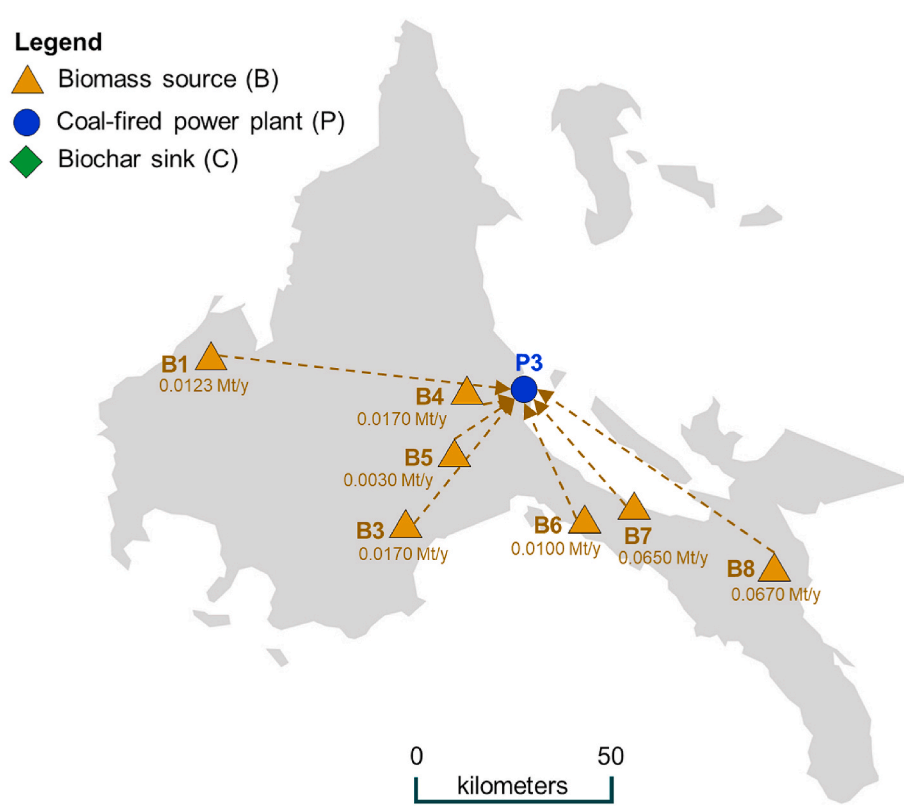


Fig. 10. The optimal CMN for P3.

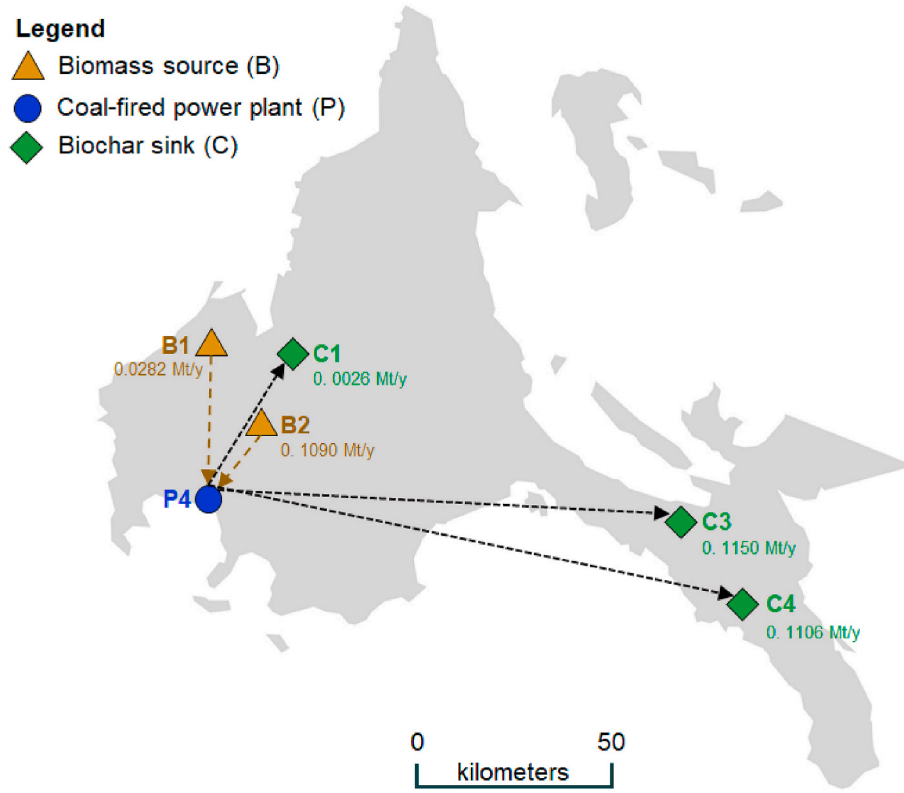


Fig. 11. The optimal CMN for P4.

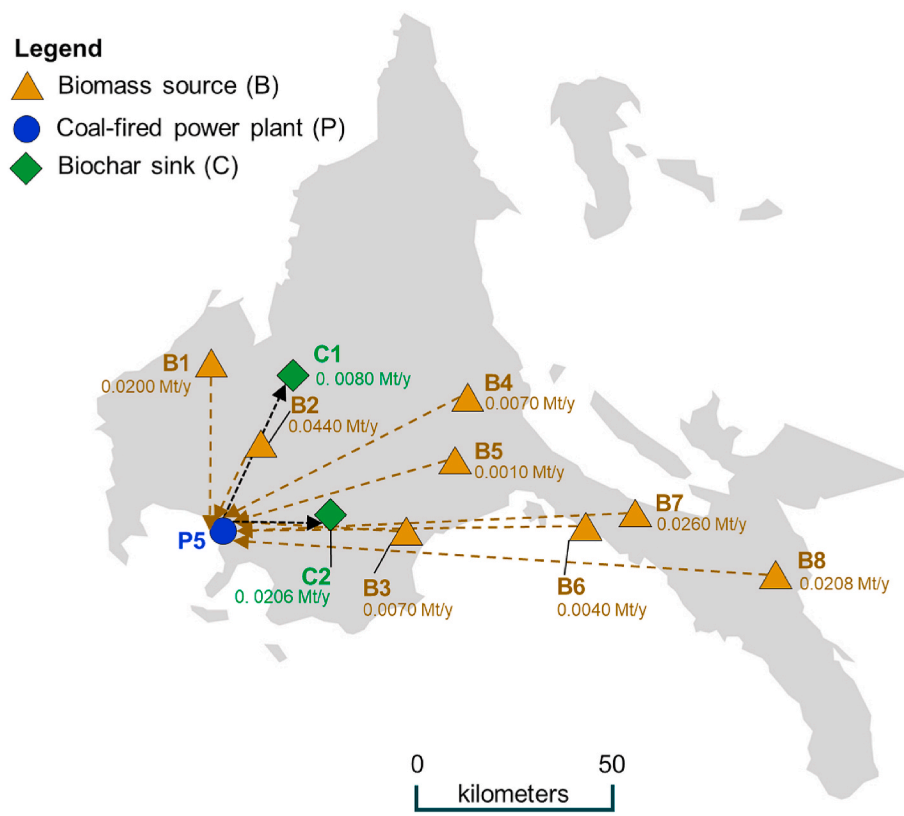


Fig. 12. The optimal CMN for P5.

Table 10
Summary of top 10 solutions.

Solution	λ	Carbon Footprint (Mt CO_2/y)	Power plants with co-firing	
			Direct	Indirect
1	0.941	−1.600	P3	P4, P5
2	0.941	−1.600	P3	P1, P5
3	0.933	−1.586	P4	P1, P5
4	0.926	−1.575	P1	P2, P5
5	0.926	−1.575	P4	P2, P5
6	0.912	−1.550	P2, P4	P5
7	0.912	−1.550	P1, P2	P5
8	0.910	−1.547	P1	P3, P4, P5
9	0.910	−1.547	P4	P1, P3, P5
10	0.909	−1.545	P3	P1, P4, P5

Table 11
Allocation of biomass and biochar in Solution #6 in Mt/y.

	P1	P2	P3	P4	P5
B1	0	0.0429	0	0.0035	0.0200
B2	0	0	0	0.1090	0.0440
B3	0	0.0170	0	0	0.0070
B4	0	0.0170	0	0	0.0070
B5	0	0.0030	0	0	0.0010
B6	0	0.0100	0	0	0.0040
B7	0	0.0650	0	0	0.0260
B8	0	0.0670	0	0	0.0208
C1	0	0	0	0	0.0109
C2	0	0	0	0	0.0177
C3	0	0	0	0	0
C4	0	0	0	0	0

Table 12
Allocation of biomass and biochar in Solution #10 in Mt/y.

	P1	P2	P3	P4	P5
B1	0.0490	0	0	0	0.0200
B2	0.0404	0	0	0.0686	0.0440
B3	0.0170	0	0	0	0.0070
B4	0.0170	0	0	0	0.0070
B5	0.0030	0	0	0	0.0010
B6	0.0100	0	0	0	0.0040
B7	0.0008	0	0.0642	0	0.0260
B8	0	0	0.0314	0	0.0208
C1	0.0109	0	0	0	0
C2	0.0029	0	0	0	0.0180
C3	0	0	0	0.0123	0.0105
C4	0.0109	0	0	0	0

Crop residues are an underutilized energy source which is available in substantial amounts, especially in agriculture-intensive countries. However, the supply of most types of residual biomass is intermittent and geographically dispersed, which creates major logistical challenges for their use as fuel. Co-firing of biomass in coal-fired power plants is an attractive interim measure for achieving substantial cuts in GHG emissions through displacement of coal, while maximizing use of the remaining economic lives of existing power plants. The GHG emissions cuts increase in proportion to co-firing rates, and the net effect is equivalent to shutting down a similar fraction of the coal-fired power plants, and then replacing the lost capacity with dedicated biomass-fired plants. Co-firing also allows for flexible use of the biomass with reduced techno-economic risk for power producers, and enables better use of dispersed biomass resources whose quality and supply may be highly variable. Additional environmental co-benefits can also result from the combustion of crop residues under optimized conditions, such as avoided emissions of persistent organic pollutants (POPs) – i.e., dioxins and furans – from the common practice of open burning in fields [100]. Accumulation of such POPs in the environment can lead to adverse ecological and health impacts.

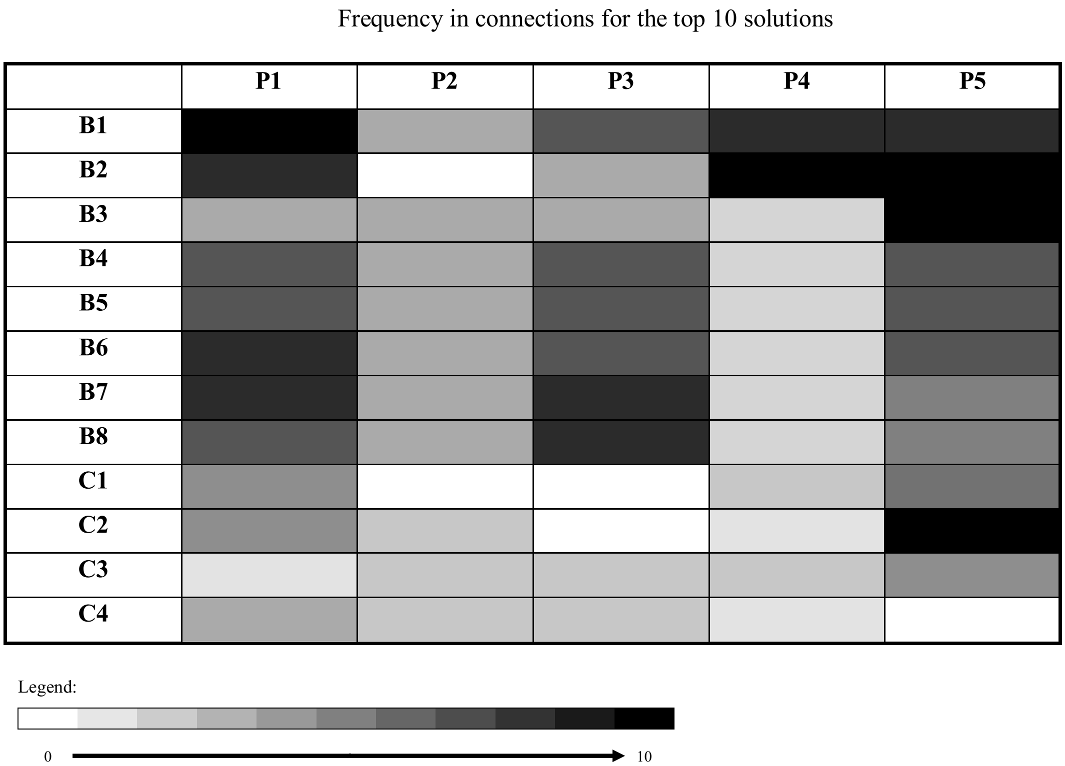
Direct co-firing of biomass reduces GHG emissions only through displacement of fossil fuel. Indirect co-firing of biomass with co-production of biochar for carbon sequestration further increases the potential to utilize biomass and cut GHG emissions. Past analysis of the total benefits of biochar-based NET systems has included carbon credits from fossil energy displacement credits, which can be achieved at a significant scale via the co-firing pathway [11]. Recent breakthroughs also present the possibility of very high co-firing rates, and even complete replacement of coal with bio-coal [44]. However, the co-production of biochar creates the logistical challenge of transporting large quantities of material from power plants to various biochar application sites. In terms of physical scale, this logistical challenge is comparable to the movement of CO_2 in CCS networks, but will rely on rail and road transport instead of pipelines as modes of transport. This additional layer in the bioenergy supply chain results in a so-called "carbon management network" (CMN) optimization problem [101]. The MILP model developed here can provide vital decision support for determining which plants to retrofit for co-firing, and whether direct or indirect co-firing options should be used. The model also accounts for biomass supply and biochar storage capacity in determining a geographically dispersed allocation network for integrated reduction of GHGs. Such features of the model provide decision-makers with better insights on the selection of technology, biomass type and network design to adopt. Results of the model for example, highlight the possibility of achieving CO_2 reduction targets without the need of retrofitting all coal-fired power plants or saturating biochar sink contamination limits. Application to a case study from the Philippines provides a representative example of how the optimization model can facilitate planning of such systems in other places, and particularly in developing countries with agriculture-intensive economies. This technique also provides an alternative NET option to bioenergy with CCS (BECCS), particularly in regions where secure and viable CO_2 storage sites are not available for geological reasons such as high seismic activity [102].

5. Conclusion

A novel FMILP model has been developed for optimizing biomass co-firing networks coupled with biochar-based CMNs for electricity decarbonization which fills a gap in NET literature. The model includes a biomass supply chain component that deals with allocation of biomass from collection points to power plants; a technology selection component that allows the choice of direct, indirect, or no co-firing; and a final component that deals with allocation of biochar from plants that use indirect co-firing to the final application sites. Furthermore, the model is able to balance the objective of reducing GHG emissions with the need to mitigate any risks that may occur from applying biochar to soil. By accounting for these factors, this model can potentially provide effective decision support for decarbonizing power generation, particularly in developing countries that still make extensive use of coal fired power plants and which have abundant biomass resources in the form of agricultural waste. While ultimately such plants will need to be phased out for full decarbonization of the power sector, direct and indirect co-firing techniques can be used to maximize reductions in GHG emissions in the interim. Results of a case study from the Philippines show that 5.9% reduction in GHG emissions can be achieved from displacing 3.8% of the coal requirements of a fleet of power plants; this multiplier effect agrees with the general prediction of Dang et al. [36]. The model developed in this work can be used as a decision support tool to optimize the allocation of biomass and biochar in such CMNs.

Future work can focus on extending the model to account for economic or social objectives. Maximizing the degree of satisfaction for environmental and social indicators while minimizing the total economic costs in the system can be considered. With the consideration of economic performance, techno-economic aspects could now be included to simulate the effects of carbon taxes or carbon trading while social indicators can reflect concerns associated with job creation or

Table 13
Frequency in connections for the top 10 solutions.



employment stability. Variable and fixed costs incurred within the supply chain as well as its impact to the roles of human capital will better illustrate tradeoffs between economic, social and environmental performance. Applying this model to specific contexts using data acquired through various methods (e.g., remote sensing, GIS) can be explored. Hybrid approaches based on PA or P-graph can also be developed. In addition, the biomass co-firing and biochar application options need to be integrated within a larger mix of various decarbonization techniques, including NETs such as enhanced weathering as well as CCS.

Credit Author Statement

Aviso, K.B.: Concept Development, Model Implementation, Case study development and analysis, Article writing and verification, Illustrations, Sy, C.L.: Concept Development, Model Implementation, Case study development and analysis, Article writing and verification, Illustrations. Tan, R.R.: Concept Development, Literature review, Model Implementation, Case study development and analysis, Article writing and verification, Illustrations, Ubando, A.T.: Literature review, Case study development and analysis, Article writing and verification, Illustrations.

Declaration of competing interest

The author declares no conflict of interest.

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