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Abstract
The targets of limiting global warming levels below 2°C or even 1.5°C set by Paris Agreement heavily rely on bioenergy with carbon capture and storage (BECCS), which can remove carbon dioxide in the atmosphere and achieve net zero greenhouse gas (GHG) emission. Biomass and coal co-firing with CCS is one of BECCS technologies, as well as a pathway to achieve low carbon transformation and upgrading through retrofitting coal power plants. However, few studies have considered co-firing ratio of biomass to coal based on each specific coal power plant's characteristic information such as location, installed capacity, resources allocation, and logistic transportation. Therefore, there is a need to understand whether it is worth retrofitting any individual coal power plant for the benefit of GHG emission reduction. It is also important to understand which power plant is suitable for retrofit and the associated co-firing ratio. In order to fulfill this gap, this paper develops a framework to solve these questions, which mainly include three steps. First, biomass resources are assessed at 1 km spatial resolution with the help of the Geography Information Science method. Second, by setting biomass collection points and linear program model, resource allocation and supply chain for each power plants are complete. Third, by assessing the life-cycle emission for each power plant. In this study, Hubei Province in China is taken as the research area and study case. The main conclusions are as follows: (a) biomass co-firing ratio for each CCS coal power plant to achieve carbon neutral is between 40% and 50%; (b) lower co-firing ratio sometimes may obtain better carbon emission reduction benefits; (c) even the same installed capacity power plants should consider...
1 | INTRODUCTION

In order to alleviate the possible impacts from climate change to the economy, ecology, and environment, the Paris Agreement sets the ambitious goal of achieving net zero emissions by the second half of this century (IPCC, 2018). This means that we not only need to reduce our current greenhouse gas (GHG) emissions, but also need to remove part of the GHG emissions that have been discharged into the atmosphere (Turner et al., 2018). The power industry is the largest CO₂ emission source in the world, and 30% of the emissions come from the coal power industry (IEA, 2019). How to achieve net zero or even negative emissions in the coal power industry has become the key to achieving net zero emissions globally. At present, on the premise of not adding huge stranded assets caused by coal phase-out, there are three technical solutions for low-carbon transformation of coal-fired power plants, namely carbon capture and storage (CCS), biomass-coal co-firing and co-firing with CCS (Fan et al., 2018; Guo & Huang, 2020; Singh & Rao, 2016; Wang & Du, 2016; Welfle et al., 2020; Wu et al., 2014). Among these technologies, only biomass-coal co-firing with CCS can actually realize the net zero emission of coal-fired power plant, which can extract carbon dioxide from atmosphere while co-firing or CCS technology can only reduce carbon emission. (Cabral et al., 2019; Larkin et al., 2018; Michailos et al., 2019; Tao et al., 2019; Zuijlen et al., 2019). Therefore, biomass-coal co-firing is the key technology to realize net zero emission and how to design an operational assessment for the deployment of biomass-coal co-firing with CCS technology in the coal-fired power industry has become an urgent problem for the scientific community.

To study how coal-fired power industry could achieve net zero emissions through co-firing with CCS, first, we need to draw a carbon emission curve for each power plant at different co-firing ratio, which can help us answer at which co-firing ratio power plants can realize net zero emission. The answer of net zero co-firing ratio can greatly help the government formulate co-firing retrofitting targets and control the process of achieving net zero emissions in the power industry. At the same time, it is of great significance to consider the life-cycle emissions of biomass-coal co-firing with CCS (Schakel et al., 2014), because additional carbon dioxide will be generated in the process of biomass collection, transportation, and pretreatment (Kumar & Sokhansanj, 2007; Kumar et al., 2006; Malladi & Sowlati, 2020; Sokhansanj et al., 2006). And it still remains unclear whether and to what extent would these additional carbon emissions impact the co-firing ratio for net zero emission target. It is also important to determine the biomass co-firing ratio for each plant, rather than the whole coal-fired power industry. As Lu et al. (2019) also mentioned that in order to better inform China’s long-term roadmap for bioenergy with carbon capture and storage (BECCS) and choose the strategies between retrofit or constructing coal-biomass power plant (CBP), plant-based evaluation is necessary. A limited number of previous studies have explored net zero co-firing ratio from life-cycle perspective based on plant-level data. These studies usually use a representative power plant as case study or make different assumptions to quantify the parameters of the power plant. Yang et al. (2019) quantified the performance parameters of different power plants and the influence of the co-firing ratio on various environmental impact categories. The result shows that co-firing ratio of 25% can achieve near-zero emission. Miedema et al. (2017) used one representative power plant to answer this question, which compared the performance of co-combustion power plant with a 100% coal supply chain scenario based on a Dutch case, and found that 60% co-firing ratio have the possibility to reduce emissions up to 48%. Nevertheless, the above-mentioned theoretical exploration or the analysis based on a representative power plant can hardly support the making of a detailed deployment plan, because coal-fired power plants have different electricity generation capacities, spatial location, and different levels of accessibility to biomass resources, which results in the difference of supply chains. If we only consider this question from theoretical perspective without combining each power plant’s real situation, there will be a large deviation from actual transformation process of the power plants. For example, some plants near the biomass resource may achieve the co-firing ratio of net zero carbon emission lower than average; a higher co-firing ratio is needed for plants far away from biomass resource to offset the higher emissions from transportation; region with a lot of power plants may have resource competition issues, so the resources nearby may not be enough for reaching an average co-firing ratio. These problems might cause the waste of biomass resources and unnecessary increase of carbon emissions, which would greatly hinder the
realization of the net zero emission goals. Therefore, to determine the co-firing ratio for net zero emission target, it is very crucial to evaluate carbon emissions from the perspective of full life cycle and consider based on real plant-by-plant data.

However, in the life-cycle and plant-by-plant assessment, there are still some parameters, such as collection area, transportation distance, needed to be determined. Also, how to allocate biomass resources or manage resources competition among multiple plants is an important topic. Most existing studies use empirical values or buffer zones to allocation resources of the power plants (Ahmadi et al., 2020; Blengini et al., 2011; Ruiz et al., 2018). There are mainly four limitations in this method: (a) buffer zones are very likely to overlap with each other, which means that the same biomass resource will be used by multiple power plants and that is not possible in reality; (b) some of the buffer zones have to be very large when the energy density of surrounding straw resource is low or the demand of power plant is large, and the power plant need to collect straws by itself from such a large area, which is not in line with the actual supply; (c) as buffer zone is a continuously expanding circle, it cannot selectively collect feedstock in certain resources-intensive places outside the circle, which results in the waste of the resources and exaggerates the collection area; (d) the buffer zone method usually uses the European distance to measure the transportation distance from the biomass resource center to the power plant, without considering the actual road distance. However, if the road network map and biomass collection points (BCPs) can be taken into consideration combined with Geography Information System (GIS) platform, the accuracy of life-cycle assessment can be improved to a greater extent (Hiloidhari et al., 2017; Kurka et al., 2012; Laasasenaho et al., 2019; Thomas et al., 2013; Yousefi et al., 2017), and the high-resolution net zero emissions analysis at the plant level can be realized (Morato et al., 2019). To our knowledge, only one study answered the co-firing question combined with real situation by integrated GIS and Mixed Integrated Linear Programming method (Mohd Idris et al., 2018). However, it only considers the optimization of pretreatment facilities for one power plant supply chain system without considering the competition relationship of multiplants. In all, most of the existing supply–demand relationship studies which use empirical value or buffer zones highly simplify the supply chain and do not conform to the actual transport process. They also reduce the high-precision advantages brought by plant-level data and would result in a non-optimal co-firing ratio for the net zero targets (Cheng et al., 2020).

Under this context, this research combines GIS with Life Cycle Assessment (LCA) method, taking road network map, BCPs, spatial distribution of biomass, and plant-based data into consideration, to investigate the net zero co-firing ratio of the power plant with CCS technology. This study can provide some key information for coal power plant retrofitting to achieve net zero or even negative carbon emission goals and provide a methodological framework for other targeted power plants to develop retrofit schemes. The specific objectives of this study are threefold:

(i) assessing the agriculture residues supply potential and their spatial distribution at 1 km resolution;
(ii) matching the biomass supply and biomass demand of each power plant through setting BCPs;
(iii) finding the net zero co-firing ratio for each power plant.

The remainder of this paper is as follows. Section 2 describes the whole study framework and the details of the methodologies. Study area, materials, and pretreatment of the data will be introduced in Section 2.6. Section 3 displays the results of this research. Section 4 discusses the policy implication, uncertainties, and limitations.

## 2 MATERIALS AND METHODS

### 2.1 Framework of the study

The framework of the study is shown in Figure 1. In order to identify the net zero co-firing ratio for each power plant, there is a need to draw a carbon emission curve in the process of 0%–100% for each power plant. This target can be divided into three subquestions and procedures. First is the assessment of the biomass production and their spatial distribution. GIS method can help distribute statistical results in space and downscale them at 1 km resolution to build a strong database for further analysis. Then allocating these biomass resources to their near power plant is the next step. The establishment of BCPs is very necessary because it can achieve many-to-many resources supply, in other words, one BCP can transport biomass feedstocks to different power plants while they receive resources from many different BCPs. Besides, we take actual road network and power plant spatial locations into consideration. In the end, we can build a supply chain for each power plant. With the completeness of supply chain for each power plant, carbon emission of each power plant can be calculated from “cradle” to “grave.” Lots of questions, such as which co-firing ratio with CCS technology can reach negative carbon emission, the influence of transportation distance on emission, and whether CCS technology is necessary, will be answered.

### 2.2 Estimation of agriculture residue potential

Agriculture residues are the portion of the crop after harvesting of the seeds and each crop has different parts that
can be used as feedstock for co-firing (Nie et al., 2020). Besides, in the process of harvesting and transportation, a certain amount of branches and leaves will be separated and remain in the field or lost during collection. Residues to product ratio (RPR) and harvest index (HI) are used for calculating the straw productions, which are listed in Table S1. After the statistics calculation, GIS method can help allocate these results to the space. During these processes, net primary production (NPP) data are used as the weight to distribute statistical data at 1 km resolution. Of special interest is that before the downscaling process, land use data need to be used as a mask for extracting NPP in different crops, as rice needs to be planted on the paddy land, and other crops are grown on the dry land. The mathematical formula is as follows:

\[
S_r = \sum_{k=1}^{n} A_k \cdot r_1 \cdot r_2, \quad (1)
\]

\[
P_{ij} = \frac{S_r \cdot npp_{ij}}{NPP_r}, \quad (2)
\]

where \(S_r\) (tonne) represents the potential of agriculture residues in region \(r\); \(A_k\) (tonne) is the crop production of \(k\) type; \(r_2\) is the residues to product ratio; \(r_1\) is the harvest index; \(P_{ij}\) (tonne) represents the crop production in pixel \((i, j)\); \(npp_{ij}\) (g/m²) represents the net primary production in pixel \((x, y)\); \(NPP_r\) (g/m²) is the sum of net primary production in region \(r\).

### 2.3 Supply chain model for biomass resources allocation

In supply chain allocation model, the research area is divided into 10 km x 10 km grid. Previous studies have considered many different sizes of collection areas (Morato et al., 2019; Sharma et al., 2013). And Huo et al. (2016) construct a straw supply model which found that the collection radius is more suitable between 6.5 and 12 km. Therefore, we choose 10 km x 10 km as the size of grid. On one hand, this size is relatively in line with the actual collection process. On the other hand, it can make the number of variable falls in a reasonable range, which ensures the solving speed of supply chain allocation model. BCPs are set up in the grid center to collect, store, and transfer straw resources. The transportation problem in operational research is used in this model to help BCPs find their target power plant and calculate the shortest transport distance and supply production. This study uses ArcGIS software to make zonal statistic of straw yield for each grid and uses network module combining with actual road network map to calculate the shortest path. The origin and destination (OD) cost matrix in ArcGIS network module can measure...
the least-cost paths along the network from multiple origins to multiple destinations, and this provides a distance matrix between the BCPs and power plant, which is used as a cost matrix to solve linear program problem.

The equations of linear program model are shown below. The objective of this model is to minimize the total emissions of the variable parts in the biomass supply chain using Equation (3), as the product of straw production and transport distance is always used as an independent unit for calculation. And there are three constrains: (a) production supply to the power plant should be greater than their demand; (b) the total supply of straw delivered to each power plant should be less than the supply capacity of the collection and storage station; (c) the straw output delivered to each power plant need to be positive. This linear program problem will be solved with the help of LINGO software. LINGO is a comprehensive tool that can build and solve linear, optimization models. It has its own modeling language, which can express the objective function and various constraints efficiently. Compared with MATLAB, the language of LINGO is closer to mathematic expression, which makes its variables to possess strong flexibility and easy to change. In our research, as we need to solve this model under different co-firing ratio, LINGO can greatly help us solve the result again with only minor adjustments and ensure the solving speed is very fast.

**Objective function**

\[
\text{Min} \sum_{i=1}^{m} \sum_{j=1}^{n} p_{ij}d_{ij},
\]

**Constrains**

\[
\sum_{i=1}^{m} p_{ij} \geq A_j \ (j = 1, 2, \ldots, n),
\]

\[
\sum_{j=1}^{n} p_{ij} \leq B_j \ (i = 1, 2, \ldots, m),
\]

\[
p_{ij} \geq 0 \ (i = 1, 2, \ldots, m; j = 1, 2, \ldots, n),
\]

where \(d_{ij}\) (km) represents the distance between BCP \(i\) and power plant \(j\); \(p_{ij}\) (tonne) represents the production that BCP \(i\) delivers to power plant \(j\); \(A_j\) (tonne) is the total production that the power plant \(j\) requires; \(B_j\) (tonne) is the production that BCP \(i\) can provide.

### 2.4 Life-cycle estimation of carbon emissions combined with each power plant’s supply chain

The scope and process considered in the calculation of carbon emissions throughout the life cycle are shown in the following Figure 2. Limited by the article length, more details of this method and calculation are shown in the Supporting Information. The emissions of coal power plant mainly happened in the processes of coal mining and processing, transport and stock, and terminal combustion. For biomass-coal power plant, we assume the carbon absorption in growth process and carbon discharge in terminal combustion offset. Thus, life-cycle emissions of these power plants mainly happen in five processes. (a) Primary transportation: pack the straw in field and use tractor to transport it to the BCP. (b) Pretreatment before storage: compress the straw into square bundle to improve its energy density. (c) Transfer and storage: use machine like grass grabber, conveyer, and so on will also generate carbon dioxide. (d) Secondary transportation: transport the straw square bundle by truck

![Figure 2](image-url)
on the road. It is noted that in this process we calculate the carbon emissions combined with the results of our supply model, which means the transportation distance of each power plant under different co-firing ratio is different, and this transportation distance is calculated based on the actual road network and the shortest path. (e) Pretreatment before co-firing: bundle straw need to be unpacked and crushed in this process. As for CBP-CCS, besides these five processes, carbon absorption rate of biomass and CCS need to be considered.

2.5 The solving process and connection of each model

Figure 3 shows the solving process and the connection between each model. First, we calculate the available straw production through parameters like RPR, and then use NPP data as a weight and allocate the statistic result into different land use space. Then, the whole area is divided into fishnet with BCPs in the center. With the help of GIS network module, OD distance matrix can be built, which contains the shortest transport distance from each potential BCP to each power plant. We take distance matrix into linear programming model and set minimum carbon emission as the objective function. At the same time, this model will be iterated for meeting the demand of different co-firing ratio. The calculated results help BCPs choose their target transport power plants, their supply production, and the shortest transport distance. These parameters can be taken into the life-cycle assessment of each power plant, which will help power plants draw a carbon emission curve at different ratio of biomass to coal from 0% to 100%.

2.6 Study area and data preprocessing

2.6.1 Study area: Hubei Province

China is the major carbon emitter in the world, which emitted 9,825.8 million tonnes in 2019, accounting for 28.8% of the global carbon emissions (Michieka et al., 2013). For China, the power industry needs to take more responsibility for the task of reducing emissions (Liu et al., 2014). The power generation of China in 2019 is 7,503.4 TWh, among which the power generated by coal is 4,853.7 TWh and it accounts for 64.7% of China's total power generation. Besides, coal-based power generation also accounts for a large proportion of global power generation. The global coal-based power generation is 9,824.1 TWh, of which China's coal power generation accounts for 49.4%. In addition, according to China's annual power industry development report, the total emission of thermal power is 4,229.0 million tonnes, which is around 43.0% of China's total emissions. Therefore, low carbon transformation and upgradation of China's power industry is urgent and necessary. At the same time, China also has great potential in biomass resources (Nie et al., 2019). If bioenergy potential can be realized to replace fossil fuels during 2020–2050, the maximum GHG emission mitigation would be 5,859.56 Mt CO₂-equivalent (Kang et al., 2020). Therefore, biomass–coal co-firing with CCS is the key solution to achieve the goal of Paris Agreement (Maamoun et al., 2020). In this study, we select Hubei Province as a case study to test the feasibility of methodology framework.

Hubei Province is located in the middle of China, the middle reaches of the Yangtze River and the north of Dongting Lake (Figure 4). It is rich in water resources and has the reputation of “the province of thousand lakes.” Because the province is located in the subtropical monsoon humid climate...
area, it has good combination of water and heat, rich solar radiation resources, and biomass energy resources. Its spatial location, administrative units and net primary productivity level are shown in Figure 3. In terms of power plant operation, the province's annual power generation in 2019 was 297.29 billion kilowatts, with an increase of 4.27% over the previous year, including 148.53 billion kWh of thermal power plants (Hubei Power Dispatching Office, 2020). In order to ensure the coordinated development of economy and environment, Hubei Province is also in an orderly layout of new energy industry in recent years. By the end of April 2019, the installed capacity of new energy in Hubei Province reached 10.05 million kilowatts, accounting for 13.16% of the installed capacity of power generation in the province, in which the installed capacity of biomass power plant was 857,200 kW (Hubei New Energy Department, 2020).

2.6.2 | Data source and preprocessing

Power plant data
The basic information about power plant is obtained from the website of IndustryAbout (https://www.industryabout.com), which contains spatial position, capacity, Owner, and so on. However, due to the slow updating process and missing data, further revision is needed through searching of news, and the final result needs to match with the value of Hubei statistics.

According to statistics of power dispatching office of Hubei Development and Reform Commission, the installed capacity of thermal power in Hubei Province was 28,842.9 MW in 2018, and the power generation capacity was 126.7 billion kWh. The total capacity of our data is 28,950 MW, which is consistent with the statistics and reflects the reliability of our data. At the same time, due to the data unavailability of operation time, this paper takes the average operation hours, which is 4,400 hr, into the following calculation.

Agriculture statistic data
The crop yield data of this study are from the statistical yearbook of Hubei 2018 (Beijing: Hubei Provincial Bureau of Statistics, 2019), which records the main crop yield of each state and city, including 13 types of main crops. From the perspective of the whole province, rice, wheat, and corn are the main food crops in Hubei Province, of which rice accounts for 60% of the production.
NPP data
With the development of remote sensing technology, the net primary productivity of ecosystem based on remote sensing observation has been widely used in ecosystem monitoring and becomes an important indicator to measure farmland productivity (Guo et al., 2009). Terra polar orbiting environment satellite with moderate resolution imaging spectroradiometer launched by NASA provides GPP and NPP products with a 1 km resolution (MOD17A3). In this study, it can be used to allocate crop statistics data to the corresponding cultivated land space.

Land use data
Based on the remote sensing monitoring data of land use in 2015 and Landsat 8 remote sensing image, Resource and Environment Data Cloud Platform (http://www.resdc.cn/default.aspx) generated the land use data in 2018 through manual visual interpretation. The data set includes six first-class types and 25 second-class types, among which paddy field and dry land in the first-class are the concerned type in this study.

Road network
The road types in this study mainly include expressway, national road, provincial road, and county road, which are shown in Figure S1. Due to the topological errors in the merging process of all kinds of road, it is necessary to check the topology before the road network is established in ArcGIS.

3 | RESULTS

3.1 | Supply-side: Available agriculture residues and their spatial distribution

Figure 5 shows the spatial distribution of the agriculture residues potential. The total crop production of Hubei Province in 2018 was 31.97 million tonnes, and the theoretical straw resources were 42.44 million tonnes. However, losses will happen in the process of actual collection. Therefore, the actual available straw resources are 33.7 million tonnes. At the same time, according to calorific value coefficient, these straws can generate 476.29 PJ energy, which can meet the demand of all power plants; in other words, these straw resources can replace all the coal required by the power plants and realize 100% direct combustion.

Figure 6 shows the straw production and energy availability for each city. Xiangyang, Huanggang, and Jingmen are the
The top three cities with the largest amount of straw production are Xiangyang, Huanggang, and Jingmen. However, due to the different size of the cities, the production density and heat density are shown in Figure 7. Under this circumstance, Tianmen, Xiantao, and Qianjiang have more biomass resources potential and are more suitable for deploying biomass–coal power plant.
3.2 The results of bioenergy resources allocation change with the dynamic process of 0%–100% co-firing ratio

Figure 8 shows the results of supply chain allocation model. Figure 8a shows the code of the power plant, which is arranged according to the install capacity from small to large. Figure 8b–h shows the BCPs selected by each power plant from the co-firing ratio of 10%–100%. These BCPs can transport biomass resources to multiple power plants and choose their shortest transport distance, which is an optimization method compared with the buffer zone. With the increase of the proportion of the blending ratio, the number of BCPs and transport distance also increase. However, different power plants have different increasing rate. Figure 9a,b show the heatmap of the BCPs’ total number and total transportation distance with the increase of co-firing ratio respectively. The plants with high capacity and located in the sparse resource will suffer from the shortage of feedstocks. Taking no. 11 and no. 17 power plants as example, it is found that the transportation distance and the number of BCPs have dramatic increase, which means the resources around them are not enough to meet their demand and they have to collect biomass resources from farther area. This phenomenon will have a great impact on their carbon emission quantity.

Besides, it should be noted that the spatial aggregation and the competition between the plants will also lead to the increase in transportation distance. Although the straw

**FIGURE 8** Supply and demand matching in the process of 0%–100% blending ratio. (a) Code for the power plant. The sequence of plant numbers also represents the size of their installed capacity. (b–k) Power plant matching with the collection and storage stations under different ratio
resources around no. 17 power plants are better than those around no. 6, the gathering of power plants nearby forced them to enlarge their transport range to get straw resources, which accounts for the increase of the number of the collection and storage stations and total transportation distance.

The total transport distance in Figure 9b can be considered as the yearly distance that power plant needs to spend on collecting biomass. In order to better understand the collection range of the power plant, we use weighted average distance as an indicator, which take biomass production as a weight and calculate the average distance from each BCP to the power plant. The histogram of weighted mean transportation distance is shown in Figure 10. The red curve represents the normal distribution curve, where the mean value 43.89 km and the SD is 29.07 km, which means around 68% transportation distance range are between the 14.82 and 72.96 km.

FIGURE 9  Heatmap of total biomass collection points (BCP) number and transportation distance of each power plant from the co-firing ratio of 0%–100% (a shows the number of BCPs selected by power plants for biomass collection under different co-firing ratios; b shows the total distance, that is the sum of these BCPs’ transport distance)

FIGURE 10  Histogram of weighted mean transport distance (the blue column is the probability of the distance and the red curve is the normal distribution curve; weighted average distance in this figure represents the average distance between the biomass collection points and the power plant)
3.3 Net zero co-firing ratio results and the carbon emission estimation of different power plants

Figure 11 draws the carbon emission curve for each power plant and this graph shows that all power plants can achieve net zero emission at the co-firing ratio between 40% and 50%. Yang et al. (2019) also have discussed this question and their result shows that the net-zero co-firing ratio is 25%. Comparing these two researches, there are still many differences. Their research pays more attention to global warming potential including N₂O, NH₃, ethylene oxide, and so on, and they choose switchgrass as half of the feedstock, which has great ability in N₂O absorption and storage. In addition, they select a 600 MW power plant as the research object and simplify the transport process, which may ignore the relationship between the power plant demand and biomass resources supply. However, from the results of our research, biomass resources competition and transportation has great influence on the carbon emissions of each power plant. With the increase of the co-firing ratio, the carbon emission curve of some power plants may show an inflection point, which can be seen from no. 11 and no. 17 power plants. In the transition from 80% to 100% co-combustion, these two carbon emission curves show an upward trend. This is because the biomass resources around them can no longer meet their demand and they have to search for biomass resources further. However, the process of long distance transportation will offset the emission reduction benefit brought by retrofit technology. Therefore, this result indicates us that rising co-firing ratio does not always mean better carbon emission reduction benefits. For these power plants, achieving 50%–60% co-firing ratio will obtain better benefits compared with 90%–100% co-firing ratio.

Additionally, we also compare the carbon emission of power plants with same installed capacity, which can help us better understand the heterogeneity of different power plants. As shown in Figure 11, for small power plants with installed capacity less than 250 MW, their total emissions are relatively small. For 700 MW power plants, no. 8 and no. 9 have better emission reduction effects. For 1,200 MW power plants and 2,400 MW power plants, no. 11 and no. 17 are obviously not suitable for retrofit as co-firing with CCS technology. Meanwhile, for power plants with installed capacity more than 3000MW, although the installed capacity of no. 21 is 640 MW larger than no. 20, no. 20 power plant shows better carbon emission reduction benefit than no. 21, which indicates the policy maker to give priority to retrofit no. 20 power plant.

Figure 12 shows a box plot of the unit carbon emission. The carbon emissions per unit of electricity generation are in the range of −410 to 220 g/kWh. With the increase of co-firing ratio, the fluctuation of unit discharge values will enlarge as there are more uncertainties in the transportation distance, which indicates that for some power plants, the resources nearby cannot meet the demand of the power plants or the resources competition forces them to collect resource in farther area.

Figure 13 shows the Hubei Province's total carbon emission reduction benefits achieved by CBP and coal-biomass
**FIGURE 12** Box plot figure of unit discharge of each power plant under different co-firing ratio

**FIGURE 13** Histogram of the carbon emission reduction benefits in Hubei Province
power plant with CCS technology (CBP-CCS). Compared with coal power plants, CBP can achieve carbon emission reduction benefits between 13 and 120 million tonnes while CBP-CCS can achieve benefits between 110 and 170 million tonnes. These results are relatively considerable as China’s coal power industry discharged 3.3 billion tonnes carbon in 2017.

4 | DISCUSSION

4.1 | Policy implication

According to the capacity of the power plant and the biomass resources nearby, different power plants may be suitable for different retrofit strategies. We use a matrix to describe the matching between the supply and demand, and select typical power plants as cases to analyze their characteristic for choosing different retrofit strategy (Figure 14). The no. 1 power plant is a typical small power plant. Even if coal is completely replaced by biomass resources and CCS technology is used, its emissions reduction benefit is very small, which is 0.2 Mt. For the no. 21 power plant with large installed capacity, until the co-firing ratio reaches 100%, the emission reduction potential of CBP barely exceeds CP-CCS. This means high proportion co-firing technology may be restricted by the relative lack of surrounding biomass resources. Therefore, CCS technology seems to be a better choice. In contrast, the no. 16 power plant is more suitable for BECCS technology, because the surrounding biomass resources are relatively sufficient to meet the needs and CCS also has a great carbon emission reduction potential and economy of scale.

Based on the analysis above, we design a simple method for power plant retrofit strategy classification and the flow-chart is shown in Figure 15. In this flowchart, $\alpha_{\text{biomass}}$ is used to describe the matching relationship between the power plants’ demand and biomass resources supply. Higher value means biomass resources are relatively rich. At the same time, $\alpha_{\text{capacity}}$ is also an important indicator for strategy making, which includes the information of power plant installed capacity and its economy of scale. The design ideas and calculation equation of these two indicators are shown in the Supporting Information.

According to the simple classification process, the detailed information and relatively suitable retrofit strategy are shown in Table S4. It can be seen that small power plants (no. 1–5) are more suitable for biomass-coal co-firing. For 700 MW power plants, no. 8 and no. 9 are more suitable for retrofitting than no. 6 and no. 7 power plants. With the increase of installed capacity, CCS technology can achieve better emission reduction benefits and economy of scale. No. 14, no. 15, and no. 16 power plants show great matching relationship between supply and demand. Therefore, they are more suitable for co-firing with CCS technology. The remaining

![Biomass potential production (supply side)](image)

**FIGURE 14** Power plants classification matrix for different retrofit strategies according to their capacity and surrounding resources (the values in each histogram graph show the carbon emissions difference between coal-based power plant and retrofitted power plant)
Large installed capacity power plants are more suitable for CCS transformation.

4.2 Discussion on the technical limitation of biomass–coal co-firing ratio

Whether the proportion of co-firing ratio can achieve 100% may be controversial. Generally, because of logistical (e.g., biomass resources supply), technical (e.g., boiler type and efficiency), economical (e.g., biomass price), and environmental (e.g., missions from sulfur and nitrogen oxides) factors, co-firing level in most commercial application is up to 5%–10% and differentiates for different boiler types and co-firing technologies (IEAGHG, 2011; Loha et al., 2020). However, from the theoretical perspective, biomass can potentially achieve more than 50% blending ratio with coal, and this co-firing ratio limitation highly relies on the type of biomass and combustion system of the boilers. Li et al. (2012) investigate the boiler performance when co-firing torrefied biomass with the aim of 100% fuel switching. The characteristic of biomass feedstock, like water content, the size of granule and so on, will greatly impact the limitation of co-firing ratio. Besides, boiler type is also different. The co-firing ratio of pulverized coal boiler is relatively lower, which is around 1%–40%. Fluidized bed boiler can achieve higher co-firing ratio and is more suitable for biomass co-combustion retrofit, especially cycle-fluidized bed, which is around 60%–95.3% (Agbor et al., 2014). In addition, this will differ if we consider the boilers’ installed capacity, machine configuration, and operating years. Therefore, this study tries to identify the net zero co-firing ratio for power plant mainly from the perspective of relationship between the biomass supply and power plant demand, and this net zero ratio can provide a basis knowledge for the transformation of the power industry.

4.3 Research limitation and uncertainties

There are three uncertainties in this framework. (a) The first uncertainty is for equipment and machine. In the life cycle of co-firing, agriculture residues would meet a series of machine, from tractor, truck, crusher to boiler. Each machine has its own type and relative parameters. Especially for boilers, which can be divided into fluidized bed combustion boiler, pulverized coal combustion boiler, packed-bed combustion boiler, and cyclone boiler, each of them have different technical features, as lack of detail information about power plants, their energy conversion efficiency, and carbon emission ratio attribute to the uncertainty. (b) As the biomass supply chain has not yet been formed, there are still many possibilities and uncertainties of the delivery system. Straw can be directly transported to the power plant without compression and packed by tractor, or with the help of mobile baler, straw can be packed in the field and transported to the plant by truck. As the demand of straw is growing with the increase in co-firing ratio, the existence of BCPs seems to be more realistic and sustainable to maintain the balance between the supply and demand, while it is only a hypothesis in this research. (c) The third uncertainty is for co-firing ratio. Different blending proportions will have different requirements for feedstock type, pretreatment way, and combustion process.
There are three major limitations of this study which will be addressed in future research. (a) Our estimation of biomass did not fully take into account the information concerning competing use of the crop residues. There are many different utilization ways of biomass-like farm fertilizers, industrial raw materials, and new energy source and so on. Which utilization method has the lowest cost, better energy, and environmental benefits is worth discussing. (b) In the supply chain allocation model, we only consider allocating the resources to meet the requirement of each power plant without consideration of the actual market economy competition and choice. In the reality, BCPs are more likely to choose their target power plant based on the profit and their partnership. (c) Transforming the power plant into the coal–biomass co-firing plant requires the upgradation of their facilities, which will cost a certain amount of money and construction time. In this study we did not consider economic factors like biomass price, investment cost, and so on, which deserve further research and help us have a clearer understanding of the carbon emission cost.

Despite these limitations, the whole framework of carbon emission assessment is relatively complete and the methodology that combined GIS and LCA is novel. By setting the BCPs and solving the supply chains, this study can draw a carbon emission curve at different co-firing ratio for each power plant, which can provide a solid suggestion for policy maker to design plant-level retrofit plan and promote the innovation technology.

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DATA AVAILABILITY STATEMENT
The data that support the findings of this study are openly available in Zenodo at http://doi.org/10.5281/zenodo.4039620, reference number 10.5281/zenodo.4039619.

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**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section.

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