

Reducing transition costs towards carbon neutrality of China's coal power plants

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The same cumulative carbon emission reduction target can correspond to multiple emission reduction pathways. This study explores how different coal power transition pathways with the same cumulative emissions reductions impact the transition costs, by assessing the dynamic transition processes for coal plants adopting multiple mitigation technologies concurrently or sequentially, such as flexibility operation, biomass and coal co-firing, carbon capture and storage, and compulsory retirement. We develop a plant-level dynamic optimization model and apply it to China's 4200+ coal plants. We find that under deep decarbonization, the majority of Chinese coal plants retrofit with multiple technologies to reduce emissions and retire naturally at lower costs while contributing to grid stability. Optimizing the pathway can potentially save over 700 billion U.S. Dollars for achieving the same target or increase cumulative emissions reduction from 30% to 50% at no additional cost. This analysis can help inform a cost-effective coal phase-out under China's carbon neutrality.

To limit global warming to well below 2 °C, it is imperative to rapidly reduce carbon emissions from existing coal-fired power plants globally¹. However, coal-dependent energy structures and significant socio-economic costs pose substantial challenges for many countries in terms of rapidly and compulsorily retiring their coal plants, particularly those with newer infrastructure^{2,3}. The final text of the 28th United Nations Climate Conference (COP28), which advocates for “transitioning away” rather than “phasing out” reflects these practical obstacles⁴. This underscores the considerable challenge of reconciling the need to address climate

change through coal phase-out with the necessity of ensuring energy security and social development.

In addition to compulsory retirement⁵, coal plants have many other options to reduce carbon emissions. These include biomass and coal co-firing (BE)^{6,7}, carbon capture and storage (CCS)^{8,9}, combining biomass and coal co-firing with CCS for negative emissions (BECCS)^{10–12}, and increasing the flexibility of coal power plants (Flex)¹³. The cost of a BE plant to reduce carbon emissions can be as low as 18 U.S. Dollars (USD, \$) per tonne if the coal plant has access to abundant biomass resources¹⁴. If electricity tariffs and other subsidy policies

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remain consistent with those for photovoltaic power, coal plants with CCS have cost advantages in most provinces in China¹⁵. The levelized cost of electricity for a BECCS plant with net-zero emissions at a 35% co-firing ratio is competitive with pulverized coal plants under a \$52 per tonne carbon price¹⁶. Flex has limited plant-level analyses but is widely discussed in current policy discourse. By adjusting generation levels responsively to match fluctuations in electricity demand, the reduced annual operation hours can effectively decrease overall carbon emissions from coal plants in the short term.

However, regarding the technology choice of coal plants, current studies primarily focus on quantifying the cost-effectiveness of one of the aforementioned technologies. They also aim to establish frameworks for deciding which coal plant should adopt a specific technology as a one-off action over time^{17,18}. This could overestimate the transition costs of coal phase-out and impede countries from raising their mitigation ambitions. In reality, compared with using simply one technology to realize carbon emission reduction targets, coal plants are more likely to make technology choices among multiple options based on their own characteristics, such as the remaining operation lifespan, the transportation and competition for biomass resources among plants, and the distance to the carbon storage site. More importantly, compared with assuming each plant taking a one-off action, the decisions made by the coal plants are typically sequential. This means that the decisions made in the previous period will influence the choices in the subsequent stage. For example, a plant that is early retired cannot achieve negative emissions through BECCS technology anymore. But a plant can adopt BE first, and further coupled with CCS in the following years. Meanwhile, the operation schedule, such as the operating hours and biomass and coal co-firing ratios, can vary in different years.

Once such a “closer-to-reality” decision-making process can be simulated at the plant level, more important questions can be raised and addressed. For example, how will emission reduction technology dynamically evolve with time for each coal plant under a country's designed carbon emission reduction pathway (CERP)? What are the differences in technology choices for coal plants across different regions? In addition to the above questions that can be analyzed under one CERP, this study also aims to explore the cumulative emission reduction target (CuER). Because limiting the rise in global temperature depends critically on managing the remaining carbon budget^{19–22}. It is important to know that one CuER can be achieved through numerous alternative CERPs with different timelines for carbon peaking, deep decarbonization (defined as an 80% reduction in carbon emissions from 2020 levels in this study), and net-zero. Therefore, identifying the CERP with the lowest transition costs for a given CuER could be the middle-ground to ensure the achievement of the Paris Agreement and allow room for countries' development.

Based on the above research gaps, this study advances the existing understanding on coal phase-out pathway design by developing a plant-level dynamic optimization model (PLATO) using a mixed integer linear programming method. PLATO enables the simulation of how coal plants make choices among multiple technologies simultaneously and sequentially under each CERP. By generating multiple CERPs for the same CuER as the model's inputs, we can explore the effectiveness of policy designs in reducing the transition costs of coal power plants. By applying PLATO to China's 4200+ coal plants as a case study, we aim to uncover opportunities for cost reduction within coal plants themselves and through effective policy design, thereby facilitating more ambitious goals for coal phase-out globally. This model can be applied to other countries once the datasets for coal plants, biomass resources, and carbon storage sites are properly provided.

We find that the majority of Chinese coal plants retrofit with different technology options and can achieve natural retirement under the power sector's deep decarbonization. Under the 50% CuER, the lowest cost CERP has the characteristics of peaking in 2030, stepping into deep de-carbonization in 2040, and postponing the 2050 net-zero

target, with a total transition cost of 1367 billion USD (price is in 2023\$; the exchange rate of Chinese yuan to U.S. Dollars applied in this study is 0.14). In this CERP, over 92.7% of coal plants can achieve natural retirement (NR). However, limiting technology options, such as excluding BE, decreases the number of NR plants to 11%, because this exclusion not only prevents coal plants from retrofitting with BE but also limits the potential combinations of other technologies over time. Among various emission reduction technologies, Flex predominates. Over 70% of installed capacity will choose Flex, with some plants coupling it with other retrofit technologies between 2025 and 2050. At the provincial level, Xinjiang, Shandong, and Inner Mongolia face the highest transition costs, totaling 107.8, 107.0, and 99.4 billion USD, respectively. The cost reductions achieved by optimizing CERPs can be substantial—it can potentially save over 700 billion USD for achieving the same target, or increase CuER from 30% to 50% at no additional costs. Additionally, sensitivity analysis shows a complementary relationship between compulsory retirement and biomass and coal co-firing technology, as one causes electricity shortage while the other provides net-zero electricity. Our study provides a model to simulate plant-level sequential decision-making processes among multiple technologies, which can effectively support the coal phase-out scenario design and enhance the feasibility of the deployment.

Results

Simulating plant-level responses to alternative emission reduction pathways

Coal power plants assessed in this study have a total installed capacity of 1376 GW, of which 988 GW have been installed by the end of 2019 (covering 95% of the total coal power capacity) and 388 GW are (expected to be) installed between 2020 and 2030 (More information about the input datasets and validation can be found in Methods and Supplementary Note 1). If these coal plants operate under business-as-usual (BAU) with a lifetime of 40 years and at today's utilization levels, the total cumulative carbon emissions between 2020 and their natural retirement are 161 GtCO₂, as shown in the black line in Fig. 1a.

We start with a 50% (around 80 Gt CO₂) cumulative carbon emissions reduction target (CuER), which is in line with keeping end-of-century global temperature change below 2 °C^{20,23,24}. The sensitivity analysis on the CuER is conducted in the fourth section of the results. To highlight the characteristics of different CERPs, we design the CERPs consisting of four carbon peak timelines (high-peak 2025, low-peak 2025, high-peak 2030, and low-peak 2030) and two carbon neutrality timelines (net-zero 2050 and post 2050 zero) for power generation based on the assumptions and modeling results from existing studies^{11,25–29}, and name these 8 CERPs according to their timeline settings. For example, a CERP labeled as “25hp-50zero” signifies the carbon emission for power generation reach a high peak in 2025 and achieve net-zero in 2050. Notably, all these CERPs correspond to the same 50% CuER, shown as the blue dashed lines in Fig. 1a. To further discuss the pace of large-scale emission reduction, we define deep decarbonization as a state where carbon emissions are reduced by 80% from the 2020 levels.

To explore how the design of CERP influences the transition process of coal plants, this study develops a recursive dynamic mixed integer linear programming model named PLATO (Method). Coal plants can reduce carbon emissions by concurrently or sequentially adopting multiple options, including compulsory retirement (CR), flexible operation (Flex), biomass and coal co-firing (BE), and CCS. Coal plants equipped with both BE and CCS technologies can be regarded as the BECCS plants. Additionally, coal plants naturally retire (NR) after reaching their designed 40-year lifetime. An NR or CR plant will not be able to choose other retrofit technologies. Moreover, coal plants should consider electricity demand from the power grid system during the large-scale integration of variable renewable energy resources. Therefore, we adopt the coal electricity scenario generated by the

power system model developed by Zhuo et al.²⁵ as electricity constraints for PLATO (Supplementary Fig. 6). Finally, the carbon emission targets from the CERP serve as the model's input every five years, and PLATO will generate the dynamic transition pathway for each coal plant based on their characteristics, previous technology choices, nearby resource potential, etc. Figure 1b illustrates this dynamic decision-making process using one hypothetical plant as an example.

The aforementioned processes demonstrate how coal plants make optimal decisions within a single CERP. To find the least-cost CERP, we compare the transition costs between different pathways. This study evaluates transition costs by comparing the Net Present Value (NPV) between the BAU scenario and the CERP scenario (calculation functions can be found in the method). This method enables us to simultaneously account for three types of costs: new investment costs, additional operational costs brought by retrofit technologies, and the stranded asset caused by early retirement. Costs that are not directly associated with coal plants are excluded, such as the investment and operation costs of renewable energy, energy storage, or transmission infrastructure.

We find that to achieve the 50% CuER, the “30lp-post50zero” CERP (Fig. 1) that achieves deep decarbonization in 2040 has the lowest transition costs among all alternative CERPs considered. The value of the transition cost of “30lp-post50zero” CERP is 1367 billion USD (Fig. 1c). Conversely, the “25hp-50zero” pathway (Fig. 1) that achieves deep decarbonization after 2045 incurs the highest transition costs at 1594 billion USD, 16.6% higher than the least-cost CERP.

Additionally, experiments on limiting technology options, such as retaining only CR or CCS technology, or removing BE from the technology portfolio, reveal that a diverse set of technologies and their inter-temporal linkages are crucial for achieving carbon emissions reduction targets, ensuring power grid stability, reducing the number of early retired coal plants, and lowering the transition costs. Leaving only CR in the technology portfolio, coal plants fail to meet electricity constraints and achieve carbon emission reduction targets at the same time. Moreover, completely relying on CCS technology results in the most expensive pathway, leading to a 5.6-fold increase in overall costs. To further explore the impact of negative carbon emission technology on the transition costs, we exclude BE from the technology portfolio to

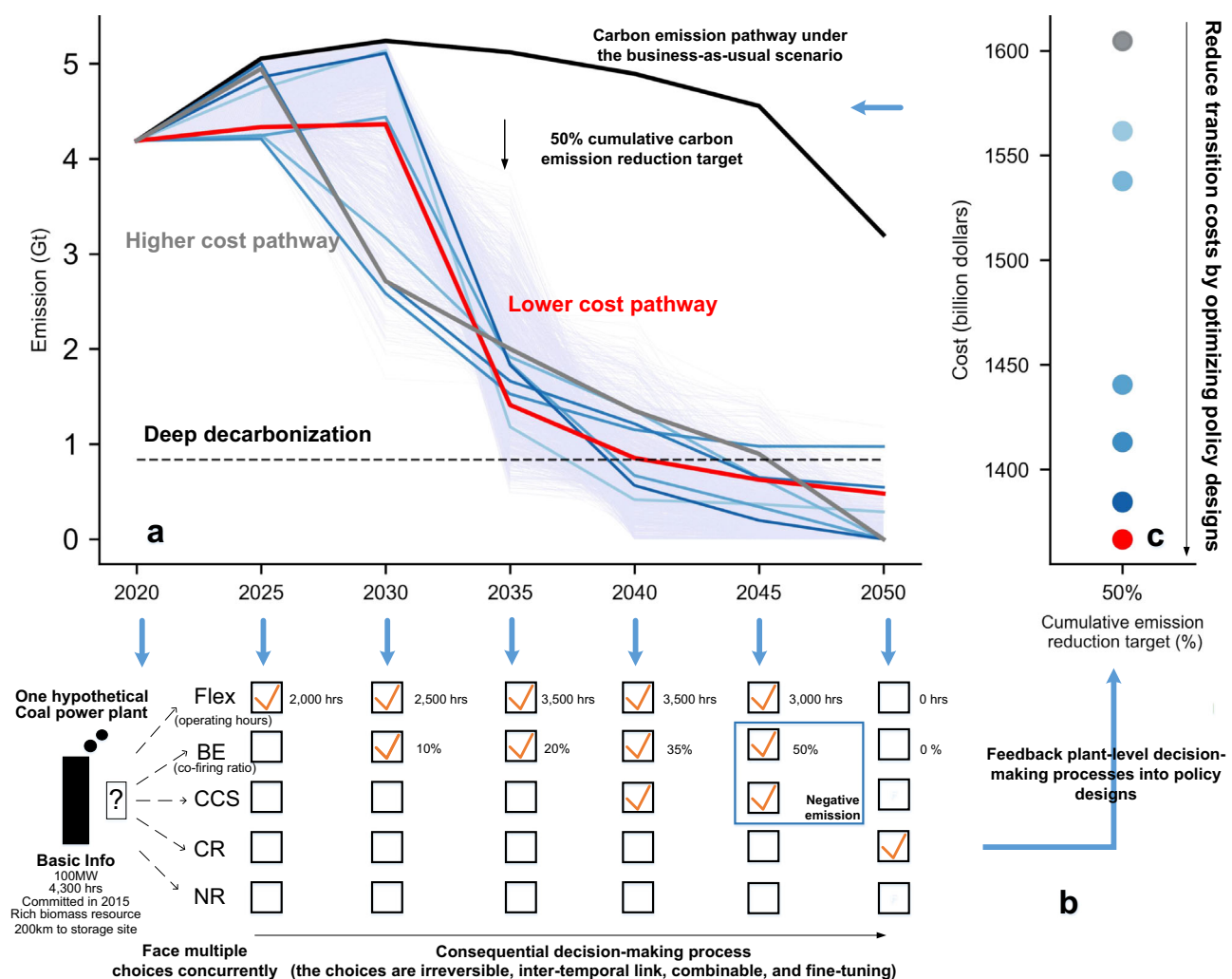


Fig. 1 | Plant-level dynamic decision-making process under the national carbon emission reduction pathways and the associated transition costs. a Alternative carbon emission reduction pathways (CERPs) under the 50% cumulative emission reduction target (these CERPs are the combination of four carbon peaks and two net-zero timelines; the carbon emission pathway under the business-as-usual scenario represents a situation where all coal plants do not adopt any emission reduction options until their natural retirement; the line colors in (a) correspond to the dot colors in (c); deep decarbonization refers to an 80% reduction in carbon emissions from 2020 levels). **b** The dynamic decision-making process for a

hypothetical coal plant on a five-year interval, where it can opt for flexibility operation (Flex), biomass and coal co-firing technology (BE), carbon capture and storage technology (CCS), or choose early retirement (CR). A coal plant reaching 40 years of age will be naturally retired (NR). If a coal plant adopts both BE and CCS, it can achieve negative emissions depending on its co-firing ratio choice. A BE plant can adjust its co-firing ratio in each decision-making year. A Flex plant can adjust its operation hours as required. **c** Transition costs associated with the alternative CERPs.

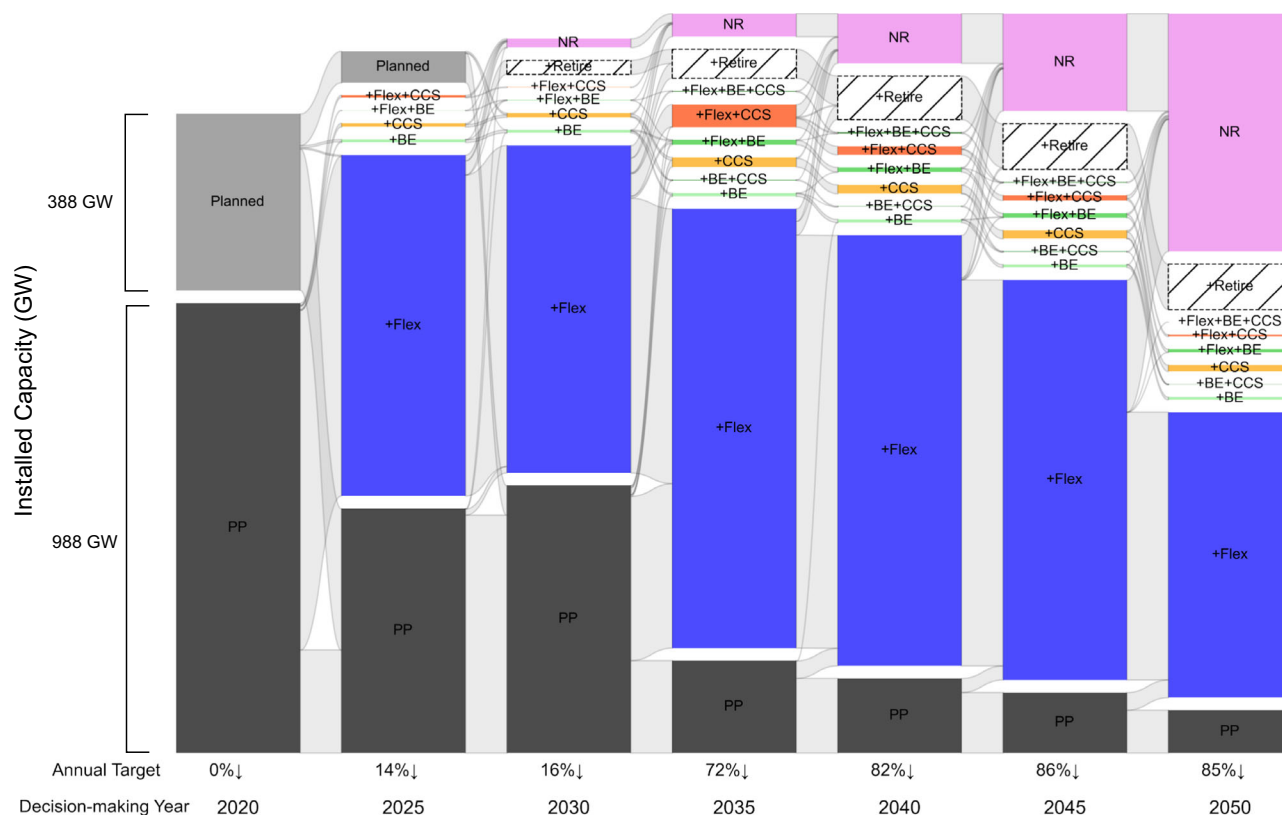


Fig. 2 | Sankey diagram that aggregates the dynamic transition pathways of coal power plants under the “30lp-post50zero” carbon emission reduction pathway. The numbers at the bottom of the graph refer to the emission reduction rate announced by the country in each decision-making year. PP, Planned, and NR

represent continued operation, scheduled for commissioning, and natural retirement. +Flex, +BE, +CCS, +Retire represent flexibility operation, retrofitted with biomass and coal co-firing technologies, coupled with carbon capture and storage technologies, and compulsory retirement).

prevent the appearance of BECCS. This exclusion not only prevents coal plants from retrofitting with BE but also limits the sequential combinations of BE with other technologies. For example, it eliminates opportunities like retrofitting with CCS before or after BE (+BE + CCS), retrofitting with Flex before or after BE (+Flex+BE), and various combinations of Flex, BE, and CCS at different decision-making stages. Consequently, 89% of the total coal plants retire earlier, including those adopting retrofit technologies before CR. This also leads to a 32% increase in costs compared to the original least-cost CERP, which has only 7.3% of early retired coal plants.

To assess the transition strategies adopted by individual coal plants, the following analyses will concentrate on the plant-level and provincial-level results of the “30lp-post50zero” CERP with multiple technologies. The parameter uncertainty for various emission reduction technologies will be discussed in the last section of the results.

Plant-level dynamic transition pathways

Our model can provide cost-effective emission reduction strategies for each coal plant at a five-year interval subject to the constraints of CERP. Consequently, each coal plant has its tailored-made dynamic transition pathways. To illustrate this, we take the “30lp-post50zero” CERP as an example. A Sankey graph is created to show the aggregated dynamic transition results of China’s 4200+ plants, depicting the technology flow between different years (Fig. 2).

Under the “30lp-post50zero” CERP, Flex predominates among various mitigation technologies. From 2025 to 2050, the installed capacity with Flex accounts for 45–70% of the total installed capacity, while BE, CCS, and BECCS account for 0.45–0.54%, 0.58–1.56%, and 0.08–0.13%, respectively. Moreover,

some plants will adopt multiple retrofit technologies, such as combining Flex with BE or CCS, or implementing all retrofit technologies (Flex+BECCS). However, these combined retrofit plants are estimated to constitute only 0.16–4.6% of the total installed capacity. Under this pathway, rapid changes occur between 2030 and 2035, where the majority of coal plants remain in operation with numerous emission reduction technologies being adopted during this period. Additionally, CR is another cost-effective mitigation strategy. The proportion of installed capacity opting for CR is estimated to reach 7% of the total after 2045.

To further explore the characteristics of each plant’s dynamic transition pathway, we roughly divide the plant-level pathways into four categories based on whether to adopt retrofit technologies and whether to retire early, named Retrofit-CR, onlyCR, Retrofit-NR, and NR. In this selected “30lp-post50zero” CERP, no plants are found to CR without taking any retrofit strategy (onlyCR). 3901 plants take at least one retrofit strategy before natural retirement (Retrofit-NR), 266 plants retrofit and then retire early (Retrofit-CR), and 87 plants naturally retire without retrofitting (NR). Among the Retrofit-NR plants, 3223 power plants adopt Flex alone, accounting for 75.8% of all coal plants. Another 534 plants couple Flex with other retrofitting technologies, making the share of plants that adopt Flex reach 88.3%. The remaining 53, 67, and 24 coal plants reduce emissions through BE, CCS, and BECCS, respectively. Among the Retrofit-CR plants, 260 plants adopt Flex before CR, and six plants adopt Flex coupled with CCS before CR. In this low-carbon transition process, 87 plants achieve NR without implementing any emission reduction technologies. These plants have relatively large installed capacities, with an average of 1085 MW.

Although no plants choose onlyCR under the “30lp-post50zero” CERP, it is adopted under other CERPs with the net-zero target. Specifically, 18 plants (20.9 GW) choose onlyCR under “25hp-50zero”, four plants (3.3 GW) under “25lp-50zero”, and one plant (0.7 GW) under “30lp-50zero”, which contributes to the increased transition costs. Furthermore, by comparing plant-level pathways across different CERPs, we find that the number of plants that can retire naturally without retrofits remains small, even if the net-zero target is postponed beyond 2050. Less than 3.8% of plants can achieve NR without any retrofits under “30hp-post50zero”, “30lp-post50zero”, “25hp-post50zero”, and “25lp-post50zero” CERP. This proportion will decrease to 0.21% under the CERPs with a 2050 net-zero target.

Transition costs and technology adoptions vary across provinces

Under the “30lp-post50zero” CERP, Xinjiang, Shandong, and Inner Mongolia have the highest transition costs, totaling 108, 107, and 99.4 billion USD, respectively. Considering the other 7 CERPs, their transition costs range from 94.4 to 138 billion USD, 105 to 144 billion USD, and 99.4 to 140 billion USD, respectively. However, these three provinces face different challenges in their low-carbon transition processes. Xinjiang, for example, has a substantial number of young coal plants and under-construction coal plants. As of 2020, the average age of coal plants in Xinjiang is only 9.5 years old, ranking lowest nationwide. Additionally, between 2020 and 2030, it is projected that 45 coal plants with a combined installed capacity of 30.8 GW will be commissioned. Shandong, on the other hand, is the province with the largest number of coal plants. As of 2020, the number of coal plants reaches 630, which is 1.7 times the number of the second-largest number province, Jiangsu. Furthermore, 58 coal plants with a total installed capacity of 34.1 GW are expected to be commissioned after 2020. In contrast, although Inner Mongolia has fewer coal plants, about two-fifths of the number in Shandong, it has the largest installed capacity in the country, totaling 116 GW, with 75.7 GW built before 2020 and an additional 40.5 GW added afterward (Supplementary Table 2).

We find that the adopted emission reduction technologies vary largely across provinces, due to differences in installed capacity, plant size, commissioning years, biomass resources, proximity to the carbon storage area, and so on. Figure 3 illustrates the composition of different technologies in each province from 2020 to 2050.

Flex is a key emission reduction technology, with the largest capacity deployment occurring in 2035, reaching a total of 1028 GW (including “+Flex+BE”, “+Flex+CCS”, and “+Flex+BE+CCS”). Leading this deployment are Xinjiang, Inner Mongolia, and Shandong, totaling 68.5, 58.2, and 55.3 GW and accounting for 87.2%, 83.0%, and 76.1% of their respective provincial installed capacity.

Similarly, the peak for installed capacity with BE technology (including “+BE”, “+BE+CCS”, “+Flex+BE”) and CCS technology (including “+CCS”, “+Flex+CCS”, “+BE+CCS”) also appears in 2035, with capacities totaling 22.9 GW and 75.5 GW, respectively. Zhejiang, Fujian, and Inner Mongolia have the largest installed capacity with BE, totaling 6.5 (11.2% of Zhejiang’s installed capacity), 3.4 (8.9%), and 3.0 (2.6%) GW, respectively. Noteworthy is Hainan’s significant adoption of BE technology, representing 12.7% of its total capacity. This can be attributed to the increased costs of CCS caused by long-distance transportation, making CCS less economically competitive.

Regarding CCS technology, Henan, Xinjiang, and Zhejiang lead with capacities totaling 7.1, 7.1, and 7.0 GW. Their proximity to CCS storage areas can be one of the important reasons. The coal plants in Xinjiang, Henan, and Zhejiang can transport their captured carbon emission to their nearest on-shore saline basin, including the Tarim Basin, Bohai Bay Basin, and Subei-Southern South Yellow Sea Basin, respectively.

The installed capacity of CR plants peaks in 2045, totaling 99.8 GW. Henan, Hebei, and Hubei have the largest CR installed capacity, totaling 27.9 (35.1% of Henan’s total installed capacity), 27.4 (45.4%), and 13.5 GW (31.0%), respectively. Additionally, 522 GW of the installed capacity will be naturally retired in 2050, with Jiangsu, Shandong, and Inner Mongolia leading in installed capacity, totaling 51.6 (52.2% of Jiangsu’s installed capacity), 47.9 (41.8%), and 45.8 (39.4%) GW. While Yunnan, Jilin, and Tianjin have higher shares of NR capacity in the province, reaching 75.1%, 69.1%, and 66.8% in 2050, respectively.

Seizing the time window for reducing transition costs

The scenarios in the ADVANCE database show that, for achieving 1.5 °C or 2 °C, the CuER for the remaining fossil fuel in the power sector can range from 30% to 70%^{20,24}, suggesting there is uncertainty regarding the CuER for the power sector. To explore how the timeline of emission reduction of the optimal CERP is affected by different CuER stringencies, we assess five different CuER levels ranging from 30% to 70%, with an interval of 10%, including the central scenario of 50%. The optimal pathways for different CuERs are shown in Fig. 4.

Our results show that carefully designing the CERP and seizing the time window is important to reduce the transition costs. The scatters in Fig. 4a reveal substantial opportunities for lowering transition costs to achieve the same CuER or even larger CuER. When achieving the same CuER between 30% and 70%, taking different CERPs assessed here can save transition costs by 238 billion to 708 billion USD (Fig. 4a). Overall, delivering larger CuER tends to cost more. However, we find that the least efficient CERP to achieve 30% CuER costs more than all CERPs assessed under 40% CuER and most CERPs assessed under 50% CuER (Fig. 4a). In other words, optimizing CERP may increase CuER from 30% to 50% at no additional costs.

Additionally, by comparing the least effective and the optimal CERPs assessed (Fig. 4b), we find that all the optimal CERPs will intersect with the least effective CERPs between 2030 and 2040. After the intersection, the optimal CERPs are consistently positioned below. This implies that the emission reduction effort during the middle phase is pivotal in reducing the transition costs. The frequently discussed peak and net-zero timing seems to be less significant compared to this timeline. For instance, under a 30% CuER, the optimal CERP does not necessitate advancing its carbon peaking time to 2025 or achieving net-zero in 2050. But its emission reduction target of 55% in 2040 surpasses the 30% target of the least effective CERP. Similarly, by setting the carbon emission reduction target at 57% and 67% in 2035 and 2040 respectively, the optimal CERP under the 40% CuER does not need to achieve net-zero or even deep decarbonization in 2050. However, if the country wants to increase its mitigation ambition, with the CuER larger than 50%, the coal power sector must enter the stage of deep decarbonization. With the ambitions increasing, the time to enter deep decarbonization needs to be advanced. For instance, under the 50% CuER, deep decarbonization should start in 2040, accompanied by a strengthened emission reduction target of 57% in 2035 compared to the 26% of the least effective CERP. Pursuing a 60% CuER requires even earlier action, with deep decarbonization targeted for 2037. Notably, for the 70% CuER, postponing the carbon peaking time to 2030 will prevent the sector from achieving this CuER target. Thus, 2025 must be set as the carbon peaking time. Despite this, the optimal CERP indicates that the carbon emission in the carbon peaking time can be relatively high, but the coal plants need to prepare for the deep decarbonization coming in 2030.

Parameters changes impact transition costs by reshaping plant-level pathways

Many factors will influence the low carbon transition of the coal power plants. For example, technology improvement will lead to the cost

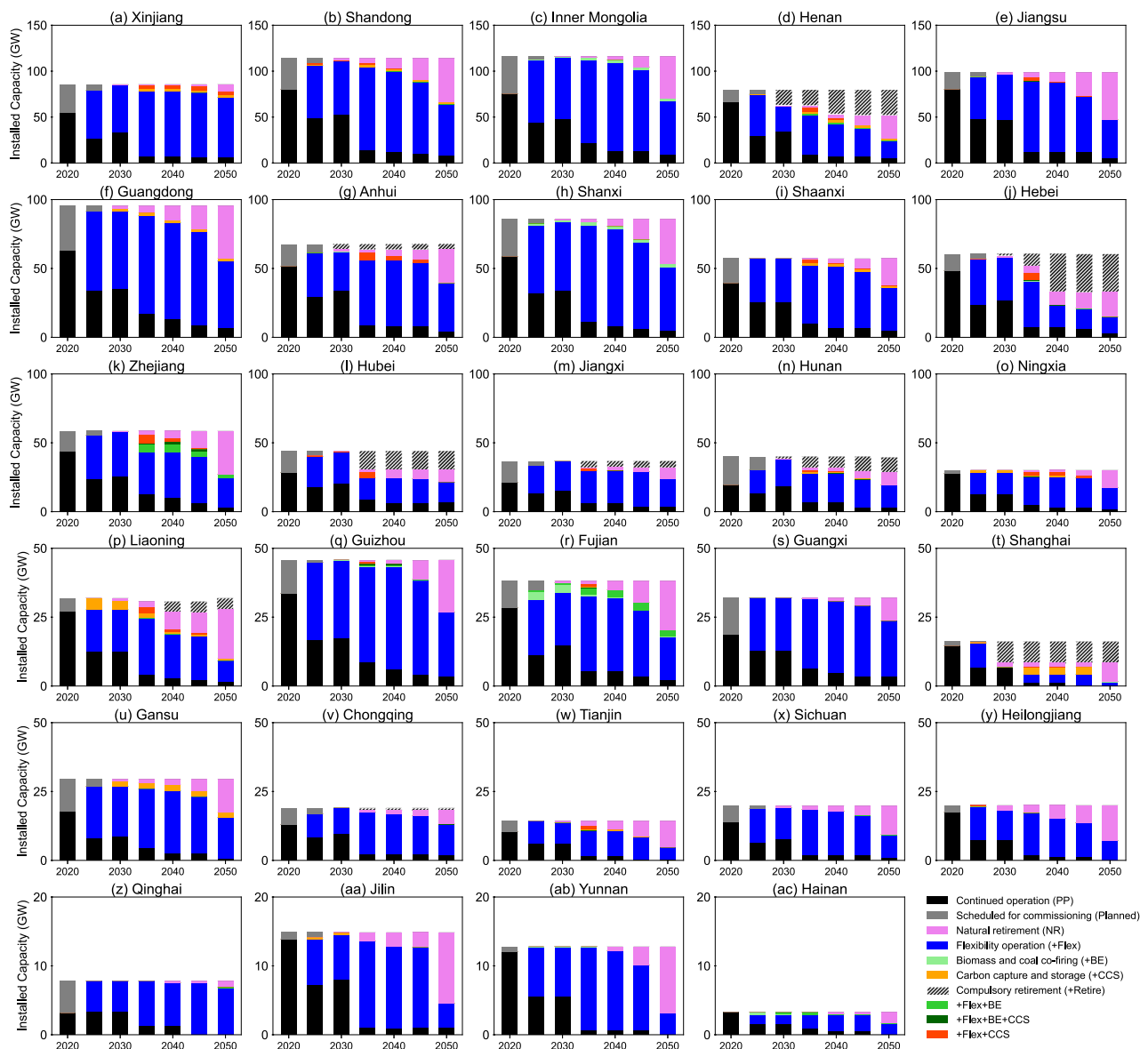


Fig. 3 | Provincial transition costs and technology adoption. a–ac Show the installed capacity of each type of emission reduction technology from 2020 to 2050 for each province. Beijing and Tibet do not have coal power plants. The panels are arranged in descending order of transition costs, from highest to lowest.

reduction of BE, CCS, and Flex. The transition of the power system can induce fluctuations in electricity prices. Additionally, the parameter setting of the model itself, including the discount rate and other parameters associated with coal power plants, also have uncertainties. Ensuring the accuracy of all parameters and the reliability of the results pose challenges. Nevertheless, conducting sensitivity analysis and comparing these results enable the observation of the possible impact of these parameters. Through the literature review, we gather the maximum and minimum values for the key variables, including electricity prices, discount rates, and parameters related to coal power plants, BE, CCS, and Flex technologies (Supplementary Table 3). By changing these parameters, we resolve the model under the same “30lp-post50zero” CERP.

The setting of these parameters not only directly influences the calculation of transition costs but also reshapes the dynamic transition pathways of coal power plants. First, increases in investment and operation and maintenance costs of coal power plants dampen the adoption of CR. In comparison to the original results, the installed capacities of CR decrease from 99.8 GW to 70.0 GW, accompanied by an increase in transition costs from 1367 to 1797 billion USD.

Second, cost reduction in BE will enhance the adoption not only of this technology but also of CR, given their complementary relationship in electricity generation. Unlike CCS, BE can act as an energy provider, furnishing net-zero electricity to power plants and even increasing the operation hours, thereby reducing the system’s reliance on CCS, and resulting in a decrease in transition costs to 47.1 billion USD. Therefore, the increased adoption of CCS due to cost reduction exerts a counteracting effect on BE and CR.

Third, CCS also competes with Flex. In the condition where CCS costs are substantially reduced, the installed capacity of CCS surges from 75.5 GW to 1091 GW, while the installed capacity of Flex decreases from 1028 GW to 286 GW, exerting a more pronounced effect compared to the situation of increased Flex cost.

Fourth, the discount rate is used to convert future cash flows into their present value. Increasing the discount rate from 5% to 8% will reduce the transition costs by 43%. Conversely, a lower discount rate of 3%, which reflects a higher value of future currency, will increase the transition costs to 2343 billion USD (Supplementary Fig. 7).

Overall, across all sensitivities tested, the installed capacity related to BE ranges from 0.8% to 57.2%, CCS from 1.3% to 79.3%, Flex from

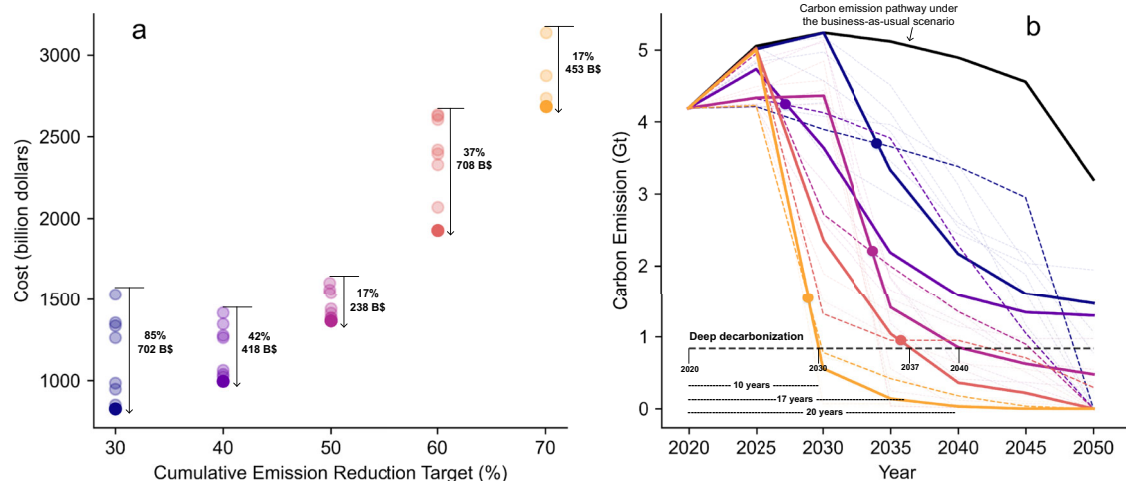


Fig. 4 | The optimal carbon emission reduction pathways for varying cumulative carbon emission reduction targets. a The transition costs under different cumulative carbon emission reduction targets (CuER). **b** The optimal carbon emission reduction pathways (CERPs) for varying CuERs (the solid and the dashed

lines represent the optimal and the least effective CERPs, respectively; the line colors in (b) correspond to the dots' colors in (a); deep decarbonization in this study refers to an 80% reduction in carbon emissions from 2020 levels).

20.8% to 78.6%, CR from 0% to 22.3%, and NR from 33.6% to 42.2% of the total installed capacity, respectively (the number refers to the largest share of the corresponding technology from 2020 to 2050). The share of NR remains relatively stable. Flex dominates the share, except in conditions with minimal CCS costs, stabilizing at $72.8\% \pm 5.8\%$. The uncertainty ranges of transition costs span from 3.45% to 17.14% (Supplementary Table 4).

Discussion

This study develops a plant-level optimization model to simulate the dynamic transition process of coal power plants and calculate the transition costs. The contribution of this study lies in demonstrating a more realistic situation in which multiple technologies, including Flex, BE, CCS, CR, and NR, are adopted by a plant concurrently or sequentially. This diverse set of technologies and their intertemporal linkages reveal the opportunities to reduce the transition costs, ensure power grid stability, and reduce the number of early retired coal plants. By conducting uncertainty analysis on CERPs and economic parameters, we can observe how CERP design and the parameter changes reshape plant-level transition pathways, consequently impacting transition costs. Additionally, this plant-level optimization model can provide higher spatial resolution results and more specific policy suggestions, for example, the technology choices for each coal plant at every time step, the corresponding supply chain, cost-effective operation hours, and more. The aggregated results can also reveal the different transition pathways at the provincial level.

Nevertheless, this model also has its limitations and several unanswered questions deserve further exploration. First, beyond the technologies discussed in this study, other mitigation options such as onsite solar PV installation and the improvement of power generation efficiency can also contribute to reducing carbon emissions from coal plants. Implementing these strategies could bring more opportunities for coal plants to lower transition costs. Second, the operating hours of the coal plants could be influenced by multiple factors. For instance, the development and deployment of renewable energy and gas-fired power plants could impact coal plants' operating hours through the power dispatch system^{13,25,30,31}. Moreover, political factors and market management mechanisms, such as carbon pricing in the carbon market, subsidies in the auxiliary peaking markets, adjustments to benchmark electricity prices, international

coal trade, etc., could also affect coal plants' profitability and, consequently, their operating hours. Addressing these considerations may require multidisciplinary model coupling work in the future. Third, as China's coal plants are state-owned enterprises, except for cost optimal principle, many other dimensions, such as livelihood, employment, and air pollution, may also play an important role in decision-making. However, incorporating these dimensions into plant-level optimization model still requires more quantitative support. Alternatively, the model outputs could serve as inputs for multidimensional impact analyses, helping decision-makers weigh trade-offs and compare coal phase-out pathways from broader perspectives. Last but not least, the simplicity of the model and fast solving speed is also important. Given the rapid advancements in mitigation technologies and the dynamic changes in the global environment and economy, policymakers often require more intuitive results and faster responses.

But what can be expected from here is that taking plant-level characteristics and their dynamic decision-making processes into account is crucial for the pathway design toward carbon neutrality. To further promote the achievement of the Paris Climate Agreement, the PLATO should be an important research direction in the future, which can prove the feasibility of the scenarios generated by the Integrated Assessment Models, identify a lower-cost alternative pathway, boost parties' ambitions and confidences, and provide a more specific plan and map for government to take actions in advance. Furthermore, more carefully designed compensation mechanisms and market instruments are also needed to ensure just transitions across different regions.

Methods

Coal power plants dataset

The coal power dataset can be divided into two parts. The first part encompasses the existing coal plants built before 2020. This part of the data is constructed by merging, de-duplicating, and cross-correcting multiple open databases and part of non-public data sources, such as the World Electric Power Plant Database, Global Coal Plant Tracker, and List of Desulfurization and Denitrification Units acquired from the Ministry of Environmental Protection, etc.^{32–34}. It includes information on installed capacity, operating hours, unit type, commissioning year, spatial location, and coal consumption per unit of electricity. By the end of 2019, the installed capacity of this dataset

reaches 988.1 GW, covering 95% of the national installed capacity. The second part, consisting of newly built and planned coal plants after 2020, is sourced from Global Coal Plant Trackers, as it is timely and rich in detail. The coal plants that are tagged with construction and operation are included in the study. Considering the 40-year designed lifetime and the natural retirement of some coal plants, the installed capacity of our dataset in 2025 and 2030 reaches 1218 and 1360 GW, respectively. These figures are acceptable by comparing with the prediction of the China Electricity Council, which anticipates that China's installed capacity will reach 1230 and 1260 GW in 2025 and 2030, respectively. More details can be found in Supplementary Note 1.

Biomass resource dataset

This study serves the 1 km resolution maps of agricultural residues and forestry residues as the model's inputs. The assessment of agricultural residues considers 9 types of agricultural products, including maize, canola, wheat, peanuts, other grain, soybeans, cotton, and potatoes. The assessment of the forestry residues consists of the residues from wood exploitation and process (including commercial wood, fuel wood, and logs), bamboo exploitation and process, and forest logging (including fuel forest, timber forest, protection forest, economic forest, special forest, shrub forest, and sparse forest). The total amount of biomass resource potential is 17.9 EJ (0.61 billion tonne of coal equivalent). This dataset is produced by Wang et al.³⁵ and is publicly available.

Carbon storage dataset

This study takes the onshore saline basin as the carbon storage area, with a total carbon dioxide storage capacity of 2317 Gt, accounting for 94.6% of the total storage potential³⁶. China's deep saline basins are distributed in the Tarim Basin, Bohai Bay Basin, Songliao Basin, Ordos Basin, etc. The spatial distribution map of carbon storage capacity can be found in Supplementary Fig. 3. To represent the transportation distance from coal plants to carbon storage areas, given the absence of carbon transportation pipelines, we simplify the process by computing the Euclidean distances between coal plants and their nearest carbon storage sites, and then multiplying this distance by the tortuosity factors^{8,37,38}.

Carbon emission reduction pathways (CERP)

China has set the targets to reach a carbon emissions peak before 2030 and achieve net-zero before 2060 for the entire economy and society. Given that the power sector is easier to achieve carbon neutrality, this study assumes that coal plants will reach a carbon peak in 2025 and 2030, and achieve net-zero in 2050 or later. Furthermore, as there is widespread discussion regarding the carbon emission levels at the time of peaking, we categorize the peak into high peak and low peak. By combining these four carbon peaking timelines (high peak in 2025, low peak in 2025, high peak in 2030, and low peak in 2030) with two net-zero timelines (net-zero in 2050 or post 2050 net-zero time), we can obtain 8 CERPs labeled as “25hp-50zero”, “25lp-50zero”, “30hp-50zero”, “30lp-50zero”, “25hp-post50zero”, “25lp-post50zero”, “30hp-post50zero”, and “30lp-post50zero”. To simulate different curve types of CERPs under each CuER, we employ the Monte Carlo method. More details about the simulation methods can be found in Supplementary Method 1. The simulation results and the representative CERPs under different CuERs can be found in Supplementary Fig. 4. The comparisons of these CERPs with current scenarios documented in the IPCC AR6 database can be found in Supplementary Fig. 5.

Cumulative carbon emission reduction target (CuER)

The cumulative carbon emission reduction target represents the differences of the cumulative carbon emission amounts between

the CERP and the business-as-usual scenario (BAU). Under the BAU scenario, the committed carbon emission amount of these 4200+ coal plants from 2020 to 2050 will reach 161.2 Gt. As there is no consensus on the cumulative carbon emission reduction target (CuER), we investigate the coal power scenarios in the ADVANCE database^{20,24} and find the cumulative emission reduction amount could range from 30% to 70%. Therefore, we set the CuER targets within the range of 30%–70%, and perform sensitivity analysis with 10% as a step.

Plant-level dynamic optimization model (PLATO)

PLATO is a recursive dynamic decision-making model built on mixed integer linear programming functions³⁹. It has four distinguishing characteristics. First, coal plants can achieve emission reduction through a variety of low-carbon transformation technologies, including biomass and coal co-firing (BE), CCS, flexibility operation (Flex), compulsory retirement (CR), choosing to remain as coal power plants (PP) or achieve natural retirement (NR). If the coal power plant has been retrofitted with BE and CCS technology, it can be regarded as a BECCS plant. Second, the decisions made by a plant during the previous period will influence its choices in the subsequent decision-making years. For example, a plant equipped with CCS can consistently capture carbon emissions from its retrofit year and can be further upgraded to a BECCS plant by retrofitting with BE technology. Third, this model addresses the resource competition issues among different coal plants. The biomass and coal co-firing ratio can vary among plants, depending on the mitigation requirement of the coal plant, the nearby biomass supply amount, and the competitiveness of the neighboring coal power plants. Fourth, the operating hours for each plant are designed as continuous variables, which means once a coal plant is retrofitted with Flex, its operation hours become flexible and will be determined by the model in each decision-making year. Moreover, to ensure that coal plants can reliably supply the necessary stable electricity amidst the integration of large-scale variable renewable energy sources, we also incorporate the scenarios generated by the power system as constraints. More details and mathematical functions can be found in Supplementary Method 2.

Objective function

The objective function is to maximize the NPV of the coal plants from commissioning to retirement described in Eq. (1). The calculation of the NPV includes revenues and costs. Revenues depend on the installed capacity, operating hours, and the electricity price. The costs depend on the investment cost, operation and maintenance (OM) costs, fuel costs, and depreciation costs. If a coal plant chooses the k th retrofit technology in year l , it will cause changes in investment costs, OM costs, and depreciation costs. The fuel costs will also change, depending on the quantities of coal and biomass purchased, as well as the actual amount of electricity generated.

$$\max \sum_j \left\{ \sum_l \left(\frac{I_j \cdot H_j \cdot f_{j,l} \cdot P}{(1+r)^l} \right) - \sum_l \left[\frac{Inv_{j,l}(y_{j,k,l}) + OM_{j,l}(y_{j,k,l}) + Fuel_{j,l}(x_{i,j,l}, f_{j,l}, Dis_{i,j}, Dis_{j,s}, H_j, l_j) - Depr_{j,l}}{(1+r)^l} \right] \right\} \quad (1)$$

where, I_j represents the install capacity of coal plant j ; H_j represents the operating hours of the j th coal plant; $f_{j,l}$ represents the rate of change in current operating hours of coal plant j in year l ; $y_{j,k,l}$ represents whether coal plant j chooses mitigation technology k in year l , which is a binary decision variable; $x_{i,j,l}$ represents the amount of biomass resources transported from biomass collection point (BCP) i to coal plant j in year l ; $Dis_{i,j}$ represents the distance between BCP i and coal plant j ; $Dis_{j,s}$ represents the distance between coal plant j and

carbon storage site s ; P represents electricity price; $Inv_{j,l}$, $OM_{j,l}$, $Fuel_{j,l}$, $Depr_{j,l}$ represent the calculation function of investment costs, OM costs, fuel costs, and depreciation costs; r represents the discount rate.

Key constraints

The mathematical formulations of the constraints are provided in Supplementary Method 2. Here, we present the underlying principles of these constraints. They can be categorized into five perspectives.

First, the model incorporates constraints related to biomass resource supply. We upscale the 1 km resolution biomass resource dataset to 20 km × 20 km grid cells and set the center of each grid cell as a potential biomass resource collection point (BCP). The total amount of biomass resources in each grid cell represents the BCP's supply capacity. Each BCP can provide biomass resources to multiple coal plants but their supply cannot exceed their capacity. In addition,

$$NPV_{CERP} = \sum_j \sum_l^{\text{retire year}} \frac{I_j * H_j * P * f_{j,l} - (Inv_{j,l}(y_{j,k,l}) + OM_{j,l}(y_{j,k,l}) + \sum_i Fuel_{j,l}(x_{i,j,l}, f_{j,l}, Dis_{i,j,l}, Dis_{j,s,l}, H_j, I_j) - Depr_{j,l})}{(1+r)^l} \quad (4)$$

this model also imposes a 200 km constraint on the biomass resource collection radius for each power plant, based on field investigations and existing literature^{6,40,41}. These constraints help limit excessive biomass inputs while enhancing the model's solving speed.

Second, the model includes the constraints of coal plants' demand. For example, coal power plants should not take biomass resources that exceed their power generation demand. This demand is determined by the installed capacity and the actual operating hours. If a coal plant is retrofitted with Flex, its actual operating hours will change, which will consequently influence its consumption of biomass resources.

The third type of constraints come from the national total target. We assume the country will update its carbon emission reduction target every five years, following a similar approach to China's five-year plan. The total carbon emission from coal plants should be smaller than the national target.

Fourth, as the low-carbon transition of coal plants should not compromise energy security or the stability of the power system, it is essential for coal plants to provide a reliable and stable electricity supply. Therefore, we collect a provincial coal power scenario from a power system model (GTEP) developed by Zhou et al.²⁵ as constraints, which considers daily power system dispatch at the micro level, the expansion of renewable energy, and the long-term technology cost changes.

The final class of constraints is crucial for enabling the model to consider the characteristics of different technologies. For instance, a coal plant can reduce its operating hours only by retrofitting with Flex technology, and these hours should not drop below 1500. Biomass resources can only be purchased if a coal plant choose BE retrofit technology. Furthermore, the technology choices made by each coal plant in previous decision-making years will influence their options in subsequent years. Each coal plant can only choose BE, CCS, Flex, or CR less than once in its life. Additionally, an early retired coal plant cannot choose any other retrofit technology.

Transformation cost of the coal power sector

NPV is a financial metric used to evaluate the profitability of an investment. Many studies use the NPV method to assess the stranded asset of coal plants' compulsory retirement^{42,43}. By comparing the NPV differences between the business-as-usual scenario (BAU)

and the low-carbon transition scenarios, we can observe the decline in the value of coal plants' assets due to CR. In fact, the adoption of retrofit technologies, such as Flex, BE, and CCS, will also result in a decrease in NPV, as they bring new investments, operating and maintenance costs, and fuel costs. To incorporate all these emission reduction technologies into the same assessment framework, we extend this NPV method and redefine the NPV differences between BAU and CERPs as the transition cost, which is used to assess the cost-effectiveness of different CERPs. The calculation functions are provided in Eqs. (2)–(4).

$$TC = NPV_{BAU} - NPV_{CERP} \quad (2)$$

$$NPV_{BAU} = \sum_j \sum_{l=0}^{40} \frac{I_j * H_j * P - (Inv_{j,l} + OM_{j,l} + Fuel_{j,l} - Depr_{j,l})}{(1+r)^l} \quad (3)$$

Where, TC represents the transition costs; NPV_{BAU} and NPV_{CERP} represent the net cash flow under the BAU scenario and the CERP, respectively. Other annotations are the same as Eq. (1).

Data availability

The biomass resource dataset used in this study is available from Figshare (<https://doi.org/10.6084/m9.figshare.c.6468319.v1>). Coal power plants dataset can be found in Global Coal Plant Tracker (<https://globalenergymonitor.org/>). Carbon storage points, the cumulative emission reduction pathways under different cumulative carbon emission reduction targets generated in this study, and the source data underlying all the figures in the main article and supplementary information are provided as a Source Data file and deposited in a public repository³⁹. Source data are provided with this paper.

Code availability

The code used in this study is publicly available and deposited in a public repository³⁹.

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Author contributions

R.W. and W.C. designed and produced an initial draft of this research. R.W., L.H., W.M., B.Q., and J.Z. (Jia Zhang), and J.B. designed and built the model. R.Y.C. and W.C. contributed to the interpretation and visualization of the results and co-designed the research. S.Z. contributed to the pathway design. H.L. and J.S. contributed to the construction of the coal plant dataset. X.Z. and J.Z. (Jiutian Zhang) contributed to the carbon storage dataset. W.L. and L.Y. contributed to the biomass resource dataset. N.Z. contributed to electricity constraints generated by the power system model. W.C. and C.W. were responsible for the supervision, coordination, and funding acquisition.

Competing interests

The authors declare no competing interests.

Additional information

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