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Cost outlook of coal power with CCS and BECCS based on a component learning curve incorporating efficiency upgrades: a case study of China

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A B S T R A C T

Grasping the cost outlook of CCS and BECSS is crucial for guiding coal power-dependent nations in technological strategy planning and investment decision-making during the low-carbon transition. Given the practical characteristics of technological learning in the coal power sector and the limitations of existing literature in forecasting technology costs, this study adopts a learning rate estimation method that incorporates efficiency upgrade based on the component learning curve approach. Taking China as a case study, it analyzes the future cost trends and economic-environmental benefits of CCS and BECCS from a systematic perspective. The case study results indicate that CCS and BECCS in China exhibit promising cost prospects. Their deployment enhances the overall learning rate of the power generation system, leading to a potential reduction in the cost of electricity (COE) of approximately \$23.10 ~ \$55.75/MWh. As technological learning effects accumulate, the economic-environmental benefits of CCS and BECCS in China are expected to improve by more than 50%, with the advantage of CCS and BECCS-equipped technologies becoming increasingly pronounced. Moreover, further analysis reveal that efficiency upgrades play a supporting role, accounting for 30% ~ 67% of cost reductions, while capital and fuel costs are the primary drivers of COE reduction in CCS and BECCS, jointly contributing 60% ~ 86% of total cost reductions. The pre-learning value, defined as the threshold at which learning effects begin to materialize, constitutes a critical source of uncertainty influencing the pace of technological cost reduction, while fuel price levels exhibit a positive correlation with the extent to which learning effects are realized. This study provides forward-looking information for coal power system technology strategy planning in China, and offers scientific insights for coal power-dependent nations to accelerate the cost reduction potential of CCS and BECCS.

Introduction

With global climate change intensifying, deep decarbonization of the power system has become a core concern for policymakers worldwide. For countries historically reliant on conventional coal power, such as China, India, and Australia, the key to achieving a low-carbon transition in the power sector lies in fully replacing fossil fuel-based electricity with renewable energy [1]. However, this transition faces significant challenges due to the spatiotemporal intermittency of renewable power [2] and the immaturity of advanced energy storage technologies [3], leading to conflicts between climate governance and energy security [4]. A widely recognized viable approach to addressing this issue is to promote the low-carbon transition of coal power, thereby enhancing the sustainability and resilience of the power system [5–7]. This strategy is particularly relevant for economies and regions with established coal infrastructure, contributing directly to global decarbonization efforts and aligning with the United Nations Sustainable Development Goals (SDGs).

As the world's largest producer and consumer of coal power, China generates more than 60% of its national electricity supply from coal, which accounts for nearly 40% of its total carbon emissions [8,9]. Prior to renewable energy becoming the dominant and sufficiently reliable source within the power system, China must rely on the low-carbon transformation of its coal power sector to achieve its carbon neutrality targets. Given the technology-intensive nature of coal-fired power generation, the key driving force of this transition lies in the commercial

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deployment of advanced low-carbon coal technologies to unlock the sector's emission reduction potential [10–12]. Among the portfolio of technologies capable of mitigating emissions from coal-fired power generation, carbon capture and storage (CCS) and bioenergy with carbon capture and storage (BECCS) are widely regarded as two of the most promising pathways for achieving deep decarbonization—and even negative emissions—in China's coal power sector [13,14]. By capturing and permanently storing large volumes of CO_2 generated from fossil fuel combustion, these technologies can substantially reduce the carbon intensity of electricity generation. The Intergovernmental Panel on Climate Change (IPCC), in its 1.5°C Special Report, emphasizes that CCS—including BECCS—is indispensable in the majority (more than two-thirds) of mitigation pathways consistent with limiting global warming to 1.5°C or well below 2°C [15]. Similarly, the International Energy Agency (IEA) projects that under scenarios incorporating technological progress, CCS could reduce carbon emissions from China's coal power sector by 184 million tonnes in 2030 and 768 million tonnes in 2050 on an annual basis. Over the longer term, the role of BECCS is expected to become increasingly prominent, accounting for approximately one-third of total CO_2 captured by 2070 [16]. Despite the well-documented mitigation potential of these technologies, their large-scale adoption and deployment remain limited, primarily due to the high costs associated with technology implementation [13,17,18]. Specifically, CCS technology in China remains at the industrial demonstration stage, while BECCS lacks concrete demonstration project planning altogether. This indicates that these technologies have not yet reached a stable stage of development, and their implementation costs remain persistently high. The high cost of technology poses economic feasibility risks for coal-fired power plants (CFPPs) in technology investment and adoption, increasing their concerns in decision-making [19]. Meanwhile, the lack of cost competitiveness weakens the incentive for CFPPs to adopt retrofitting measures in response to external policy instruments such as carbon trading and carbon taxes, hindering the large-scale deployment of CCS and BECCS [20]. This creates a dilemma: on one hand, CFPPs, facing excessive deployment costs, adopt a "wait-and-see" approach, delaying the marketization of CCS and BECCS; on the other hand, these technologies, lacking large-scale production and operational experience, fail to realize their cost reduction potential through technological learning effects. Given that technological learning effects can substantially accelerate technological maturation and the formation of cost competitiveness through multiple channels, including learning-by-doing, learning-by-researching, and scale effects, they provide endogenous momentum for technology diffusion. For policymakers, the key to overcoming the above challenges lies in effectively recognizing the central role of learning effects in driving cost reductions for CCS and BECCS in coal power, thereby enabling the scientific guidance of strategic deployment to foster a virtuous cycle of technology diffusion and accelerated learning. Therefore, it is essential to systematically evaluate the future cost prospects of CCS and BECCS under the influence of technological learning effects.

For a long time, learning or experience curves, which demonstrates the effect of accumulated production experience on reducing unit production costs, has been widely utilized in the energy sector for technology cost assessment and strategic planning [21–24]. Through continuous refinement by researchers, various types of learning curves have emerged, including single-factor, two-factor, and multi-factor models [25,26]. While incorporating more factors can improve cost estimation accuracy, an increasing number of variables may introduce potential collinearity issues, leading to estimation errors [22,27]. Moreover, more variables require detailed historical data, which is often difficult to obtain, particularly for emerging technologies lacking commercial deployment experience [21]. To address these challenges, some scholars have proposed the component-based learning curve (CLC) approach, which decomposes complex technological systems into key components and estimates the overall technology learning rate based on the independent learning rates of these components [28]. In reality, for complex technological systems, cost reductions largely depend on the learning effects of key components. Additionally, CLCs account for differences in component maturity, allowing different components to evolve at varying rates [26,29]. This provides a reliable methodological foundation for assessing the costs of CCS and BECCS that have yet to reach commercial deployment.

As the urgency of low-carbon transitions in global power systems intensifies, the International Energy Agency (IEA) has explicitly stated that experience effects should be "explicitly considered when exploring CO_2 reduction strategies and calculating the costs of achieving emission targets"[30]. In response, some scholars have focused on low-carbon power generation technologies, applying learning curves to predict cost dynamics across different technologies to inform effective energy technology diffusion policies. Compared to the extensive research on the cost evolution of renewable energy technologies—such as photovoltaic modules [31], wind turbines [32], and bioenergy [33]—only a limited number of studies have developed component-level learning curves for conventional CFPPs to estimate the cost trajectories of these technologies [34–36]. To assess the cost of electricity (COE) for advanced coal power technologies, several insightful studies have inferred the learning rates of technologies lacking commercial-scale deployment by leveraging technological similarities [29,37,38]. For example, they have substituted flue gas desulfurization systems for carbon capture and storage (CCS), subcritical boilers for supercritical boilers, and oxygen production for air separation units, deriving plant-level learning rates based on CLCs. This approach offers a valuable methodology for constructing learning curves for complex emerging or demonstration-stage technologies.

While existing studies have made significant progress, several gaps remain. First, although the academic community widely recognizes efficiency upgrades as an outcome of technological learning in energy technologies and considers them instrumental in further cost reductions [37–40], empirical evidence from the historical efficiency evolution of pulverized boilers and integrated gasification combined cycle (IGCC) systems in the United States and Japan substantiates this view [29]. However, few studies have quantitatively assessed the contribution of efficiency gains to overall cost declines, thereby potentially underestimating the true cost-reduction potential of these technologies. Second, existing literature primarily focuses on capital cost trends, without adopting a system-level perspective to capture the overall cost of technology implementation [29,35,36]. In CFPPs, capital cost is only one component of the total implementation cost. Focusing solely on capital costs overlooks expenses related to system inputs and routine operation and maintenance, leading to biased cost estimations. Additionally, cost predictions for CCS and BECCS are often used to inform energy system optimization, indicating that beyond cost evolution, it is crucial to understand the dynamic changes in economic-environmental benefits associated with cost variations to provide a comprehensive basis for decision-making [41]. However, existing studies have rarely conducted effective analyses of economic-environmental benefits under different cost scenarios.

In response to the above research gaps, this study makes three key contributions. First, it applies a learning rate estimation method that explicitly incorporates efficiency upgrades into the forecasting of energy technology costs. By doing so, it quantitatively reveals the driving role of efficiency gains in cost reductions, thereby providing a more realistic assessment of the long-term cost trajectories of these technologies. Second, it estimates the cost of CCS and BECCS from a systematic perspective rather than focusing solely on capital costs, thereby avoiding estimation bias caused by partial cost analysis. This approach also provides insights into the cost-reduction effects of different cost items within the system. Finally, by selecting China as a representative case,[1] this study obtains the cost and economic-environmental benefit trajectories of key CCS and BECCS technology pathways. It quantitatively validates their role in driving cost reductions and further elucidates the relative contributions of different cost components within the system to overall cost decline. The research results provide forward-looking information for coal power system technology strategy planning in China, and offer scientific insights for coal power-dependent nations to accelerate the cost reduction potential of CCS and BECCS technologies.

Research framework and methodology

Research framework

This section presents the overall research framework (as shown in Fig. 1), which mainly includes four parts: technology selection, technology modeling, learning rate estimation, and cost prospect analysis. Specifically, this study takes China as a case study and, based on the technological foundation of China's coal power industry as well as the strategic planning of the Chinese government for this sector, selects the key power generation system types along with their corresponding CCS and BECCS technology pathways, thereby defining the research scope and objects. Next, the economic and performance modeling of these technologies is conducted using Integrated Environmental Control Model (IECM11.5) and Aspen Plus V12, capturing the economic and performance characteristics of different technologies under various scenarios at both the component and plant levels. Then, the learning rate estimation method, incorporating efficiency upgrades, is applied to calculate plant-level learning rates from a systematic perspective, based on component-level data across different technology scenarios. Finally, the technology modeling results are adjusted according to the current cost levels of CCS and BECCS in China, and learning curves are constructed to analyze corresponding cost trends and changes in economic-environmental benefits. On this basis, the role of efficiency upgrade in cost reduction is examined, and the primary drivers of cost reduction and the uncertainty introduced by pre-learning value are analyzed.

Component based learning curve (CLC)

The learning curve describes the relationship between unit production cost and cumulative production experience. The magnitude of this relationship is measured by the learning rate (LR), which represents the percentage reduction in unit cost for each doubling of cumulative experience。Given that CCS and BECCS projects are still in the industrial demonstration stage, there is insufficient historical cost and experience data to derive their corresponding LR. Additionally, these technologies typically consist of multiple core components for which learning curves can be obtained. Therefore, this study adopts a CLC approach to estimate the cost reduction potential of the entire technology. assuming that learning effects for each component follow a power-law relationship between cost reduction and cumulative experience. For ease of implementation, following Ref. [28], this study links the learning curves of individual components to the cumulative experience of the entire system, resulting in Eq. (1). Although this approach neglects spillover effects among components, it has been shown to be sufficiently effective for estimating component-level learning rates (LRs) [42]. A detailed description of the learning curve is provided in Appendix A.1.

$$
\begin{aligned}
C(X_t) &= \sum_{i=1}^{n} \lambda_i C_{0i} \left(\frac{X_{ti}}{X_0}\right)^{bi} \\
&= \lambda_1 C_{01} \left(\frac{X_{t1}}{X_0}\right)^{b1} + \lambda_2 C_{02} \left(\frac{X_{t2}}{X_0}\right)^{b2} + \cdots + \lambda_n C_{0n} \left(\frac{X_{tn}}{X_0}\right)^{bn}
\end{aligned}
\tag{1}
$$

$C(X_t)$ represents the unit cost at time t, X_t denotes the cumulative experience at that moment, C_0 and X_0 denote the initial unit cost and the initial cumulative experience level, respectively, and b is the experience exponent. Where the subscript i denotes the relevant information for the $i-th$ component, λ represents the initial cost of the component as a proportion of the total technology cost, and n is the number of components.

Cost indicators

Coal power generation technology, as a complex system engineering technology, encompasses multiple cost components in practical operation, including capital investment, operation and maintenance expenses, and fuel costs, all of which ultimately determine the level of the COE. Accordingly, this study adopts COE as the primary indicator for evaluating the cost implications of different technological configurations.

For scenarios involving the integration of CCS or BECCS, the associated carbon mitigation costs are further assessed through the cost of carbon avoided (COA) and the cost of carbon captured (COC). The detailed calculation procedures for these cost indicators are presented in Eqs. (A5) to (A7), and the corresponding derivation of learning rates is provided in Appendix A.2.

Efficiency upgrade characterization

Considering the impact of factors such as process optimization and system integration on the overall efficiency of CFPPs, this study assumes that plant efficiency upgrades with technological learning. This process is characterized as an exponential function based on the features of technological evolution, as shown in Eq. (2), with efficiency growth rate ν is expressed as Eq. (3).

$$\eta = \eta_1 \nu^{\frac{X_t}{X_0}} \tag{2}$$

$$\nu = \frac{\Delta\eta}{\eta_1} = \frac{\eta_d}{\eta_1} - 1 \tag{3}$$

where η_1 and η_d represent the plant efficiency at the initial stage and when the cumulative experience has doubled, respectively.

Technological economic-environmental benefit assessment

For CCS and BECCS, the economic and environmental benefits of the technology determine their application potential. To evaluate and compare the economic-environmental benefits of different technology pathways, this study combines the COE and carbon intensity (EI) indicators to construct a technical economic-environmental effectiveness index (TEEI), which reflects the economic-environmental benefit levels of various technologies, as shown in Eq. (4).

$$TEEI = \frac{1}{\mu_1 COE' + \mu_2 EI'} \tag{4}$$

A higher TEEI value indicates better economic-environmental

[1] As the world's largest producer and consumer of coal-fired power, China can be regarded as a representative case in addressing the diffusion challenges of CCS and BECCS in the coal power sector—confronting immense decarbonization pressures while ensuring a stable electricity supply for its 1.4 billion population [11]. Meanwhile, the Chinese government has long been committed to promoting the large-scale retrofitting and deployment of CCS in coal-fired power plants; however, these efforts continue to be constrained by substantial cost pressures. Therefore, China's endeavors to advance the deployment of CCS and BECCS in coal power carry broad and generalizable implications, particularly for other coal-dependent economies (e.g., India, Australia, and South Africa) as well as for countries undergoing a "just transition" of fossil fuel–based infrastructure.

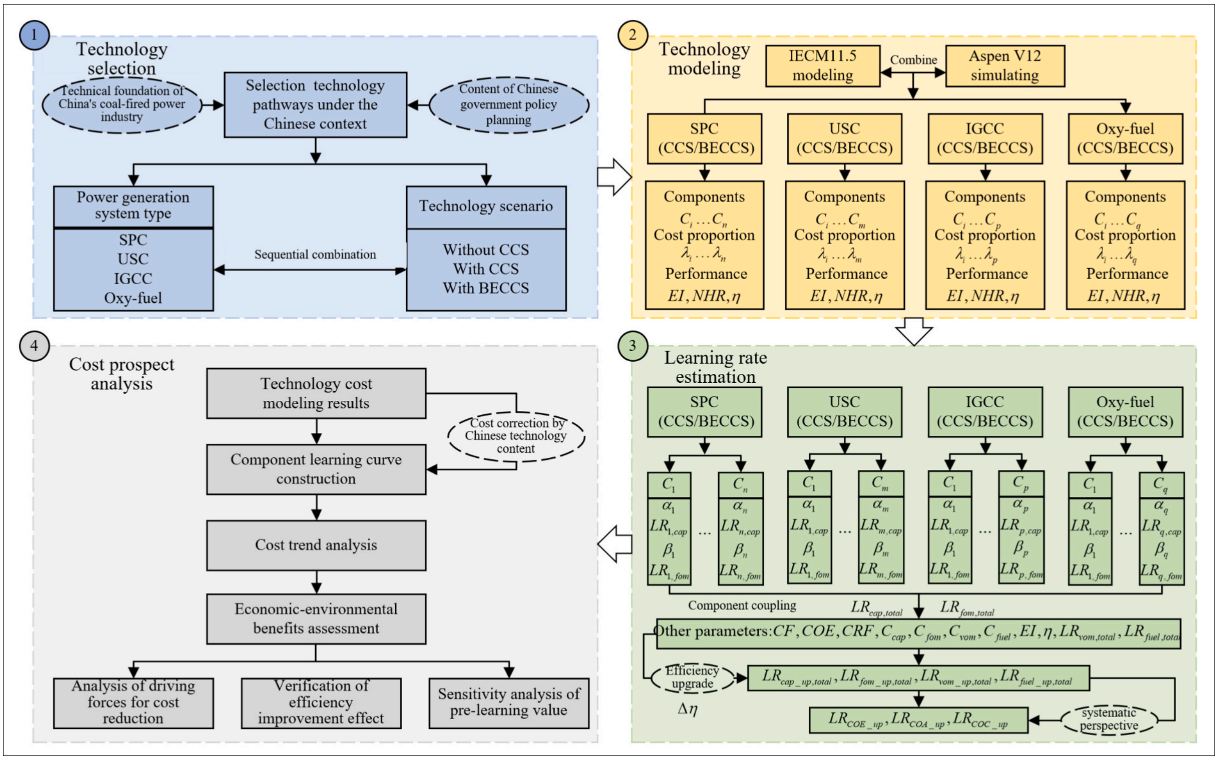

Fig. 1. Overall research framework.

benefits of the technology. COE' and EI' represent the normalized maximum absolute values of COE and EI, respectively, while μ_1 and μ_2 denote the weights for COE and EI.

CCS and BECCS in China's coal power: Status and future pathways

Since the *12th Five-year plan (2011–2015)*, China has incorporated CCS research and deployment into its national carbon mitigation strategy. Following the implementation of the Plan, the Chinese government issued a series of guiding policy documents—including the *Notice on promoting pilot demonstrations of carbon capture*, utilization, and storage, the *National climate change plan (2014–2020)*, and the *13th Five-year work plan for greenhouse gas emission control*—aimed at supporting and advancing the development of CCS. Concurrently, national R&D programs such as the *Special program for clean and efficient coal utilization technologies*, the *2017 National key energy-saving and low-carbon technology promotion catalogue*, and the *Green and low-carbon advanced technology demonstration projects (First Batch)* have identified CCS as a critical breakthrough technology for industrial emission reductions. In recent years, policy attention has further focused CCS deployment specifically on the coal power sector through documents such as the *National coal-fired power unit retrofit and upgrade implementation plan*, the *Coal power low-carbon retrofit action plan 2024–2027*, and the *Next-generation coal power upgrade special action implementation plan 2025–2027*. Compared with CCS, BECCS has received relatively later policy attention in China. Although early policies did not explicitly reference BECCS, support for biomass energy utilization and CCS research and demonstration projects has implicitly established a technological foundation for its future development. During the 14th Five-year plan period (2021–2025), with the deepening emphasis on "negative-carbon" production, BECCS has gradually been incorporated into national policy and research agendas. The *Science and technology support implementation plan for carbon peak and carbon neutrality (2022–2030)* explicitly calls for the construction of a "low-carbon–zero-carbon–negative-carbon" innovation system, supporting BECCS research and development. In addition, the *14th Five-year plan for renewable energy development* and various provincial-level dual-carbon action plans recognize BECCS as a key technological option for achieving deep decarbonization and net-negative emissions. Under the guidance of these policies, by the end of 2025, China had put six coal-fired CCS demonstration projects into operation, encompassing 14 units, while eight additional CCS projects are either under construction or proposed (see Table B1 for details). BECCS projects, however, have not yet reached the laboratory or industrial demonstration stage in China. Nonetheless, the National energy administration and the Ministry of ecology and environment have launched a series of coal-biomass co-firing retrofit pilot projects through the *Notice on pilot work for coal-biomass co-firing power generation technology upgrades*, providing foundational conditions for the future development of BECCS projects. It can be reasonably anticipated that, as climate governance frameworks continue to intensify in the future, the deployment scale of CCS and BECCS in China's coal power sector will exhibit a sustained expansion trend.

As shown in Table B1, the current deployment pathways for CCS in China's coal-fired power sector encompass three main technological routes: post-combustion capture based on pulverized coal boilers, pre-combustion capture integrated with IGCC systems, and oxy-fuel combustion [43–45]. All three CCS configurations are systematically incorporated into the analytical framework of this study. Notably, for post-combustion capture based on PC boilers, performance characteristics and cost structures are closely linked to unit type. Given the consensus that supercritical (SPC) and ultra-supercritical (USC) units will constitute the mainstream fleet in China's coal power sector [7], this study explicitly differentiates between SPC and USC units when evaluating post-combustion CCS pathways to capture heterogeneity arising from varying unit-level technological conditions. Regarding BECCS, its core configuration involves the coupled deployment of CCS technologies with biomass co-firing [14]. Accordingly, BECCS scenarios in this study are constructed by integrating biomass co-firing into each of the three CCS pathways. Although biomass co-firing can be implemented through direct co-firing, parallel co-firing, or gasification-based co-firing, considerations of technological maturity and economic feasibility indicate that direct co-firing currently offers the most commercially viable and scalable option within China's coal power system [46]. Therefore, the modeling of BECCS pathways in this study focuses exclusively on direct co-firing to enhance the practical relevance of the results. The composition of each technological system is illustrated in Fig. B1.[2]

Results and discussion

Cost and performance accounting of various CCS and BECCS technology pathways

Accurate cost and performance accounting for power generation systems and their integration with CCS and BECCS requires a comprehensive understanding and systematic compilation of the various cost and performance parameters associated with these technologies. This study utilizes the IECM 11.5 to simulate CFPPs equipped with various technologies, and to assess their respective costs and performance. The IECM model, which has been widely used for evaluating the economic-environmental benefits of fossil fuel power plants [47,48], has also been adapted for modeling biomass fuel scenarios with appropriate modifications [46,49]. Consequently, based on the calculation of various technical costs in coal-fired scenario, this study extends the IECM system's fuel library and incorporates Aspen Plus V12 to model biomass co-firing scenario in power generation systems, thus conducting corresponding technical and economic analysis. The relevant parameters used in IECM 11.5 are listed in Table E1, while cost and performance data for different CCS and BECCS technology pathways are provided in Tables D1 (coal-fired scenario) and D2 (biomass co-firing scenario).

It can be seen that SPC has the lowest capital cost and FO&M cost, followed by USC, with IGCC having the highest costs. Conversely, VO&M cost is lowest for IGCC. In terms of COE, IGCC is significantly higher than SPC and USC. However, it is important to note that despite USC's higher capital and FO&M costs compared to SPC, its superior net efficiency results in lower COE due to reduced fuel and VO&M costs. When equipped with CCS, all technologies see a noticeable increase in costs, while carbon emissions significantly decrease. In addition, the installation of CCS results in energy penalties, reducing the net output efficiency of various technologies by 5.98% to 11.12%. When biomass co-firing is used instead of single coal combustion, although the COE of various technologies generally increases slightly, biomass co-firing further reduces the EI compared to the coal-fired scenario, without almost losing the net output power and net efficiency of the CFPPs.

Learning rate estimation of CCS and BECCS

The premise of calculating the LR considering efficiency upgrade is to clarify the current efficiency and anticipated future changes in efficiency for the technologies. This study uses IECM simulation results and IEA's estimates for future energy technologies [50] to set the current and maximum efficiency values for different technologies. Meanwhile, referring to existing studies [13,37,51], this study posits the existence of a pre-learning value C_{pre} where incremental experience does not lead to significant cost reduction and efficiency upgrades until this threshold is reached. Based on the current maturity of each technology, different pre-learning values are set for technologies with and without CCS, and it is assumed that efficiency will peak when cumulative experience reaches 100 GW [38]. On this basis, the efficiency growth rates of each technology are calculated based on Eqs. (2) and (3), with the results presented in Table C1. Furthermore, based on the cost information in Table C1 and the LRs of each component in Table C2, the LRs of CCS and BECCS, accounting for efficiency upgrades, are obtained by formulas in section A1, and results are shown in Table C3.

Overall, the estimation results of LRs considering efficiency upgrades are generally higher than those reported in previous studies [37,48,52], with detailed analysis provided in section 4.5.2. At the same time, it is evident that, except for FO&M cost, the LRs for IGCC costs are generally higher than those for SPC, USC, and Oxy-fuel(Ref) at the same learning level. When equipped with CCS system, the LR for all technologies improves significantly, with Oxy-fuel showing the greatest increase. However, IGCC-CCS consistently shows superior LRs across multiple cost items compared to other technologies. Due to similarities in technological characteristics, the LRs for SPC-CCS and USC-CCS are close but lower than IGCC-CCS and Oxy-fuel. In addition, LRs for the same technology vary greatly at different learning levels, which means that the actual learning level of the technology is a crucial factor affecting the speed of cost reduction.

Analysis of cost reduction potential for CCS and BECCS

Based on the pre-learning values and corresponding LRs for different technologies, the cost changes for each technology in scenarios with and without CCS and BECCS can be determined at various learning levels.[3] This allows for the evaluation of the potential for cost reduction in each scenario.

Without CCS

Based on the aforementioned work, the COE trends for the four key power generation systems without CCS are illustrated in Fig. 2. It is important to note that SPC and USC are already at a mature level in China, with cumulative installed capacities exceeding 100 GW (see section 3). Therefore, unlike IGCC, this does not simulate the future cost change for SPC and USC in China to clarify their cost reduction potential.[4] Instead, the focus is on evaluating the effectiveness of using the efficiency upgrades learning curves to estimate cost trends due to data availability. Currently, the actual COE for SPC and USC in China ranges between \$35–55/MWh and \$40–60/MWh, respectively [53], which aligns with the mature-stage cost evolution results shown in Fig. 2.

[2] "*12th Five-year plan (2011–2015)*", http://www.npc.gov.cn/zgrdw/npc/xinwen/2011–03/17/content_1647851_2.htm; "*Notice on promoting pilot demonstrations of carbon capture, utilization, and storage*", https://zfxxgk.ndrc.gov.cn/web/iteminfo.jsp?id=1686; "*National climate change plan (2014–2020)*", https://www.gov.cn/zhengce/zhengceku/2014–09/19/content_9083.htm; "*13th Five-year work plan for greenhouse gas emission control*", https://www.mee.gov.cn/ywgz/ydqhbh/wsqtkz/201904/t20190419_700360.shtml; "*Special program for clean and efficient coal utilization technologies*", https://www.gov.cn/zhengce/zhengceku/202410/content_6978315.htm; "*2017 National key energy-saving and low-carbon technology promotion catalogue, and the Green and low-carbon advanced technology demonstration projects (First Batch)*", http://big5.www.gov.cn/gate/big5/www.gov.cn/xinwen/2017–04/01/5182743/files/2bd3969838834328971fdb44a44f698d.pdf; "*National coal-fired power unit retrofit and upgrade implementation plan*", https://ideacarbon.org/news_free/56291/; "*Coal power low-carbon retrofit action plan 2024–2027*", https://www.gov.cn/zhengce/zhengceku/202407/content_6963501.htm; "*Next-generation coal power upgrade special action implementation plan 2025–2027*", https://www.gov.cn/zhengce/zhengceku/202504/content_7018738.htm; "*Science and technology support implementation plan for carbon peak and carbon neutrality (2022–2030)*", https://www.gov.cn/zhengce/zhengceku/2022–08/18/content_5705865.htm; "*Notice on pilot work for coal-biomass co-firing power generation technology upgrades*", https://nyj.guizhou.gov.cn/zwgk/xxgkml/zcwj_2/zfgz/201712/t20171206_27993158.html.

[3] Since the current cumulative experience levels of all CCS and BECCS pathways in China remain below their corresponding theoretical pre-learning values (see Tables B1 and C1), the initial experience parameter X_0 is uniformly set equal to the respective pre-learning value C_{pre} when estimating the cost trajectories of each technology.

[4] The Oxy-fuel(Ref) is essentially an SPC power plant equipped with FGD and ESP [33], resulting in similar cost parameters to those of the SPC in this study. The purpose of designing Oxy-fuel(Ref) is to serve as a reference plant for evaluating the COA and COC of Oxy-fuel, and thus, Oxy-fuel(Ref) itself does not participate in the technical–economic analysis.

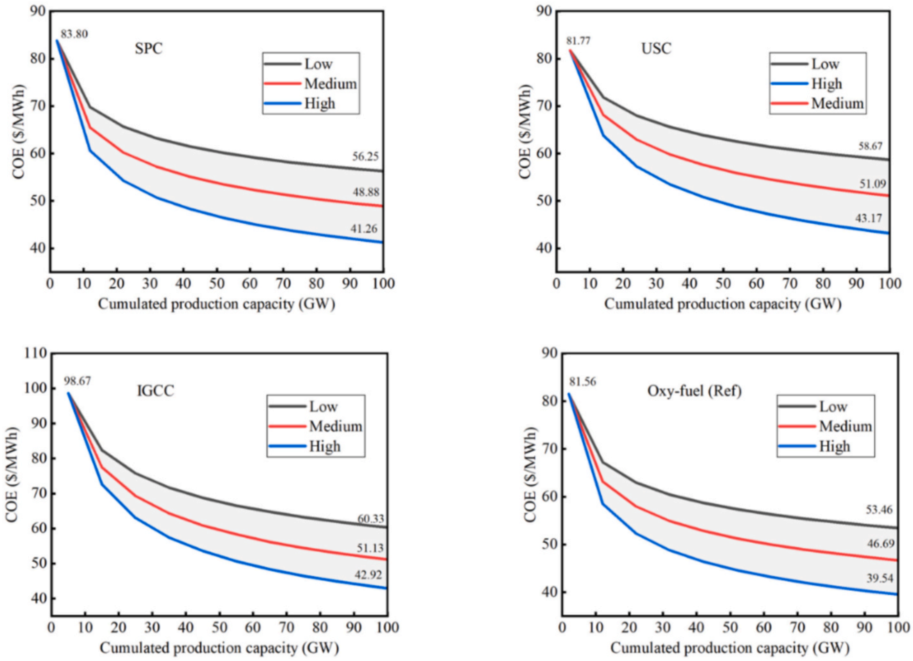

Fig. 2. COE trends for various technologies without CCS.

Compared to other technologies, IGCC has the highest COE in the early stages of learning. However, due to its significant LR advantage, the COE decreases from an initial $98.67/MWh to $60.33/MWh, $51.13/MWh, and $42.92/MWh at high, medium, and low learning levels, respectively, as learning experience increases, making it cost-competitive with other technologies. Notably, although USC initially has a lower COE than SPC and a higher LR, USC's COE exceeds that of SPC once the cumulative installed capacity reaches 100 GW. This is attributed to USC's higher pre-learning value (Table C1), which results in a lower cumulative learning effect compared to SPC.

In the long term, IGCC in China has greater potential for cost reduction. With a moderate level of learning as a reference, as the learning effect accumulates, its COE will decrease by $47.54/MWh, which is higher than the $34.92/MWh reduction for SPC and $30.18/MWh for USC.

With CCS

For coal power technologies with CCS, in addition to examining the COE trends of technologies, this study also draws corresponding learning curves based on the LRs of COA and COC to clarify the impact of CCS on overall power system costs. The trends in COE, COA, and COC for each technology are illustrated in Fig. 3.

Given that SPC and USC are already mature in China while CCS remains at the industrial demonstration stage, the initial COE for SPC-CCS and USC-CCS should not be directly derived from IECM modeling results. Instead, this study accounts for the maturity differences between SPC/USC and CCS technologies in China. The cost difference between SPC/USC and SPC-CCS/USC-CCS in the IECM results is treated as the cost of CCS, and couples this with the COE of SPC and USC when their cumulative capacity reaches 100 GW at a medium learning level. This approach sets the initial COE for SPC-CCS and USC-CCS as $112.88/MWh and $106.82/MWh, respectively. For IGCC-CCS and Oxy-fuel, since these technologies are still at the demonstration stage in China, their initial COE values can be directly adopted from the IECM modeling results, at $140.20/MWh and $145.60/MWh, respectively.

Regarding COE, when equipped with CCS, the plant costs of various technologies increase to varying degrees. Compared to SPC-CCS and USC-CCS, IGCC-CCS and Oxy-fuel have higher initial COE, both exceeding $140/MWh. However, as learning experience accumulates, the COE for IGCC-CCS and Oxy-fuel decreases more rapidly, with greater reductions than those observed in SPC-CCS and USC-CCS. Taking the medium learning level as an example, the COE of IGCC-CCS drops from $140.20/MWh to $75.41/MWh, and Oxy-fuel's COE decreases from $145.60/MWh to $89.59/MWh, representing reductions of $64.79/MWh and $56.01/MWh, respectively. In comparison, the COE for SPC-CCS and USC-CCS decreases by $52.03/MWh and $42.29/MWh, respectively. The differences in cost reduction potential can be attributed to two main factors. On one hand, IGCC-CCS and Oxy-fuel have higher LRs, leading to a faster decline in COE; on the other hand, they also have greater room for cost reduction compared to SPC and USC, which are already mature technologies in China.

The learning curves of COA and COC across different technologies can highlight the differences in cost changes after CCS implementation. From the performance of COA and COC, IGCC-CCS exhibits significantly lower COA and COC compared to the other three technologies. The key to this phenomenon is that IGCC-CCS typically employs pre-combustion carbon capture, which requires a lower capital investment ($595.40/kW) than post-combustion capture for SPC-CCS ($968.50/kW) and USC-CCS ($877.50/kW), or Oxy-fuel combustion capture for Oxy-fuel ($1409.6/kW). This partially explains why the initial COE of IGCC is greater than that of Oxy-fuel(Ref), but IGCC-CCS ultimately has a cost advantage over Oxy-fuel. At the same time, it can be observed that despite SPC-CCS and USC-CCS having higher COA and COC than IGCC-CCS, their COE is significantly lower, attributable to the cost advantages of SPC and USC being mature technologies in China. Additionally, although SPC-CCS initially has a higher COE than USC-CCS and both have similar LRs, as cumulative installed capacity increases, the COE of SPC-CCS gradually falls below that of USC-CCS. This is due to the fact that USC-CCS (7GW) has a higher pre-learning value compared to SPC-CCS (4GW), which restricts its learning accumulation effect to drive cost reduction progress. At the same time, the difference in COA/COC LRs between USC-CCS and SPC-CCS is insufficient to offset the influence of cumulative learning effects, such as COA trends at high learning level.

Comparing the learning curves of COA and COC, it is evident that the COC trend of each technology is steeper, indicating that the cost reduction of carbon capture is greater than that of integrated CCS systems covering carbon capture, transportation, and storage. For instance, at a medium learning level, the COC of technologies equipped with CCS

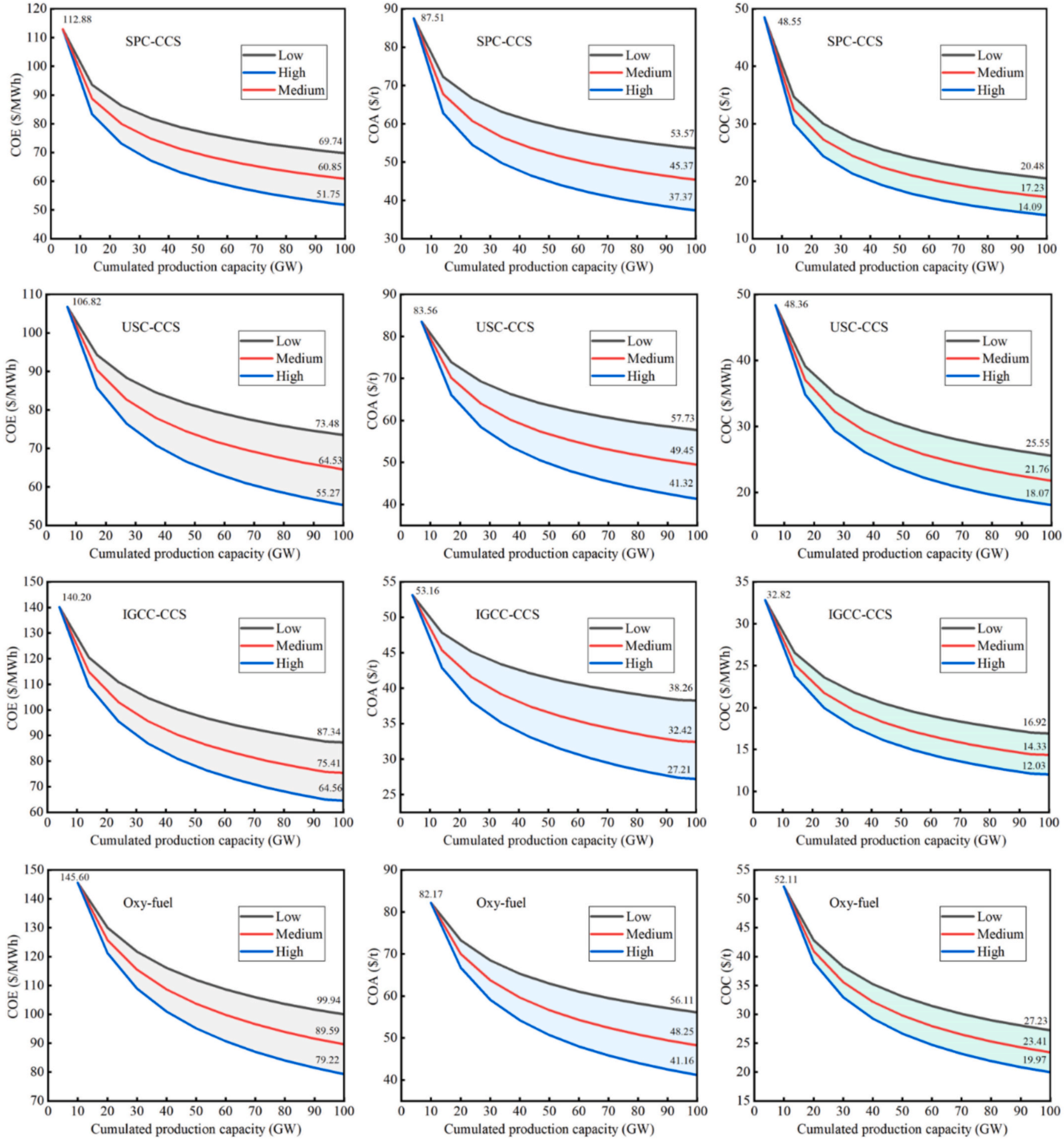

Fig. 3. COE, COA and COC trends for various technologies with CCS.

drops to below 50% of the initial value when cumulative installed capacity reaches 100 GW, whereas COA generally remains around 60% of the initial value. This difference primarily stems from the treatment of the cost of CT&S. Since IECM considers cost of CT&S in CCS as the annual O&M cost of power plants, this study extrapolates their cost trends using the VO&M cost LRs, resulting in lower LRs for these components compared to carbon capture. For example, in SPC-CCS, the LR for CT&S is estimated at 7.19%, while carbon capture achieves 11% at a medium learning level. Nevertheless, the LRs used in this approach are consistent with the estimated results in academia, and the cost reduction potential of CT&S should not be underestimated. Specifically, scholarly assessments of the LRs for CT&S range from 4.8% to 7.7% [26], which is lower than the 6% to 18% range for carbon capture.

With BECCS

Integrating biomass co-firing with CCS is a primary way for achieving BECCS in CFPPs. Based on the modeling results in Table D2, this study evaluates the economic and performance aspects of different technologies equipped with BECCS. Since the cost shares of various components under different biomass co-firing rates remain largely consistent with coal-fired scenarios, the technology LRs estimated for the coal-fired scenario can be applied to assess the cost reduction potential in the biomass co-firing scenario. Similarly, the initial COE for SPC-CCS and USC-CCS in biomass co-firing scenario is also determined by coupling the mature values of SPC and USC at a medium learning level with CCS cost, reflecting the impact of the actual development levels of SPC and USC in China on the corresponding initial technical costs of biomass co-firing scenario. Based on this, the current cost information and cost reduction potential for each technology equipped with BECCS are shown in Fig. 4.

Fig. 4 illustrates that, compared to technologies equipped only with CCS, the addition of biomass co-firing increases the COE of power generation systems, with the extent of this increase positively correlating with the co-firing rate. Among the technologies, IGCC experiences the most significant increase in COE for the same co-firing rate, while SPC, USC, and Oxy-fuel show relatively smaller changes. This is primarily because IGCC systems, which rely on the fuel gasification cycle, are more sensitive to fuel quality [54], and biomass generally has poorer quality. As a result, IGCC-BECCS systems require higher investments, leading to a more pronounced increase in COE. In contrast, the

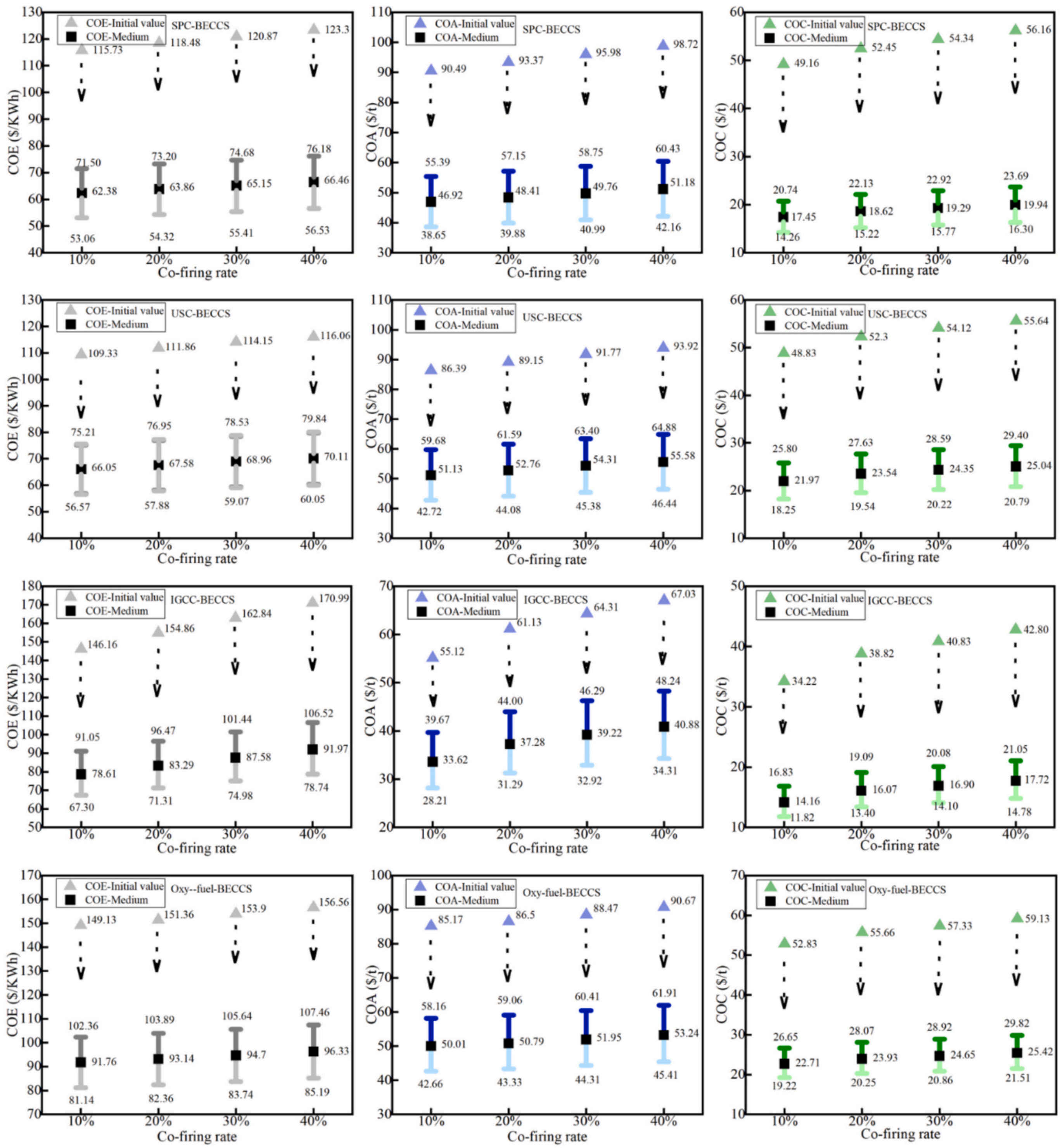

Fig. 4. COE, COA and COC trends for various technologies with BECCS.

performance of the other three boiler-based technologies remains relatively stable with fuel variations, resulting in smaller COE changes. The trends in COA and COC align with those observed in coal-fired scenario, with IGCC-BECCS demonstrating a clear cost advantage due to its pre-combustion carbon capture. SPC-BECCS and USC-BECCS, which utilize post-combustion carbon capture, have higher COA and COC, while Oxy-fuel-BECCS, due to its higher capital investment, exhibits the highest COC.

In terms of cost reduction potential, IGCC-BECCS and Oxy-fuel-BECCS exhibit greater COE reduction potential compared to SPC-BECCS and USC-BECCS, similar to the coal-fired scenario. For instance, at a medium learning level, the COE reduction for IGCC-BECCS and Oxy-fuel-BECCS ranges from \$67.55 to \$79.02/MWh and \$57.37 to \$60.23/MWh, respectively, across four co-firing rates, while SPC-BECCS and USC-BECCS decreased by \$53.35 ~ 56.84/MWh and \$43.28 ~ 45.95/MWh, respectively. Additionally, the performance of COA and COC for these technologies mirrors that observed in the scenario with CCS.

Overall, while biomass co-firing increases the cost of each technology compared to those equipped only with CCS, the substantial potential for cost reduction and favorable carbon emission performance suggest that technologies equipped with BECCS have promising market potential.

Assessment of the economic-environmental benefits of CCS and BECCS

On the basis of obtaining the cost trend of CCS and BECCS in China, the TEEI metric was calculated for each power generation system by assigning equal weights to the COE and the EI, i.e., $\mu_1 = \mu_2 = 0.5$, to evaluate the changes in their economic-environmental benefits at different levels of technological learning. The results are shown in Fig. 5.

Fig. 5 illustrates that, at the current cost levels in China, the economic-environmental benefits of the four categories of power generation systems are relatively low without the integration of CCS and BECCS. In comparison, USC performs the best and IGCC the worst. However, it is evident that despite the cost increases associated with CCS and BECCS integration, these technologies experience a significant improvement in economic-environmental benefits due to their advantages in EI, with a growth rate exceeding 56%. Additionally, for SPC, USC, and Oxy-fuel, the economic-environmental benefits with BECCS are comparable to those with CCS, while the TEEI value of IGCC-BECCS is lower than that of IGCC-CCS, and this value decreases as the biomass co-firing rate increases. This decline is attributed to the higher cost increments associated with IGCC when BECCS is equipped (see Table D1).

As technology learning progresses, the release of cost reduction potential significantly enhances the TEEI of various technologies and systems. Compared to the current level, the TEEI of SPC and USC shows modest increases of 3.4% and 3.7%, respectively, at a medium learning level, which is still due to their maturity in China and limited cost reduction potential. In contrast, IGCC, with greater room for cost reduction, exhibits the most substantial TEEI improvement (21.4%), reaching a level comparable to SPC. In scenarios equipped with CCS, the cost reduction space brought by CCS further amplifies the TEEI across all technologies, with increases exceeding 50% at a medium learning level. Specifically, IGCC-CCS sees the highest increase (69%), while USC-CCS has the smallest (50%). Notably, SPC-CCS, with a substantial TEEI increase of 62%, surpasses USC to become the technology with the highest economic-environmental benefits, whereas Oxy-fuel, due to a lower TEEI growth (54%), is overtaken by IGCC-CCS, making it the technology with the lowest economic-environmental benefits. In the BECCS-equipped scenarios, unlike the current level, technology learning enables SPC-BECCS and USC-BECCS to achieve higher TEEI values than their CCS-only counterparts, with this advantage becoming more pronounced as the biomass co-firing rate increases, while the TEEI relationship between CCS and BECCS remains largely unchanged for IGCC and Oxy-fuel. This phenomenon indicates that SPC and USC are more promising for application in biomass co-firing scenario.

Overall, cost reduction driven by technological learning will enhance the economic-environmental benefits of all technologies and systems, particularly in scenarios involving CCS and BECCS. It is also important to recognize that the magnitude of improvement in the economic-environmental benefits of a given technology increases with higher levels of technological learning, due to the cumulative learning effects. Therefore, the actual level of technological learning will be crucial in determining the future trajectory of the economic-environmental benefits of CCS and BECCS in China.

It should be noted that Fig. 5 presents the TEEI results only under the assumption of equal weights assigned to the economic factor (COE) and the environmental factor (EI). To further examine the differentiated impact of technological learning on the economic–environmental performance of CCS and BECCS under varying evaluation preferences, a sensitivity analysis was conducted on the weighting parameters μ_1 and μ_2. The corresponding results are reported in Table F1. The findings indicate that when the evaluation of power generation technologies

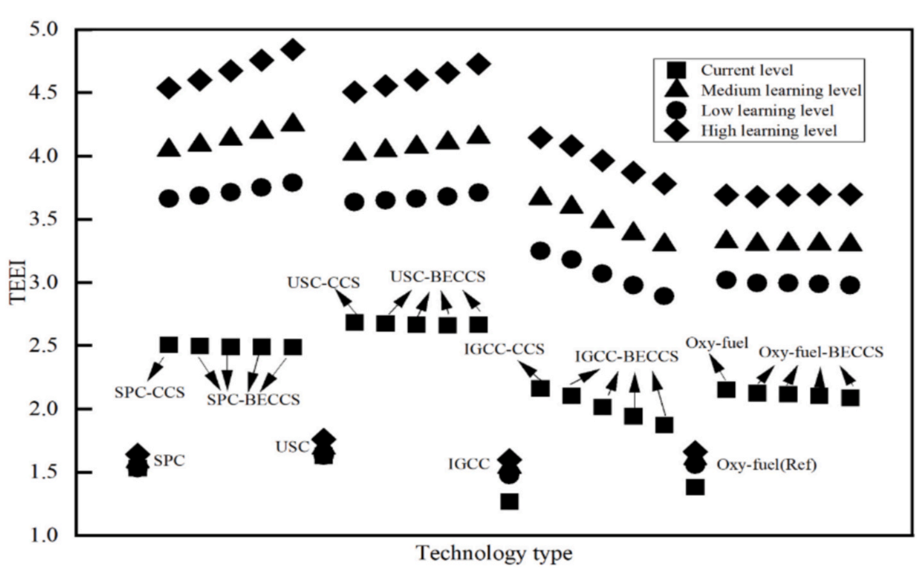

Fig. 5. TEEI values of various technologies Note: The biomass co-firing rates for each technology equipped with BECCS correspond to 10%, 20%, 30%, and 40% from left to right.

places greater emphasis on economic considerations—i.e., when the value of μ_1 increases—the TEEI of generation systems without CCS and BECCS tends to be relatively higher. Conversely, as the weight assigned to environmental performance increases (i.e., a higher μ_2), the TEEI values associated with various CCS and BECCS technology pathways rise significantly, and their comparative advantages become more pronounced. The underlying mechanism can be explained as follows. In the absence of CCS and BECCS, generation systems typically exhibit lower COE but higher EI, thereby gaining an advantage under evaluation frameworks dominated by economic criteria. Although the integration of CCS and BECCS increases generation costs, it substantially reduces carbon emissions. As the weight of environmental considerations in the evaluation framework increases, the carbon mitigation value of CCS and BECCS is more fully recognized, leading to an overall increase in their TEEI.

These results suggest that the comprehensive economic–environmental performance of different technology pathways is highly contingent upon the evaluator's value orientation. With increasingly stringent climate policy targets, strengthened emission constraints, and the progressive improvement of carbon pricing mechanisms, environmental considerations are likely to receive greater weight in integrated assessment frameworks. Under such circumstances, the strategic importance of CCS and BECCS in achieving long-term low-carbon transitions will become increasingly prominent.

Further discussion

Analyzing technology cost from systematic perspective

Unlike previous literature that focuses solely on capital cost, this study analyzes the cost trends of power generation technologies from a systematic perspective, that is, clarifying the overall production costs with specific technology used for power generation and its reduction potential. This approach more accurately reflects the actual application cost of technologies, providing insights that better meet the decision-making needs of the industry. An example demonstrating the necessity of this approach is that, although USC has a higher capital cost than SPC, its superior thermal efficiency and fuel utilization lead to lower VO&M and fuel cost, resulting in a lower COE for USC compared to SPC. A similar phenomenon is also observed in the cost comparison of IGCC-CCS, Oxy-fuel, and SPC-CCS under the same technology maturity conditions. Furthermore, analyzing cost evolution trend from a systematic perspective clarifies the driving forces behind system cost reduction, capturing the key factors contributing to cost decreases. For instance, in the case of CCS-equipped technologies, the proportion of different cost items contributing to the reduction in COE as accumulation of learning effects is shown in Fig. 6.

The visualized results of the contributions of different cost items to COE reduction reveal that, across varying levels of technological learning, changes in capital cost account for approximately 40% to 54% of the COE decrease. This underscores the significant role of capital cost in reducing system cost, which is closely tied to the capital-intensive nature of the coal-fired power industry and explains why many studies

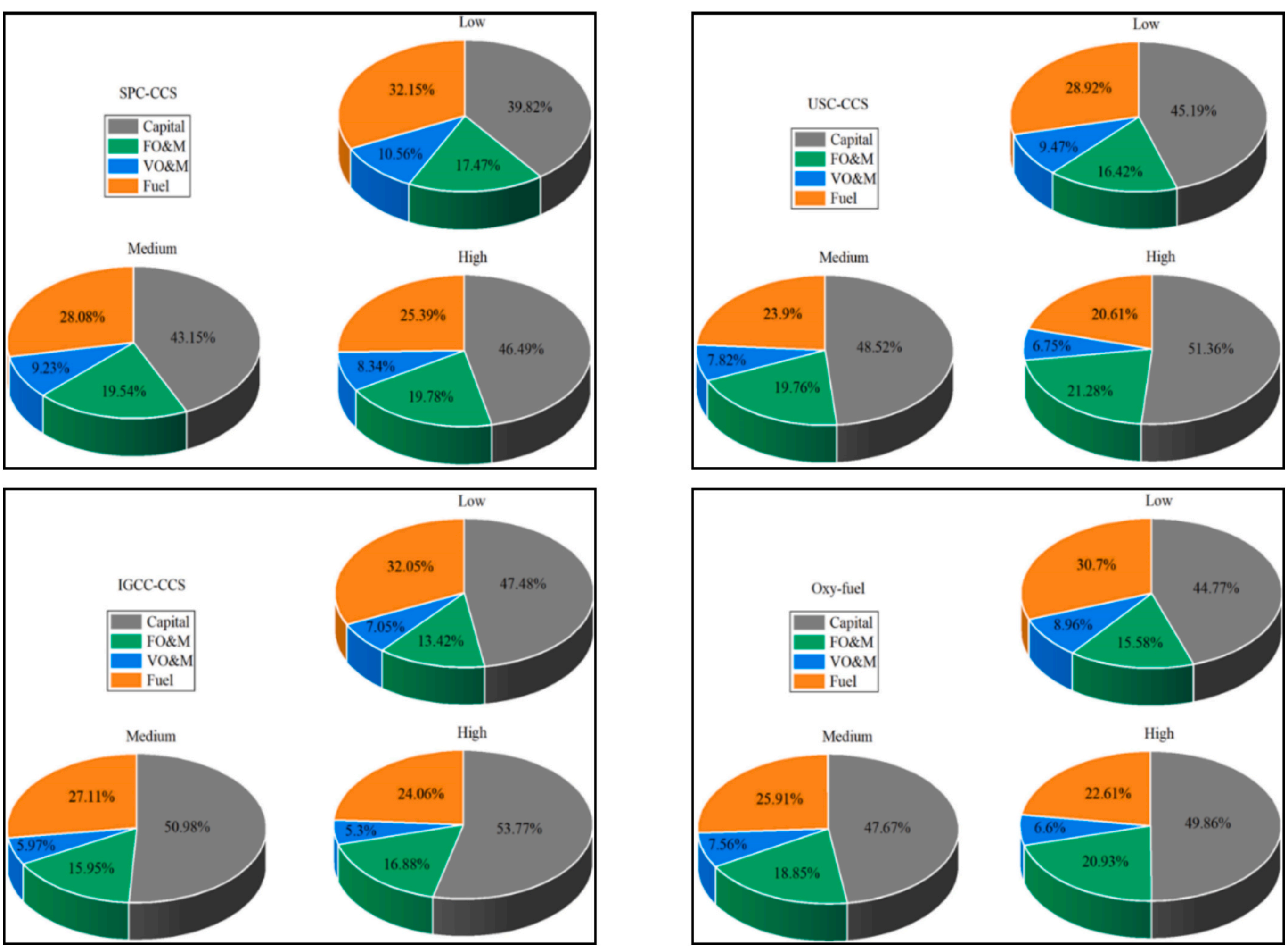

Fig. 6. Proportions of promotion of COE reduction by different cost items of various technologies.

primarily focus on the capital cost of coal power technologies. However, Fig. 6 shows that fuel cost also contributes to about 20% to 32% of the COE reduction, a factor often overlooked in existing literature. Relatively, VO&M cost contributes the least (around 5% to 9%) to COE reduction. Additionally, within the same technology, the proportionate impact of capital and FO&M costs on COE reduction increases with higher learning levels, while the impact of fuel and VO&M costs decreases. This indicates that the promotion in reducing COE by the improvement of learning level also depends on the greater cost reduction potential of capital cost and FO&M cost. In fact, due to the uncertainty of factors such as prices for labor, fuel, and consumables, the influence direction of fuel and VO&M costs on COE is random. However, technological learning can reduce production cost at fixed price level by improving system efficiency and lowering the consumption rate of production factors. Therefore, this study assumes constant production factor prices and reflects the contribution of fuel and VO&M cost changes to COE reduction based on efficiency upgrades driven by technological learning.

The effect of efficiency upgrades on cost reduction

To validate the promoting effect of efficiency upgrades on technology cost reduction, Table C4 presents the LRs of technologies without considering efficiency upgrade, which are significantly lower than those that do consider efficiency upgrade (see Table C3). This is because, with a fixed fuel input, lower efficiency results in less electricity generated, leading to higher unit output cost and consequently smaller cost reduction, and therefore lower LR. Taking with CCS as an example, the COE evolution trends of various technologies without considering efficiency upgrade were obtained based on the relevant formulas in section 2.3. Fig. 7 shows the differences in COE reduction potential with and without considering efficiency upgrade. Similar curves can also be drawn for scenarios without CCS and with BECCS.

The results indicate that, during the cost evolution of technologies with CCS, efficiency upgrades account for a cost reduction of $18.05/MWh to $30.45/MWh at a medium learning level. The extent to which efficiency upgrades promote cost reduction varies among technologies, with IGCC-CCS and Oxy-fuel experiencing greater reductions compared to SPC-CCS and USC-CCS. This difference is attributed to the larger gap between the current efficiency level and the theoretical maximum efficiency of IGCC-CCS and Oxy-fuel, which results in a higher efficiency growth rate during the learning process (see Table 1), thereby enhancing their cost reduction effect. Additionally, the influence of efficiency upgrades on cost reduction is linked to the level of technological learning, with lower learning levels showing a more pronounced impact. For instance, at a low learning level, 62% to 67% of the COE reduction across technologies is attributable to efficiency upgrades, whereas this proportion decreases to 43% to 51% at a medium learning level, and 30% to 38% at a high learning level. This trend occurs because higher learning levels accelerate overall cost reduction rates, while the efficiency growth rate for the same technology remains constant, diminishing the relative contribution of efficiency upgrades to cost reduction. Nevertheless, efficiency upgrades still play a significant role in reducing technology costs.

Overall, efficiency upgrades are a critical factor in driving technology cost reduction, especially during the early deployment stage (i.e., before the cumulative installed capacity reaches 20 GW). At this stage, efficiency upgrade has already realized about 30% to 60% of the potential cost reduction.

Sensitivity analysis of pre-learning value

The empirical analysis reveals that the size of the pre-learning value is a key uncertainty factor influencing technology cost reduction, as it determines the number of times learning experience can double. Therefore, this study conducts sensitivity analysis on this uncertain factor, using CCS-equipped technologies as an example. Table 1 presents the cost situation for each technology at a cumulative installed capacity of 100 GW, when the pre-learning value is set at the scale of a single plant (indicating that learning begins with the second plant) and at 20 GW (indicating that learning begins later).

Table 1 demonstrates the critical importance of the pre-learning value in shaping the future cost trajectory of technology. A smaller pre-learning value is more conducive to leveraging the potential of technology learning for cost reduction. This indicates that efforts should be made to initiate learning activities as early as possible in the deployment of technology, reducing the threshold for technology learning and accelerating technology cost reduction.

Impact of fuel price on the cost-reduction effects induced by efficiency upgrades

The results presented in Section 4.5.1 indicate that under CCS technology scenarios, variations in fuel costs account for approximately 20% to 32% of the reduction in the COE across different power

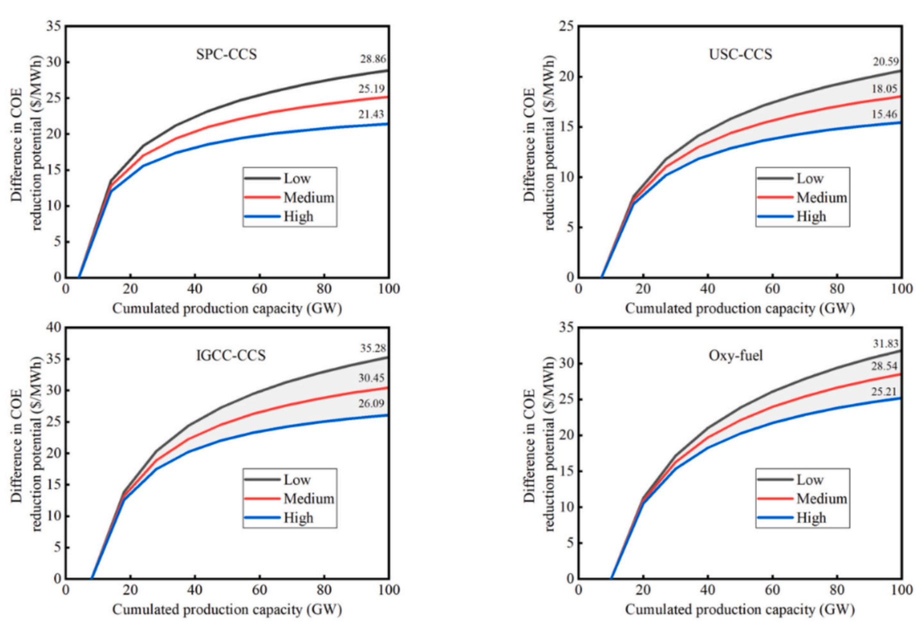

Fig. 7. Differences in COE reduction of technologies with CCS with & without efficiency upgrades.

Table 1
Sensitivity analysis results of pre-learning value [a.]

Technology type	Initial cost	Final cost (L/M/H)	Final cost (L/M/H)
SPC-CCS	COE ($/MWh):112.88	C_{pre} = 0.6 GW 52.51/42.27/ 32.68	C_{pre} = 20 GW 88.73/82.88/ 76.43
USC-CCS	COE ($/MWh):106.82	C_{pre} = 0.6 GW 52.01/40.51/ 30.07	C_{pre} = 20 GW 85.18/78.74/ 71.69
IGCC-CCS	COE ($/MWh):140.20	C_{pre} = 0.7 GW 55.33/41.46/ 30.56	C_{pre} = 20 GW 103.70/94.43/ 85.53
Oxy-fuel	COE ($/MWh):145.60	C_{pre} = 0.6 GW 63.10/49.50/ 37.66	C_{pre} = 20 GW 111.93/103.69/ 95.15

a. Based on the LR in Table 4.

generation systems. This effect arises because efficiency upgrades reduce the fuel consumption rate, thereby lowering the unit fuel cost of technology deployment under a given fuel price level. These findings suggest that fuel price constitutes a critical factor influencing the magnitude of COE reduction attributable to efficiency upgrades, as it determines both the initial COE level at the time of technology deployment and the corresponding potential margin for cost decline. Accordingly, it is necessary to further examine how fluctuations in fuel prices affect the magnitude of learning effects during the process of technology deployment. Given that fuel price changes operate exclusively through the fuel cost component of the power generation system, the differentiated impact of efficiency upgrades on COE reduction potential under varying fuel price levels can be evaluated by measuring the proportion of fuel cost reduction relative to the total COE reduction potential.

Fig. 8 presents the proportion of fuel cost reduction in the total COE decline for each power generation system under the CCS scenario when the current coal price level changes by 20% and 50%, respectively. The results show that as coal prices rise, the share of fuel cost reduction in the overall COE decrease increases correspondingly across all generation systems. This pattern can be explained by the fact that higher coal prices raise the initial COE level of each technology-specific power generation system. When the learning rate and the potential for efficiency improvement remain constant, the learning effect associated with the fuel cost component becomes more pronounced under higher fuel price levels. In contrast, other cost components are independent of coal prices and, therefore, their associated learning effects are not influenced by changes in fuel prices. Under the influence of efficiency improvements, the overall COE reduction potential of power generation systems increases with rising fuel prices. In other words, there exists a positive correlation between fuel price levels and the magnitude of learning effect realization. It should also be noted that, in the BECCS scenario, variations in both biomass fuel prices and coal prices would generate similar effects on the realization of technological learning. Therefore, this mechanism is not elaborated further here.

Strategic measures to efficiency penalties associated with CCS and BECCS deployment

Our results demonstrate that efficiency upgrades amplify the technological learning effects of coal power systems. However, it should be noted that while the deployment of CCS and BECCS reduces the carbon intensity of power generation, it is typically accompanied by an efficiency penalty [55]—that is, a decline in the overall net efficiency of the power generation system (see Tables D1 and D2). This efficiency loss weakens the environmental–economic benefits generated by CCS and BECCS deployment and constrains further improvements in the comprehensive environmental–economic performance of coal power systems from a technological learning perspective.

In response, the power sector should place greater emphasis on compensating for the net efficiency losses associated with CCS and BECCS deployment when formulating strategic plans for the low-carbon transition of coal power. First, the carbon pricing mechanism should be optimized to enhance the environmental returns of low-carbon technology investments. Second, differentiated electricity pricing schemes and capacity compensation mechanisms could be introduced for coal-fired units equipped with CCS and BECCS, thereby offsetting the COE increase induced by efficiency losses through power market revenues. Third, greater efforts should be devoted to advancing the integrated R&D of coal thermal cycle systems and carbon capture systems, with the aim of reducing the magnitude of efficiency penalties from a technological standpoint and improving overall system performance.

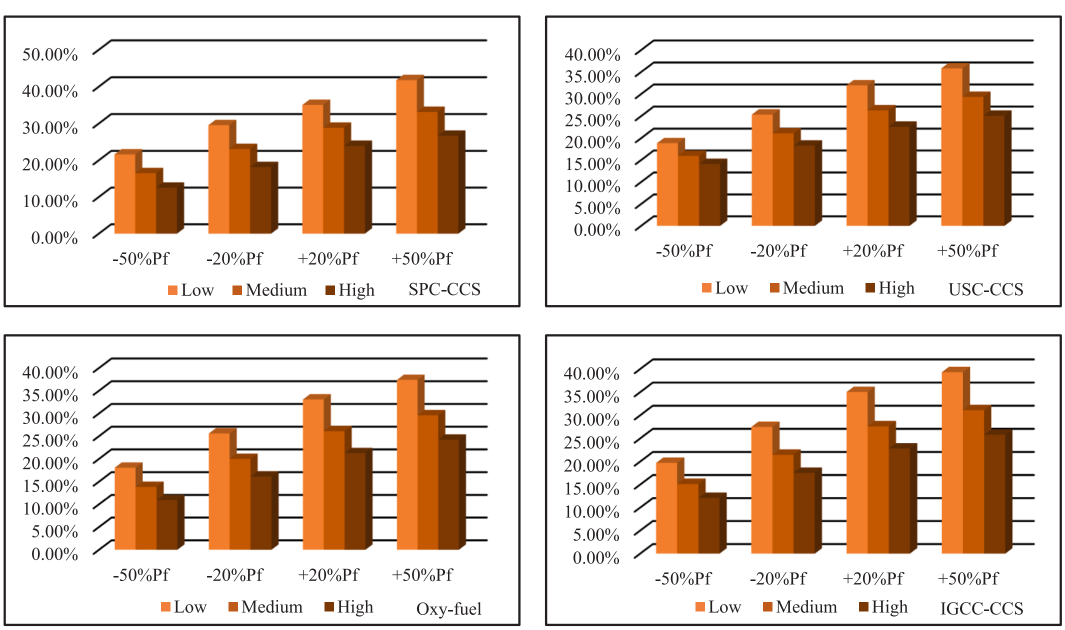

Fig. 8. The proportion of fuel cost reduction in total COE decline under different fuel price (Pf) levels.

Conclusions, implications and outlook

Conclusions

Given the importance of understanding the cost outlook of CCS and BECCS for coal power–dependent nations undergoing power system transitions, as well as the limitations of the existing literature in cost forecasting, this study employs a component-based learning curve model incorporating efficiency upgrades. Taking the Chinese technological context as a case study, the analysis is conducted from a system-level perspective to evaluate the future cost trajectories and the evolution of economic–environmental benefits of key CCS and BECCS technology pathways. Furthermore, the study quantitatively assesses the driving effects of efficiency upgrades and individual cost items on overall system cost reductions, and examines the impacts of pre-learning values and fuel price levels on the magnitude of technological learning effects. The main conclusions are summarized as follows:

The component learning curve that incorporates efficiency upgrades is an effective tool for predicting cost trends in complex engineering technologies, particularly for demonstration technologies lacking commercial operation data. This method not only estimates the learning rate of complex technological systems at the component level, allowing different components to evolve at different rates, but also integrates the concept of efficiency growth, capturing its role in cost reduction. Its effectiveness has been validated by the cost evolution processes of SPC and USC in China.

The overall cost outlook for representative coal power generation systems in China, including configurations integrated with CCS and BECCS, appears promising, with a potential COE reduction of approximately 23.10 to 55.75 USD/MWh. Due to differences in learning rates and accumulated experience, IGCC and oxy-fuel exhibit greater cost reduction potential compared to SPC and USC. While the integration of CCS and BECCS significantly increases the overall system costs of each technology, it also enhances their COE learning rates. This implies that, with continued technological learning, the cost gap between systems with and without CCS and BECCS will gradually narrow.

The current economic-environmental benefits of representative coal power systems in China, along with their corresponding CCS and BECCS technology pathways, remains relatively limited. However, with the accumulation of learning experience, the economic–environmental benefits of these technologies are expected to improve by over 50%. As technological learning progresses, the advantages of systems equipped with CCS and BECCS become increasingly pronounced, particularly in the case of SPC-CCS/BECCS configurations. By contrast, the economic–environmental performance of IGCC with BECCS is hindered by its sensitivity to fuel, while oxy-fuel lacks a relative advantage due to its high COE.

Efficiency upgrades contribute 30% ~ 67% to cost reduction, particularly in the early stages of technological development. Capital cost and fuel cost changes are the primary drivers of COE reduction in CCS and BECCS, collectively contributing 60% ~ 86% of the reduction. The additional COE decline resulting from higher learning levels stems mainly from the greater reduction potential of capital and fixed O&M costs. Additionally, the magnitude of the pre-learning value is a critical uncertainty factor in determining the pace of cost reduction, while fuel price levels exhibit a positive correlation with the extent to which learning effects are realized.

Implications

Based on the previous research conclusions, key implications for the strategic technological deployment of coal power and the accelerated realization of the cost reduction potential of CCS and BECCS are proposed.

Policymakers should account for the impact of efficiency upgrades in evaluating and promoting CCS and BECCS, as system integration and process optimization significantly contribute to cost reductions. Meanwhile, given the efficiency penalties associated with the deployment of CCS and BECCS, the power sector can adopt multiple measures to compensate for and mitigate the net efficiency losses induced by technological implementation. These measures include optimizing carbon pricing mechanisms to enhance the economic returns of low-carbon investments, implementing differentiated electricity pricing and capacity compensation schemes to offset COE increases resulting from efficiency losses, and strengthening integrated research and development efforts between coal-fired thermal cycle systems and carbon capture systems to reduce efficiency penalties at the technological level.

Given the varying cost-reduction potentials and future economic-environmental benefits of different technologies under technological learning, the government should adopt a differentiated technology cultivation strategy. For instance, priority support should be given to frontier technologies with high cost-reduction potential such as IGCC and oxy-fuel combustion, while CCS and BECCS retrofits for mature technologies like SPC and USC should be steadily promoted. Moreover, a tiered deployment roadmap spanning short-, medium-, and long-term horizons should be established—for example, prioritizing the deployment of SPC-CCS/BECCS in the near term and promoting USC-CCS/BECCS and IGCC-CCS in the medium to long term—to enhance the efficiency of coal power's low-carbon transition.

The government should establish a technology promotion mechanism linked to environmental benefits. Although CCS and BECCS entail high deployment costs, their substantial environmental benefits indicate their potential to offset these costs. Therefore, policymakers should quantify the environmental gains of CCS and BECCS and create a favorable environment for the large-scale adoption of high-cost, high-benefit technologies.

The government should prioritize the early deployment and promotion of CCS and BECCS. Since efficiency upgrade plays a significant role in cost reduction during the early stages of technological learning, policy support should ensure the rapid deployment of CCS and BECCS during the initial phase of innovation. This would accelerate efficiency upgrades at power plants and advance the pre-learning process, thereby unlocking the cost reduction potential of technological learning.

The government should establish an effective industry knowledge-sharing mechanism. Given that the pre-learning value is a key uncertainty factor influencing the speed of cost reduction, policies should focus on fostering knowledge exchange and technology dissemination mechanisms within the industry. This would lower the threshold to technological learning, reduce pre-learning values, and accelerate cost reduction.

Outlook

This study provides scientific insights into the cost evolution pathways of CCS- and BECCS-integrated coal power generation systems in China and offers important implications for coal-dependent countries seeking to accelerate the realization of cost reduction potential in CCS and BECCS. Despite these contributions, several limitations should be acknowledged and addressed in future research. First, this study employs a component-based learning curve model incorporating efficiency upgrades to analyze the cost outlook of CCS and BECCS. However, the temporal effect of learning-induced “efficiency upgrades” is implicitly assumed to persist throughout the entire technological learning cycle, without explicitly specifying its underlying micro-level mechanisms. According to the theory of technological evolution, performance improvements—namely, efficiency upgrade effects—typically exhibit pronounced stage-specific characteristics over the course of technology development and deployment [56–58]. Therefore, future research could adopt a staged modeling framework to construct learning curve models that explicitly incorporate phased “efficiency upgrade” effects, thereby enabling a more precise assessment of the role of efficiency gains in shaping long-term technology cost trajectories under technological learning. Second, due to data unavailability and limited theoretical guidance, this study is unable to rigorously characterize component-level spillover effects in advanced power generation systems. Consequently, potential inter-component learning spillovers in complex systems such as IGCC and oxy-fuel combustion technologies are not incorporated into the modeling process. This omission may inevitably introduce bias into technology cost estimations derived from a technological learning perspective. Addressing this issue in future research would help refine the modeling logic of energy technology cost forecasting under the technological learning framework and improve the accuracy of long-term cost prospect assessments.

CRediT authorship contribution statement

Delu Wang: Validation, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Fan Chen:** Methodology, Software, Data curation, Writing – original draft, Visualization, Validation, Funding acquisition. **Chunxiao Li:** Visualization, Validation, Software. **Lawrence Loh:** Supervision, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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The information in Appendices A/B/C/D/E/F is provided in the Supplementary Material.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.seta.2026.104950.

Data availability

Data will be made available on request.

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