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Integrated Multi-Sectoral Approach for Planning of Carbon Capture and Storage Projects

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The chemical, mining, iron and steel, and power sectors are the main CO_2 emitting industries in China. Promoting the low-carbon and green development of various sectors has become an important link to achieve dual carbon goals. Carbon capture and storage technologies are the important means of carbon sequestration. To optimally match the sources and sinks, an integrated approach which combines process integration with orthogonal experimental design method is developed. Through setting up the reservoirs of four sectors, carbon storage composite curves (CSCC) are developed to investigate CO_2 sequestration from 2020 to 2060 to solve the problem of matching carbon sources and sinks. Then, the orthogonal experimental design is used to investigate the influence of the four factors (e.g., the start-up time, the number of the storages, the storage capacity, and the storage operation interval) on the CO_2 storage. The optimal storage scheme is obtained. The matching of carbon sources and sinks at the regional scale will contribute to deploying CCS to realize carbon neutrality by 2060.

1. Introduction

Carbon capture, utilization and storage (CCUS) refers to the industrial process in which carbon dioxide (CO_2) is separated or used directly from industrial emissions sources to achieve CO_2 emissions reduction. The captured CO_2 is either utilized as an industrial feedstock, or is permanently sequestered in a reservoir; for the latter case, the scheme is known as carbon capture and storage (CCS). As an emerging technology that is expected to achieve large-scale low-carbon utilization of fossil energy, CCUS/CCS technology has attracted high attention from the international community (Shu, 2023). Greenhouse gas (GHG) emissions need to be eliminated by mid-century to limit warming to a tolerable level, but deep decarbonization of human activities poses major hurdles. For example, the dual carbon goals in China face great challenges. The trends of carbon reduction in key sectors are different. Efforts should be made to promote the integration of low-carbon development with CCS and other technologies, and accelerate the implementation of low-carbon technologies to meet the 2060 net zero target.
There is still some CO_2 that are difficult to reduce. Hu et al. (2023) shows that CCS technology could capture 1.21 - 4.13 $\times$ 10^{12} t CO_2. In the process of deploying CCS, factors such as injection rate, storage capacity, power generation and consumption, and time will affect the carbon capture capacity, so it is necessary to plan and design the factors to optimize the source-sink matching model. Tan et al. (2013) proposed a multi period mixed integer linear programming (MILP) model, considering the injection rate, storage capacity and time factors to maximize the CO_2 storage amount. He et al. (2014) addressed the robust optimal source–sink matching in CCS supply chains under uncertainty. Wu et al. (2015) discussed the minimum cost strategy to achieve the source-sink matching in regions with multiple CCS options. Zhu et al. (2019) used a linear programming (LP) model to optimize location matching relationship of the source and sink under the constraints of time, capacity, and annual emissions. Xu et al. (2021) established the optimal source-sink matching model and the techno-economic evaluation model.

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Large-scale deployment of CCS can reduce the total carbon emissions of a country or region. CCS can be used based on the overall matching of available storage sources and sinks to promote the comprehensive multi-sectoral carbon emissions reduction. In this paper, a graphic tool of carbon storage composite curves (CSCCs) is used to solve the CCS planning problem, and to solve the selection and planning of multiple sources and sinks to optimize the source and sink matching (Ooi et al., 2013). From a multi-sector perspective, this work uses the orthogonal experimental design to optimize the deployment of CCS according to the factors affecting the CSCCs.

2. Methodology

CO_2 flows physically from sources to sinks, but the storage service flows from the sinks to the sources. At the same time, the storage demand is fluctuating, and the storage capacity is relatively fixed. The CO_2 captured by various sectors are regarded as carbon sinks, and the reservoirs are regarded as carbon sources. Therefore, meeting the CO_2 storage demand is in the opposite direction to capturing CO_2. However, in the actual storage process, due to the limitation of storage time and storage capacity, not all captured CO_2 is converted into storage demand, and whether the storage demand can be met depends on the storage capacity. According to the relationship between storage demand and storage, there are three states: total storage capacity, additional storage requirement, and additional storage capacity. CCS is deployed based on the overall matching of available storage sources and sinks, and finally additional storage requirement, total storage capacity, and additional storage capacity are obtained.

2.1 Carbon storage composite curves (CSCC)

The CSCCs are shown according to the factors affecting the time and amount of CCS. The y-axis represents the planning time, the time of CO_2 capture in each sector and the start storage time of the reservoir, usually in years. The x-axis represents the annual CO_2 capture of each sector and the storage capacity of each reservoir. The reservoir is plotted as a horizontal segment on the CO_2 storage capacity, and the CO_2 storage demand of various sectors is represented by a diagonal line. As shown in Figure 1, reservoir 1 and reservoir 2 with different operation time and storage capacity are used to store the captured CO_2, forming a carbon source composite curve in the form of a staircase. The carbon emissions of various sectors in each time period are accumulated to form a carbon sink composite curve, and the slope of each part represents the CO_2 capture load in a given time. For example, if sector 1 and sector 2 have carbon emissions from 2020 to 2030, their total carbon emissions will be added up to form a separate segment.

At the same time, to obtain a feasible storage scheme, the reservoir (carbon source) should be deployed in advance to store the CO_2 captured. Therefore, it is necessary to move the carbon source composite curve horizontally to the right until it intersects and is completely above the carbon sink composite curve.

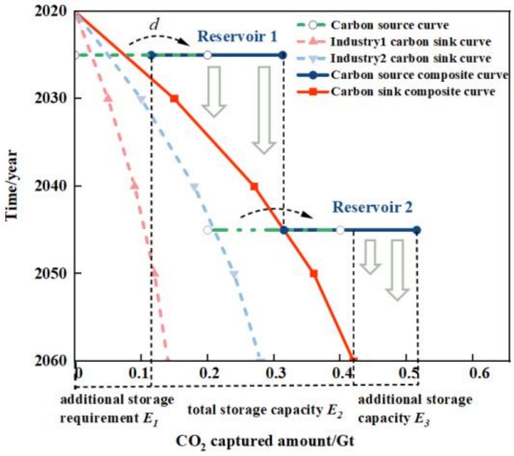

Figure 1: Carbon storage composite curves

The area indicated by the arrow of the composite curve of carbon source and carbon sink indicates that the reservoirs are ready for storage (Figure 1). Within a given time interval, reservoir 1 will store the CO_2 emitted by various sectors from 2025, and a certain amount of CO_2 can be captured and transported to the reservoir. The unclosed area on the left side of the curve is the additional storage requirement E_1. Due to the need to establish a reservoir in advance to store the captured CO_2 as early as 2025, the amount of CO_2 emitted before 2025

needs to be outsourced (such as other nearby areas) to meet this additional storage requirement E_1. On the other hand, the unclosed area on the right side of the curve is the additional storage capacity E_3. The excess storage capacity can be used by other areas with insufficient storage capacity.
By modeling the CSCC curve, we can directly obtain the additional storage requirement E_1 (the maximum reservoirs moving distance d), CO_2 storage capacity E_2, and additional storage capacity E_3. Suppose that the abscissa CO_2 capture amount of the carbon source composite curve is expressed as x_i; if the ordinate time is expressed as y_i, the points on the curve are (x_1, y_1)... (x_m, y_m) respectively. The intersection of the composite curve is (X_i, Y_i). k_i represents the slope of the carbon sink composite curve, the sector carbon capture per unit time. Through graphic analysis, the expression of the moving distance d and the curve is as follows:

$$E_1 = M \begin{Bmatrix} X_i\,, & n = 1 \\ X_i - \sum_{i=1}^{n-1} C_i\,, & n > 1 \end{Bmatrix} \tag{1}$$

$$X_i = x_{i+1} - \frac{y_{i+1} - Y_i}{k_i} \tag{2}$$

$$k_i = \frac{y_{i+1} - y_i}{x_{i+1} - x_i} \tag{3}$$

$$E_2 = \begin{Bmatrix} x_m - d, & \sum_{i=1}^{n} C_i + d \geq x_m \\ \sum_{i=1}^{n} C_i\,, & \sum_{i=1}^{n} C_i + d < x_m \end{Bmatrix} \tag{4}$$

$$E_3 = \sum_{i=1}^{n} C_i + d - x_m \tag{5}$$

Where C_i is the CO_2 storage capacity of the reservoir i; X_i represents the CO_2 capture load at the intersection of the reservoir i and carbon source composite curve, and Y_i represents the storage time of the reservoir i; The curve moving distance d is the maximum horizontal moving distance of the reservoir, which indicates the additional storage requirement, the limit of the operation time and storage capacity factors on the storage capacity of CO_2 load. If the additional storage capacity E_3 is positive, it indicates that there is additional storage capacity available for use in other regions. If E_3 is negative, it indicates that the storage capacity is not enough to CO_2 captured from the region.

2.2 The orthogonal experimental design

Orthogonal experimental design is an important mathematical statistics method to study multiple-factor problems. Experiments are arranged according to a series of standardized orthogonal tables that are designed to minimize the number of experiments as much as possible. These techniques can also be used for global sensitivity analysis through computational experiments. Compared to local (“one factor at a time”) sensitivity analysis, global sensitivity analysis can detect the joint effects of variations in parameters. The factors affecting the deployment of CCS were analyzed by using the orthogonal experimental design, and the appropriate table was designed according to the factors and level numbers. Range analysis and variance analysis were conducted on the results of each test scheme to determine the optimal CCS deployment.
By analyzing the CSCC curve, factors such as the number of reservoirs, the start storage time of reservoir and the storage capacity affect the total amount of CO_2 storage. Four factors are selected, including the number of reservoirs, the start storage time of reservoir, the storage capacity, and the operation time interval of reservoir. The deployment of CCS under the general emissions reduction scenario is analyzed by using the orthogonal method, and the optimal storage scheme aiming at maximizing the amount of CO_2 storage is obtained, and the influence degree of each factor is compared. Table 1 shows that four factors and three levels are set. In addition, in the orthogonal experimental design, it is assumed that the storage capacity of each reservoir is the same. The test arrangement and results are shown in Table 2.

Table 1: Factor level

Factor level	A (Number of reservoirs)	B (Start storage time of reservoir/year)	C (Storage capacity /Gt)	D (Operation time interval of reservoir/year)
1	1	5	0.9	0
2	2	10	1.0	5
3	3	15	1.1	10

Table 2: Orthogonal test table

Schemes	A (Number of reservoir)	B (Start storage time of reservoir/year)	C (Storage capacity /Gt)	D (Operating time interval/year)	Total CO_2 storage (Gt)
1	1	5	0.9	0	0.9
2	1	10	1.0	5	0.904
3	1	15	1.1	10	0.7325
4	2	5	1.0	10	1.0
5	2	10	1.1	5	0.561
6	2	15	0.9	0	0.7325
7	3	5	1.1	5	1.0645
8	3	10	0.9	10	0.858
9	3	15	1.0	0	0.7325

3. Results

3.1 The amount of multi-sectoral CO_2 capture

According to the classification of China's national economic sectors (GB/T4754-2011), the economy is divided into eight sectors: mining, light, textile, petroleum, chemicals, iron and steel, mechanical and electrical, and coal-fired power sectors (Yuan, 2020). Based on emissions data of Shandong Province from 2015 to 2019, the chemicals (1.43 %), mining (5.01 %), iron and steel (9.32 %), and power (48.67 %) sectors are considered in the case study. Predictions of the CO_2 capture of these four sectors from 2020 to 2060 are based on Luan (2012). It can be seen from Figure 2 that the total CO_2 captured of the four sectors showed an upward trend, with 1.23 Gt to be captured by 2060. CCS will start to capture CO_2 in 2020, and the theoretical value of CO_2 captured will reach 321 Mt in 2030. Each bar represents the accumulated carbon capture over the different sectors decade. With the development of negative emissions technologies, the carbon emissions reduction of various sectors has decreased, and the amount of CO_2 captured has also decreased. In 2040, the amount of CO_2 captured reached the peak and showed a downward trend. The points on the line chart show the carbon capture in different sectors in different years. The power sector presented the most significant downward trend, followed by the steel, mining, and chemical sectors.

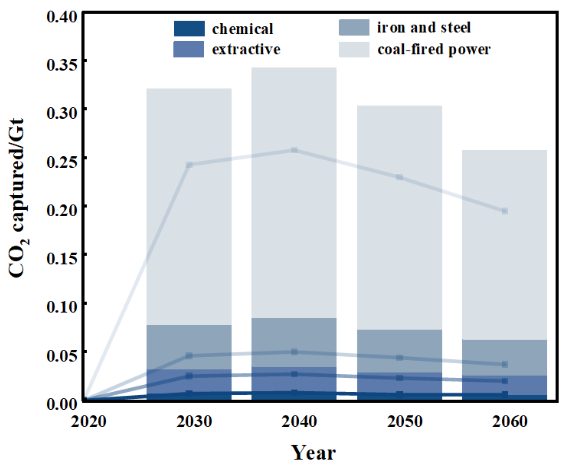

Figure 2: CO_2 captured in Shandong Province from 2020 to 2060

3.2 Analysis of orthogonal experimental design

Range R approximately represents the degree of index change caused by the level change of different factors. The greater the R value, the greater the influence of factors on the index. Table 3 shows that the impact of different factor levels on different indicators is that the range R of the start storage time of the reservoirs is large, which has a significant effect on the total amount of CO_2 storage. The start storage time of the reservoirs should be taken as the main factor to be considered in the process of deploying CCS, and the rest is the number of reservoirs, storage capacity, and reservoir operation time interval in turn. The optimal combination of the total amount of CO_2 storage is A_3, B_1, C_2 and D_3, namely, three storage reservoirs, the start storage time of the reservoir is 2025, the total storage capacity is 1 Gt, and the operation time interval of the reservoir is 10 years.

Table 3: Range analysis results (Gt)

	A	B	C	D
T1	2.5365	2.9645	2.4905	2.365
T2	2.2935	2.323	2.6365	2.5295
T3	2.655	2.1975	2.358	2.5905
R	0.3615	0.767	0.2785	0.2255

Although range analysis can rank the effects of different factors and obtain the main factors affecting the index, it cannot measure the degree of significance of the factors, so analysis of variance is introduced. In the analysis of variance table, the larger the F or the smaller the P-value, the higher the influence of this factor on the test results. Through the variance analysis of the variables affecting the total amount of CO_2 storage, it can be seen from Table 4 that F_B was the largest, with the rest F_D, F_C, F_A in order. The main factor affecting the amount of CO_2 storage is the storage start time B, followed by the storage operation time interval D, storage capacity C, storage number A. At the same time, the significance of the number of storage A, storage capacity C and storage operation time interval D are above 0.05, indicating that they have no significant impact on the total amount of CO_2 storage. The P-value of the start operation time B of the reservoir is below the typical level of significance (α) of 0.05, so factor B has a highly significant impact on the total amount of CO_2 storage.

Table 4: Analysis of variance results

Subject		Sum of squares	Free degree	Mean square	F	P-value
A	Between group	0.269	2	0.135	0.107	0.9
	Within group	7.551	6	1.259		
	Sum	7.821	8			
B	Between group	7.147	2	3.574	31.845	0.001
	Within group	0.673	6	0.112		
	Sum	7.821	8			
C	Between group	0.355	2	0.178	0.143	0.87
	Within group	7.465	6	1.244		
	Sum	7.821	8			
D	Between group	2.33	2	1.165	1.273	0.346
	Within group	5.491	6	0.915		
	Sum	7.821	8			

3.3 Optimal carbon storage composite curves combination of multi-sectors

As shown in Figure 3, the optimal combination deployment of CCS, with a storage time of nearly 33 years, can store a total of 1 Gt of CO_2, with an average annual storage of 31 Mt of CO_2 captured, providing 81.63 % of the emissions reduction contribution.

4. Conclusions

Carbon storage composite curves (CSCC) were used to determine the matching of carbon sources and sinks in multiple sectors in China. The results showed that the amount of CO_2 storage changed under the constraints of different physical and time factors. The CO_2 storage capacity and reservoir are planned through the CSCC curve, which more intuitively shows the total amount of CO_2 storage capacity relative to CCS deployment, additional storage requirement and additional storage capacity. Through orthogonal experimental design, this paper systematically performs global sensitivity analysis of the impact of four factors on the storage capacity, including the number of storages, the start storage time, the storage capacity, and the storage operation time interval, and determines the optimal storage scheme (three storage reservoirs, the start storage time of the reservoir is 2025, the total storage capacity is 1 Gt, and the operation time interval of the reservoir is 10 years). The results show that the integration of the optimal conditions makes the CO_2 storage capacity reach one billion tons, and the contribution of CCS to emissions reduction reaches 81.63 %. In future work, CCS planning process needs to consider the cost and storage location, and should optimize use of CCS technologies by mathematical programming.

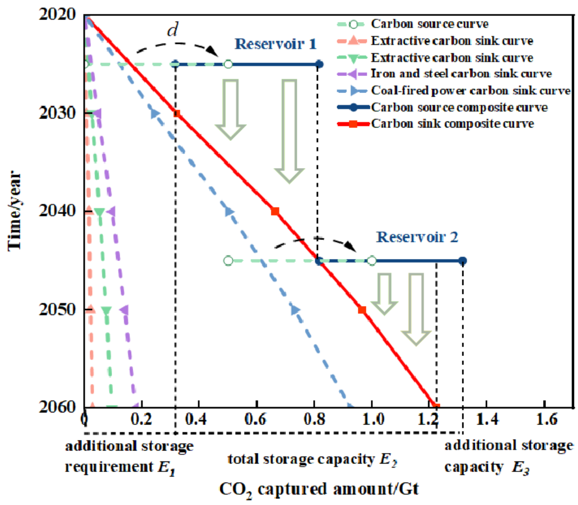

Figure 3: Optimal combination diagram of multi-sector carbon storage composite curves

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References

He Y.J., Zhang Y., Ma Z.F., Sahinidis N.V., Tan R.R., Foo D.C., 2014, Optimal source-sink matching in carbon capture and storage systems under uncertainty. Industrial & Engineering Chemistry Research, 53, 778-785.

Hu Y., Wu W., 2023, Can fossil energy make a soft landing?—the carbon-neutral pathway in China accompanying CCS. Energy Policy, 174, 113440.

Luan S.S., 2012, Analysis of carbon emission forecast and emission reduction path in Shandong Province. Ms. thesis, Ocean University of China.

Ooi R.E., Foo D.C., Ng D.K., Tan R.R., 2013, Planning of carbon capture and storage with pinch analysis techniques. Chemical Engineering Research and Design, 91, 2721-2731.

Shu D.Y., Deutz S., Winter B.A., Baumgärtner N., Leenders L., Bardow A., 2023, The role of carbon capture and storage to achieve net-zero energy systems: Trade-offs between economics and the environment. Renewable and Sustainable Energy Reviews, 178, 113246.

Tan R.R., Aviso K.B., Bandyopadhyay S., Ng D.K.S., 2013, Optimal source-sink matching in carbon capture and storage systems with time, injection rate, and capacity constraints. Environmental Progress & Sustainable Energy, 32, 411-416.

Wu Q., Lin Q.G., Wang X.Z., Zhai M.Y., 2015, An inexact optimization model for planning regional carbon capture, transportation and storage systems under uncertainty. International Journal of Greenhouse Gas Control, 42, 615-628.

Xu M., Zhang X., Shen S., Wei S., Fan J.L., 2021, Assessment of potential, cost, and environmental benefits of CCS-EWR technology for coal-fired power plants in Yellow River Basin of China. Journal of Environmental Management, 292, 112717.

Yuan X.L., Chi J.H., Li Z.P., Zhang W.L., 2020, Carbon emission peak forecast and emission reduction potential research in China's industrial sector. Journal of Statistics and Information, 35,72-82.

Zhu Q., Wang C., Fan Z., Ma J., Chen F., 2019, Optimal matching between CO_2 sources in Jiangsu province and sinks in Subei‐Southern South Yellow Sea basin, China. Greenhouse Gases: Science and Technology, 9, 95-105.