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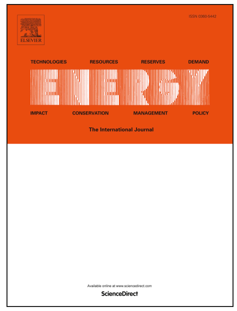

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Analysis of China's olefin industry using a system optimization model considering technological learning and energy consumption reduction

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Abstract

Recently, China has been increasingly producing olefins from alternative resources, especially coal. Technological learning, energy consumption reduction, and environmental policies/regulations will have a great impact on the economic and environmental values of coal-to-olefin (CTO) projects. How should China configure its future olefin industry considering these factors? Little work has been performed to explore this question. This study develops a system optimization model to analyze the optimal configuration of China's olefin industry under different scenarios of technological learning, energy consumption reduction, and environmental policies/regulations. Our results show that in all scenarios, the oil-to-olefin process will remain dominant in China's olefin industry in the next two decades, and with technological learning, the CTO process is competitive in China's olefin industry, especially when CO_2 emissions are not controlled. To control the CO_2 emissions of China's olefin industry, our study indicates that requiring CTO implementation along with carbon capture and storage (CCS) would have both economic and environmental value compared with imposing a carbon tax (assume 20$/t CO_2 from the year 2021). However, policymakers should be cautioned about the uncertainties and risks of CCS. This study also provides some insights for those who are considering investing in China's olefin industry.

Keywords: Olefin industry; technological learning; energy consumption; CCS; carbon tax.

1. Introduction

Olefins are used mainly in the production of polymers, which drive the development of organic chemicals [1]. Ethylene and propylene are the most important

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olefins; in 2015, the consumption of these materials in China was approximately 4.03 $\times 10^7$ t and 3.18 $\times 10^7$ t, respectively [2]. These equivalent consumption rates are expected to increase as a result of the increase in the global population combined with rising living standards [3]. Before 2010, olefin production in China depended mainly on crude oil. Recently, China has been producing olefins increasingly from other resources (e.g., coal, methanol, and propane), especially coal, for which China has rich reserves. More than 23 coal-to-olefin (CTO) plants (see Table A1) are already under operation or planned in China. Due to its complexity, a CTO plant requires high capital investment cost and consumes considerable energy, which is roughly double that of an oil-to-olefin (OTO) plant [4]. Furthermore, a CTO plant produces huge CO_2 emissions, which are estimated at approximately 6~10 t per ton of olefin, whereas the emissions for an OTO plant are approximately 1 t per ton [5]. Thus it makes sense to address the questions of how China should configure its future olefin industry and what kind of policies should be implemented to control carbon emissions if more olefins are produced via CTO in China.

Researchers have conducted considerable techno-economic analyses of different olefin production technologies, such as estimating the future costs of different olefin production technologies with bottom-up techno-economic engineering models[1] [7-10] that consider possible technical innovations, economics and energy use. A common argument against coal for olefin production is the high capital investment costs, energy consumption and huge CO_2 emissions. One prominent example where this argument does not hold is Shenhua Energy's 2015 and 2016 Annual Report, which states that CTO has continued to make profits despite the decline in the oil price since in the middle of 2014 [12]. However, the success of CTO technologies did not come from nowhere. Olefins began to be produced from coal in China in 2010, thus leading to the first successful construction and commissioning of a CTO plant in China [13]. China's CTO production capacities have grown from 1.1×10^6 $t \cdot a^{-1}$ in 2010 to the current rate of 1.50×10^7 $t \cdot a^{-1}$, which is mainly due to favorable government policies (see Table A1 in appendix). The ethylene and propylene capacity from CTO technologies has been estimated to account for nearly 20% of the national olefin production capacity in China in 2020 [14]. Since 2010, capital investment costs of

[1] Bottom-up engineering estimates are based on expert judgements on the potential development of disaggregated components of power plants [11].

CTO technologies have decreased gradually due to both technological progress and learning in the production of olefins [4]. Aspects of technological learning can be captured by the so-called experience curve approach[2]. The experience curve method is based on the empirically observed phenomenon that the costs of a technology decrease by a constant fraction with every doubling of either installed capacity or exercised activity [20]. For many decades, the experience curve has been one of the methods used to estimate the future costs of energy technologies (e.g., see [11,15-18, 21-22]). Novel technologies for olefin production need to be viable from an environmental perspective as well as from a technical one [5]. Researchers have used different methods to accessing environmental impacts of a petrochemical industry, such as LCA (life cycle assessment), material flow analysis (e.g., see [23]), environmental footprint analysis (such as water, energy, and carbon footprint) (e.g., see [24]), and so on. In this study, we mainly consider the carbon emission of each olefin production process.

Although existing techno-economic analyses indicated that future capital investment costs in CTO technology may decline through technological learning, little work has been done to explore how China should configure its olefin industry in terms of different production technologies and the potential carbon emissions of the industry. Given this knowledge gap, the main aim of this paper is to explore these questions by developing a system optimization model of China's olefin industry. The model is developed from a long-term perspective and aims at minimizing the total costs of the industry while satisfying a series of constraints, e.g., demand constraint and capacity limitations.

Configuring China's olefin industry system entails evaluating the costs of different technology paths. The costs of different technologies are influenced by many factors, such as the feedstock price, technological learning, energy consumption, scaling up of individual units, and technology localization (the cost difference of a technology in different nations and districts) [1,6,19, 25-27]. The impact of feedstock prices (such as dynamic oil and coal prices) on the configuration of the olefin industry has been analyzed in our previous work [28]. Among other aspects, empirical studies have shown that technological learning and energy consumption reduction play

[2] We use the term experience curve instead of learning curve because the latter is typically used for approaches that quantify the decrease in labor costs only (e.g., Junginger et al. [19]).

important roles in cost reductions in emerging technologies. For example, Yu et al. [29] showed that learning is the most important factor associated with the larger turbine price reductions in China. Ren et al. [6] estimated a reduction potential of 20–30% for the capital investment costs of coal chemical plants and cited the effects of technological learning and economy of scale in their study period (2010–2050). Energy consumption reduction is another important way to reduce production costs and increasing earnings, especially in times of high energy prices [30]. For example, Saygin et al. [26] and Rubin et al. [27] suggest a global energy consumption reduction potential of 20% at the country level if Best Practice Technologies (BPTs) were implemented in chemical processes. BPTs include the scaling up of individual units, higher levels of process integration, combined heat and power (CHP) and postconsumer plastic waste treatment, and technology localization. Future CTO plants in China are expected to achieve a specific energy consumption reduction of 18% by 2020 through BPT and research and development (R&D) efforts [2, 31-32]. A study in 2018 found that the straight power supply scheme is relatively feasible and better solution in order to meet the requirements of energy efficiency [33]. Of course, a number of concerns about the uncertainties and risks of BPTs remain to be addressed, especially when trying to implement the BPTs by reforming those existing ones. Therefore, in our study we also did a sensitivity analysis on the reductions rates (0% to 18%) of energy consumption (see subsection 4.4). In a short word, these studies imply that technological learning and energy consumption reduction will play an important role in China's olefin production industry. For this reason, this study constructed four different future scenarios based mainly on technological learning and energy consumption reduction associated with CTO. The technological learning and energy consumption reduction of oil-to-olefin (OTO), methanol-to-olefin (MTO), and propane dehydrogenation (PDH) technologies are not included in the analysis.

The first scenario is treated as a business-as-usual case in which the energy consumption reduction and the capital investment cost of CTO remain unchanged (i.e., not considering technological learning). In the second scenario, technological learning is calculated as proposed by McDonald & Schrattenholzer [34] and Zhou et al. [35], while energy consumption remains unchanged. In the third scenario, energy consumption is reduced as proposed in MIITC [2] and technological learning is not considered. In the fourth scenario, technological learning and energy consumption reduction are combined. We intend to compare the results under these four scenarios.

This study does not aim to predict the development of China's olefin industry but rather to explore the optimal configuration (mainly for capacities of different olefin production technologies) of China's olefin industry under different scenarios of technological learning and energy consumption reduction. Although a number of techno-economic analyses have been performed for different olefin production paths in China, little work has been done to explore the optimal configuration of China's olefin industry in terms of different production technologies. The choice of the system optimization model in this study can provide insights on this question as well as implications for relevant policymaking.

The rest of the paper is organized as follows. Section 2 presents the system optimization model. Section 3 presents the initial values of parameters. Section 4 explores the optimal configurations of China's olefin industry under the four defined scenarios and their corresponding system costs and CO_2 emissions without considering controlling CO_2 emissions. Section 5 analyzes the impact of a carbon tax and a carbon capture and storage (CCS) regulation based on the four defined scenarios. Section 6 discusses the validation/verification and limitations of the study. Section 7 presents the conclusions.

2. System optimization model considering technological learning

2.1. Model framework

Our model framework follows that of the MESSAGE (Model for Energy Supply Strategy Alternatives and their General Environmental Impacts), which was developed originally by the International Institute for Applied Systems Analysis and was enhanced by the International Atomic Energy Agency. The MESSAGE provides a framework for representing an energy system that includes important interdependencies from resources refineries, imports, different conversion technologies, transport and distribution to the provision of energy end-use services, such as heat, motor fuel, and electricity [36-38].

As shown in Fig. 1, in this study, following the MESSAGE, the olefin industry is structured as a supply network (physical flow model) that includes four levels: resource, primary, secondary, and final. The linking among different levels is realized using conversion technologies (refinery, olefin plant, transportation, distribution, etc.). Details of the four levels are introduced as follows.

- Resource level: Resources of the system include domestic coal, crude oil and methanol, imported propane (the main four resources we mentioned in the introduction), and imported olefin.
- Primary level: The primary level includes three forms of products (coal, oil, and propane) that are either refined from resources or imported from abroad.
- Secondary level: The secondary level includes olefins converted from coal, oil, methanol, and propane using different technologies, i.e., CTO, OTO, MTO, and PDH.
- Final level: The final level denotes the distribution of olefins to olefin consumers and is identical to the demand of olefins.

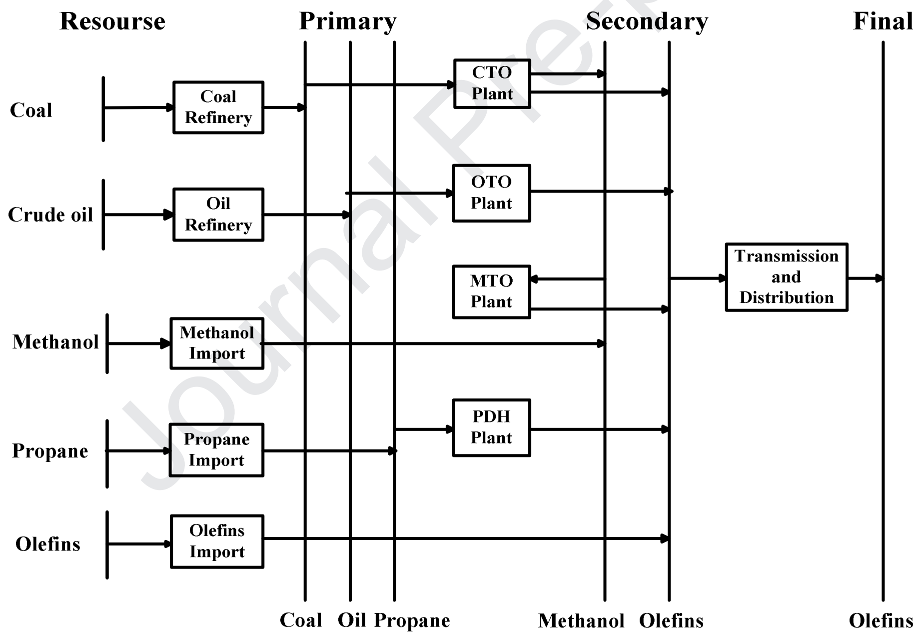

Fig. 1. Model framework

2.2. Mathematical formulation of the model

The objective function of our model is to minimize the total costs of China's olefin industry, including the investment costs, feedstock costs, and operation and maintenance (O&M) costs. All costs that will occur in the future are discounted with a fixed discount rate.

The model is formulated as follows. The demand is exogenous and increases over time as shown in Eq. (1):

$$D^t = D^0(1+\alpha)^t \tag{1}$$

where t is the time period (year), D^t denotes the demand at time t, D^0 denotes the initial demand, and α is the annual increasing rate of demand.

Let N ($i \in N, i = 1,2,...,5$) denote the set of technologies, including OTO, CTO, MTO, PDH, and olefin import, and let y_i^t denote the annual new expansion capacity of technology i at time t. Then, the total installed capacity of technology i by time t, denoted by C_i^t, can be calculated with Eq. (2).

$$C_i^t = \begin{cases} \max(\frac{\tau_i - t}{\tau_i} C_i^0, 0) & t \le ct_i \\ \sum_{j=1}^{t-ct_i} y_i^j + \max(\frac{\tau_i - t}{\tau_i} C_i^0, 0) & ct_i < t \le \tau_i + 1 + ct_i \\ \sum_{j=t-\tau_i-ct_i}^{t-ct_i} y_i^j + \max(\frac{\tau_i - t}{\tau_i} C_i^0, 0) & t > \tau_i + 1 + ct_i \end{cases}, \tag{2}$$

where C_i^0 denotes the initial installed capacity of technology i, τ_i denotes the plant life of technology i, ct_i denotes the construction time of technology i, and $\frac{\tau_i - t}{\tau_i} C_i^0$ denotes the remaining initial capacity of technology i.

The cumulative installed capacity of technology i by time t, denoted by E_i^t, can be calculated with Eq. (3)

$$E_i^t = E_i^0 + \sum_{h=1}^{t} C_i^h , \tag{3}$$

where E_i^0 denotes the initial cumulative installed capacity of technology i, which means the cumulative experience on technology i before $t = 1$.

Technological learning is based on experience, which is quantified by the cumulative installed capacity, and thus future investment cost CF_i^t is a function of the cumulative installed capacity as shown in Eq. (4).

$$CF_i^t = \begin{cases} CF_i^0 & i = 1, 3, 4 \\ CF_i^0 \times (E_i^{t-1})^{-b_i} & i = 2 \end{cases}, \tag{4}$$

where $i = 1,3,4$ denotes OTO, MTO, and PDH, respectively; $i = 2$ denotes CTO, which has the potential for technological learning; CF_i^t denotes the investment cost of technology i in time t; CF_i^0 denotes the initial investment cost of technology i; 1 - 2^{-b_i}

is technology i's learning rate, which means the percentage reduction in future investment cost for every doubled cumulative capacity; and 2^{-b_i} is the progress ratio.

According to Yelle [40] and Li et al. [41], the learning rate of a technology can be described in Eq. (5):

$$LR_{inst,total} = \alpha_1 LR_{1,inst} + \alpha_2 LR_{2,inst} + \ldots\ldots + \alpha_i LR_{i,inst} , \quad (5)$$

where $LR_{inst,total}$ denotes the learning rate of technology i's investment cost, α_i denotes the portion of investment cost of the ith subunit in the total investment cost of the technology i, and $LR_{i,inst}$ is the learning rate of investment cost of ith subunit. In this study, CTO includes three main subunit conversion technologies, namely, coal gasification, methanol synthesis, and MTO.

To the best of the authors' knowledge, although research on CTO has been performed for a long time, few commercial operations have been implemented in countries other than China, although South Africa might be an exception. Thus, in this study, the technological learning effect is assumed to mainly depend on China's experience in CTO, which could be approximately treated as global experience in commercial CTO operations.

Let R_j^t represent the quantity of the jth types of refined resources at time t, which is a function of production with different technologies, as shown in Eq. (6).

$$R_j^t = \sum_{i=1}^{N} \frac{x_{ij}^t}{\eta_i} , \quad (6)$$

where j (= 1, 2, …, 5) denotes a resource type from coal, crude oil, methanol, propane, and imported olefin; x_{ij}^t represents the output of technology i using the jth resource at time t, and η_i denotes the energy efficiency of technology i, which usually should be no greater than 1. The term energy efficiency in this paper is different (but also somehow borrowed) from the energy efficiency of energy conversion plants. In this paper, energy efficiency is defined using Eq. (7) as the ratio of product energy to total energy consumption following the work of Xiang et al. [32].

Energy efficiency =Product energy (GJ) / Total energy consumption (GJ), (7)

where the *Product energy* contains the energy of ethylene, propylene, and butane and the *Total energy consumption* contains the energy of feedstock, steam, and electricity.

The energy of olefins and feedstock is calculated based on their lower heating value.

The objective function of our model is to minimize the total cost, which can be expressed with Eq. (8).

$$\min \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{1}{(1+\delta)^t}(CF_i^t \cdot y_i^t)+\sum_{t=1}^{T}\sum_{j=1}^{J}\frac{1}{(1+\delta)^t}(CE_j^t \cdot R_j^t)+\sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{j=1}^{J}\frac{1}{(1+\delta)^t}(Fom_i^t \cdot C_i^t + Vom_i^t \cdot x_{ij}^t) \quad (8)$$

The objective function is subject to the following constraints (9) - (12):

$$D^t \le \sum_{i=1}^{N} x_i^t, \forall t \quad (9)$$

$$x_i^t \le f_i^t C_i^t, \forall i, t \quad (10)$$

$$x_i^t \ge 0, \forall i, t \quad (11)$$

$$y_i^t \ge 0, \forall i, t \quad (12)$$

where T denotes the number of periods, δ denotes the discount rate, Fom_i^t denotes the fixed operating and maintenance cost of technology i at time t, Vom_i^t denotes the variable operating and maintenance costs of technology i at time t, and CE_j^t denotes the feedstock price of the jth resource at time t. Eq. (9) denotes that the demand must be satisfied by the output of the different technologies. Eq. (10) denotes that the production should be no more than the total installed capacities, where f_i^t is the annual operation time percentage (i.e., plant factor) of the ith technology at time t. Eq. (11) and Eq. (12) denote that the decision variables x_i^t and y_i^t are nonnegative.

If a carbon tax is imposed, the objective function can be described with Eq. (13).

$$\min \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{1}{(1+\delta)^t}(CF_i^t \cdot y_i^t)+\sum_{t=1}^{T}\sum_{j=1}^{J}\frac{1}{(1+\delta)^t}(CE_j^t \cdot R_j^t)+\sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{j=1}^{J}\frac{1}{(1+\delta)^t}(Fom_i^t \cdot C_i^t + Vom_i^t \cdot x_{ij}^t) + \sum_{i=1}^{N}\sum_{t=1}^{T}\frac{1}{(1+\delta)^t}(CT \cdot \frac{\lambda_i}{\eta_i} x_i^t), \quad (13)$$

where CT denotes the carbon tax, and λ_i denotes the emission coefficient of technology i. This objective function is also subject to constraints (9) – (12).

OTO was developed a half-century ago. This process has been highly optimized, and its capacities have been increased, resulting in a well-established technology whose economics can hardly be challenged. OTO was developed half-century ago. This process has been highly optimized and its capacities have been increased, resulting in a well-established technology whose economics can hardly be challenged. Methanol synthesis processes were implemented over the world in 1960s, and MTO was introduced in the late 1970s by ExxonMobil scientists and was later patented by different companies, and PDH process also has been successfully commercialized worldwide. These processes are high energy efficient and the specific energy consumption is near to the theoretical minimum [5,42-43]. CTO includes three main energy conversion technologies: coal gasification, methanol synthesis, and MTO. Coal gasification is still under development in China or world [34-35,44]. For this reason, the technological learning and energy consumption reduction potential of CTO technologies were considered in our analysis.

With the technological learning effect, the resultant mathematical problems are nonconvex and nonlinear optimization problems. The model was developed with MATLAB and solved with the *fmincon* function of MATLAB's Optimization Toolbox (R2008a), which applies a sequential quadratic programming (SQP) method. In this method, the function solves a quadratic programming (QP) sub-problem at each iteration. An estimate of the Hessian of the Lagrangian is updated at each iteration using the BFGS formula. A line search is performed using a merit function. More details of the method can be found in the user's guide to MathWorks (2008) [45]. The global optimality of the solutions was checked by using di□erent starting points.

3. Initialization of parameters

Development plans in China are commonly made every five years. In our study, we consider 4 connecting five-year plans, from 2016 to 2035, as the decision periods of the optimization problem. The year 2015 is assumed to be the base year, and the annual discount rate is assumed to be 5% (a sensitivity analysis on the discount rate is provided later in section 4.4).

3.1. Demand of olefins

China's initial demand for olefins was approximately 80,683 ktoe in 2015. The average predicted growth rate of olefins demand is 4.12% in the period from 2015 to 2020 (see Table A2 in appendix). Future demand might be influenced by uncertain economic changes, such as weak trade. In our study, considering these uncertainties, we assume that the model will meet an increasing demand at an annual growth rate of 3.9% [46].

3.2. Feedstock price and capacity in olefin production technologies

Table 1 presents the international prices of resources used to produce olefins, and these data were obtained from NBSC [47] and CIR [48,49]. As discussed in the introduction, this study focuses particularly on how China should configure its future olefin industry in terms of different production technologies considering technological learning and energy consumption reduction of CTO. For this purpose, we assume that the feedstock prices of these technologies will be constant and the olefin import price will be at its highest level (assumed as double the present price) [47].

Table 1

Olefin feedstock prices in the base year.

Year	Oil[a]	Coal[b]	Methanol[c]	Propane[c]	Olefins import[c]
	US$/toe	US$/toe	US$/toe	US$/toe	US$/toe
2015 (base year)	357	94.4	592.2	423	1007

Source:

[a] Crude oil (West Texas Intermediate) price is converted from the National Bureau of Statistics of China (NBSC) [47].

[b] Coal price is converted from the National Bureau of Statistics of China (NBSC) [47].

[c] These data on methanol and propane prices were converted from the China Industry Research (CIR) [48,49].

Table 2

Initial total installed and initial cumulative capacities of olefin production technologies in 2015 and the planned expansion capacity for 2016–2020 in China.

Technologies	Initial total installed capacity in 2015[a] (ktoe)	Share of technology in 2015	Initial cumulative installed capacity in 2015[a] (ktoe)	Planned expansion capacity in 2016-2020[b] (ktoe)
OTO	42,099	76.57%	300,000	10,407
CTO	4,521	8.22%	23,395	13,328
MTO	4,219	7.67%	9,996	1,511
PDH	3,984	7.25%	4,355	5,170
Others	157	0.29%	-	-
	54,980			

Source:

[a] Data were taken from Yu [50].

[b] Data were taken partly from Xiang [51], and PDH data were calculated from the CNCIC [52].

Table 2 presents the initial total installed and initial cumulative capacities of olefin production technologies in 2015 and the new expansion capacity for 2016–2020 in China [50-52]. From this, we can see that OTO dominated the olefin production in 2015 and accounted for approximately 76% of the total production, and CTO was the second most widely used olefin production technology in China in 2015. In this study, we also assume the planned expansion capacity of olefin production technologies (from 2016 to 2020 [51-52]) will be established as planned.

Following the optimization model framework, in our study, olefin industry technologies are characterized by their initial investment cost, operation and maintenance (O&M) cost, energy efficiency, CO_2 emissions coefficient (i.e., total CO_2 emissions per ton olefins), learning rate, plant factor, construction time, and plant life. Table 3 summarizes these technical parameters.

Table 3

Techno-economic parameters of the olefin industry.

Technology	Initial investment cost[1]	Fix O&M cost[2]	Variable O&M cost[2]	Energy efficiency[3]	CO_2 emission coefficient[4]	Mean learning rate[5]	Plant factor[6]	Construct time[6]	Plant life[6]
	(US$[1]/toe)	(US$/toeyr)	(US$/toeyr)	(%)	t_{CO2}•t^{-1}	%	(%)	(yr)	(yr)
OTO	1722.1	93.7	330.1	70.96	0.71	-	90	3	30
CTO	3615.7	446.8	522.6	36.16-44	8.94-7.61	15	81.8	3.5	30
CTO with CCS	3832.6	495.9	590.4	35.7-43.5	4.16-2.83	14	81.8	3.5	30
MTO	1648.8	116.1	185.1	81.02	1.59	-	90	2.5	30
PDH	638.1	49.2	226.5	69.77	0.81	-	90	2.5	30

Note: This table goes through the basic scenario calculations.

[1] 2015 US$/¥ = 6.2284. These data were taken partly from a recent review by Xiang et al. [4,53], and PDH investment cost data were taken from Xu et al. [54].

[2] OTO, CTO, and MTO data were calculated from Xiang et al. [7] and Wan et al. [55], and the PDH cost data were calculated from Xu et al. [54].

[3] These data were taken partly from a recent review by Xiang et al. [4,53]. CTO data were taken from Xiang et al. [4] and MIITC [2], and the energy efficiency of PDH was calculated from Xu et al. [54] and Xu et al. [56].

[4] These data were taken partly from a recent review by Amghizar et al. [5], and PDH emission data were assumed to be equal to the SC (ethane) reference. The highest CO_2 emissions coefficient of the CTO data were based on Xiang et al. [7,53]. With its energy efficiency reaching 44%, the CO_2 emissions coefficient of CTO will be 7.61 t_{CO2}•t^{-1}[2].

[5] These data were calculated via Eq. (5), and the original data were taken from McDonald & Schrattenholzer [34] and Zhou et al. [35]. CTO's technological learning was calculated via Eq. (5) as follows.

a. $LR_{CTO,\,inst} = \alpha_1 LR_{CTM,\,inst} + \alpha_2 LR_{MTO,\,inst}$

= (3615.7-1648.8)/3615.7 × 27%+1648.5/3615.7 × 0% ≈ 15%.

b. $LR_{CTO(CCS),\,inst} = \alpha_1 LR_{CTM,\,inst} + \alpha_2 LR_{MTO,\,inst} + \alpha_3 LR_{CCS,\,inst}$

= (3615.7-1648.8)/3832.6 ×27%+ 1648.5/3832.6 × 0% + (3832.6-3615.7)/3832.6 × 6.3% ≈ 14%.

[6] These data were evaluated based on the CNCIC [52].

4. Four scenarios without controlling carbon emissions

4.1. Four scenarios of technological learning and energy consumption reduction of CTO

As discussed in the introduction section, previous studies have shown that technological learning and energy consumption reduction play important roles in investment cost decline and CO_2 reductions of emerging technologies, such as CTO technology [6,25-26]. We designed the following four scenarios of technological learning and energy consumption reduction of CTO, where the technological learning of CTO is estimated via Eq. (5) based on previous empirical research [34,35], and the energy consumption reduction in CTO is based on China's official documents for future planning [2] as well as existing studies [32].

(A1) Reference scenario. The reference scenario is a business-as-usual scenario, in which the energy consumption of CTO is 129.98 GJ/t (i.e., its energy efficiency is 36.16%) [4] and the investment cost will not be changed since technological learning is not considered.

(A2) Scenario with technological learning. In this scenario, the CTO's technological learning is 15% as calculated via Eq. (5) and using data from McDonald & Schrattenholzer [34] and Zhou et al. [35] (see more details in Table 3 and its notes), while there is no energy consumption reduction in CTO.

(A3) Scenario with energy consumption reduction. In this scenario, the energy consumption of the CTO capacity will be 106.58 GJ/t (i.e., its energy efficiency is 44%) following China's official documents [2] and Xiang et al. [32], and the investment cost of CTO will not decrease in the future, i.e., no technological learning effect.

(A4) Scenario with both technological learning and energy consumption reduction. In this scenario, the combination of technological learning is set as 15% following McDonald & Schrattenholzer [34] and Zhou et al. [35], and the energy consumption of CTO is set as 106.58 GJ/t (i.e., its energy efficiency is 44%) following the MIITC [2] and Xiang et al. [32]. As mentioned in the introduction section, the olefin industry could reduce its energy consumption by implementing Best Practice Technology and R&D efforts.

In the following, we present and discuss the optimal results (including the capacity configuration of different technologies, the accumulated total system costs, and CO_2 emissions) of the four defined scenarios. Based on the four scenarios, we also conduct sensitivity analysis on the technological learning rate and energy consumption reduction (see section 4.4).

4.2. Impacts of technological learning and energy consumption reduction

The capacities of different technologies for the A1, A2, A3, and A4 scenarios from 2016 to 2035 are illustrated in Fig. 2. In all four scenarios, OTO will still dominate China's olefin industry in the next two decades and accounts for more than 67% of China's olefin production using OTO technology (see Table A3 in appendix). This result is consistent with those of Peng's study [58], which has predicted that OTO will account for approximately 60% of olefin production in China in 2018 and dominate the olefin production in China in the coming decade.

Moreover, in both the A2 and A4 scenarios, which consider technological learning of CTO, CTO is competitive and will be significant in China's olefin production, accounting for approximately 12–13% of China's olefin production using CTO technology even when the oil price is as low as 357 US$/toe (i.e., 48.71 US$/bbl, see Table A3 in the appendix). In the year 2035, the adoption of CTO technology will reach approximately 22.60% and 27.11% in the A2 and A4 scenarios, respectively, as shown in Fig. 2. These results are consistent with China's official estimation that CTO technologies might account for nearly 20% of the national olefin production capacity in China in 2020 [14].

The expansion of PDH capacities in the study period is obvious in all four scenarios, and approximately 11% of China's olefin production will use PDH technology (see Table A3 in appendix) mainly because the abundance of cheap propane from shale gas would cause the OTO industry to shift to production by catalytic dehydrogenation of propane. This finding is consistent with the recent observations that a dozen new PDH plants are to be built worldwide [5,58].

The expansion of the capacities of MTO in the study period are nearly the same in all four scenarios, and approximately 3.3% of China's olefin production will use MTO technology (see Table A3 in appendix).

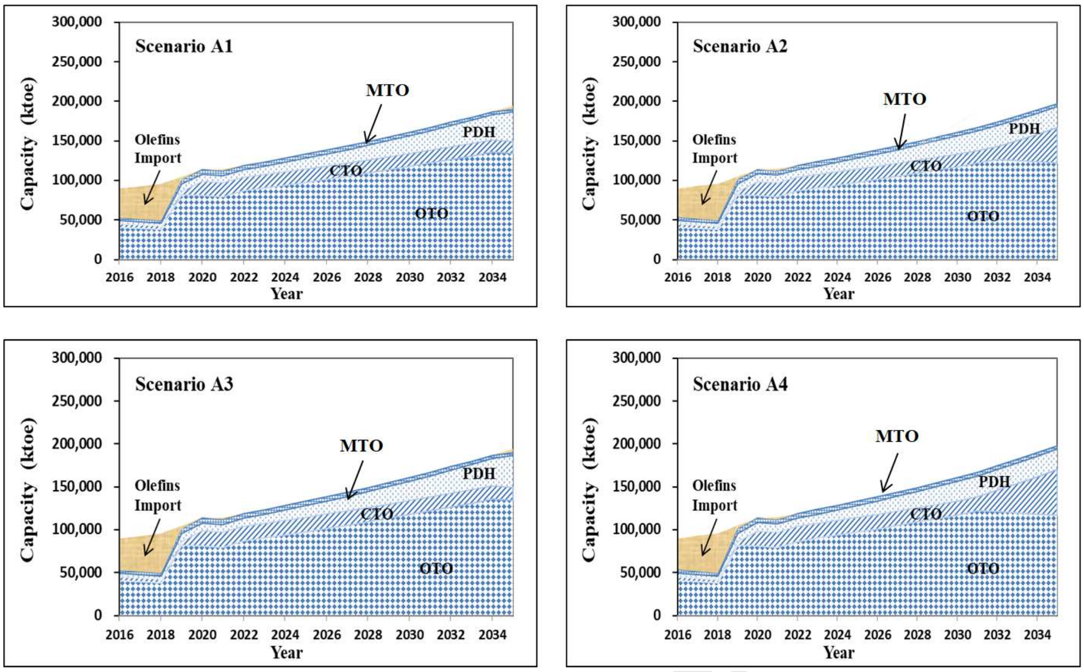

Fig. 2. Capacity of different technologies in scenarios A1, A2, A3, and A4.

4.3. System cost and CO_2 emission

As denoted in Eq. (8), the total system cost includes the investment costs, O&M costs, and feedstock costs. As shown in Table A4 in the appendix, in scenarios A2, A3, and A4, in which CTO's technological learning and/or energy consumption reduction are modeled, the accumulative total system costs are lower than those in scenario A1. In scenario A4, with the combination of technological learning and energy consumption reduction, the accumulative total system cost is the lowest of all four scenarios and approximately 0.65% lower than that in scenario A1. In brief, technological learning and energy consumption reduction do not change the accumulative total system cost by much.

Fig. 3 illustrates the CO_2 emissions from the olefin industry in the four scenarios. In 2035, CO_2 in scenario A2 and A4 reaches approximately 396 million tons, which is approximately twice that of scenario A1. This finding is because CTO becomes more competitive and will be significant in China's olefin production with technological learning, thus accounting for 22.60% and 27.11% of China's olefin production in 2035 in scenario A2 and A4, respectively (see Fig. 2). Scenario A2 results in the highest total CO_2 emission (3763.6 Mt, see Table A4 in appendix) in the four scenarios. In scenario A3, the total CO_2 emissions are decreased by 8.05% compared with that in scenario A1 due to the decreased energy consumption of CTO plants (see

Table A4 in appendix). In short, the reduced energy consumption of CTO could contribute considerably to CO_2 emissions in China's olefin production technology.

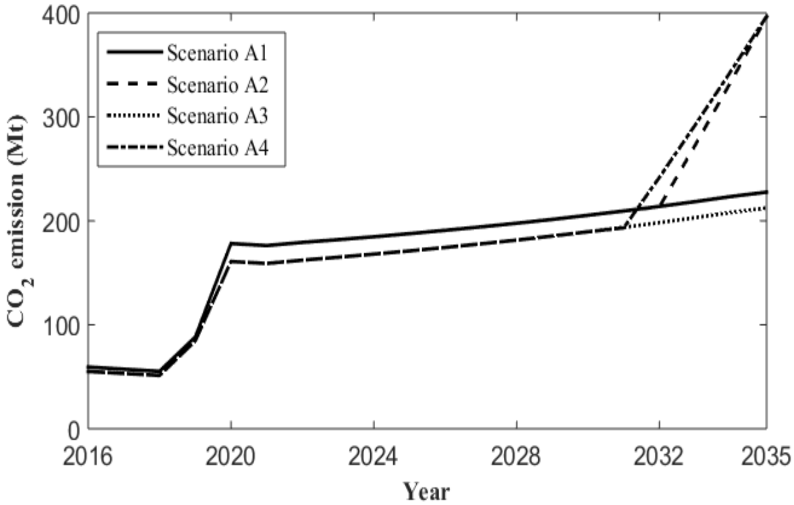

Fig. 3. CO_2 emissions from the olefin industry in the four scenarios.

4.4. Sensitivity analysis

With scenario A2, we experiment with different learning rates of CTO, i.e., 3%, 6%, 9%, 12%, and 15%. Fig. 4 shows that higher technological learning corresponds to the greater adoption of CTO technology, which is very sensitive to the learning rate when it increases from 9% to 12%. In this scenario, since the reduction of energy consumption is not considered, CTO technology benefits significantly from technological learning and dominates the olefin industry.

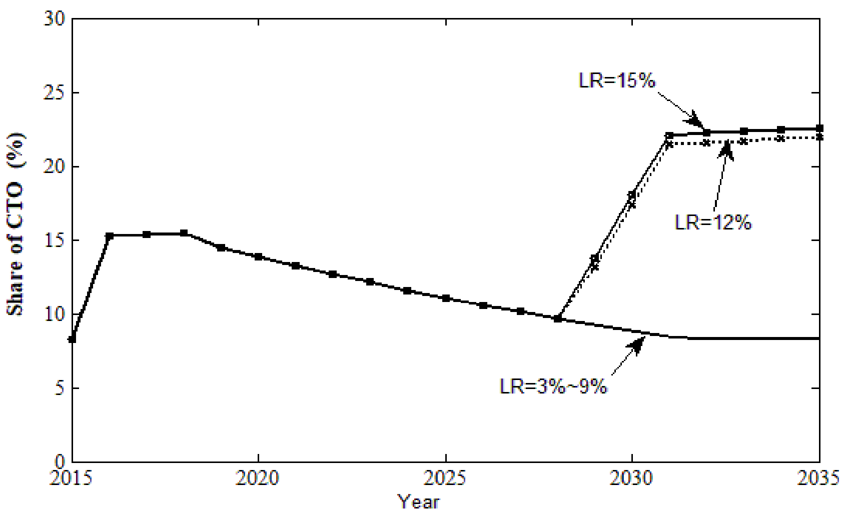

Fig. 4. Adoption of CTO technology with different technology learning in scenario A2.

With scenario A3, we experiment with different energy consumption reductions, and the energy efficiency of CTO is assumed to vary from 36.16% to 44%, with 8 different values in intervals of 1.12%. The results show that this energy efficiency improvement does not lead to the greater adoption of CTO, which is mainly because even with 44% efficiency, CTO still has the lowest efficiency (i.e., approximately half that of other technologies, see Table 3); thus, this energy efficiency improvement does not influence the adoption of CTO.

With scenario A4, we experiment with different combinations of technology learning and energy consumption reduction. Fig. 5 shows the adoption of CTO in 2035 with different combinations and indicates that the combination of high technology learning and large energy consumption reduction will promote the adoption of CTO.

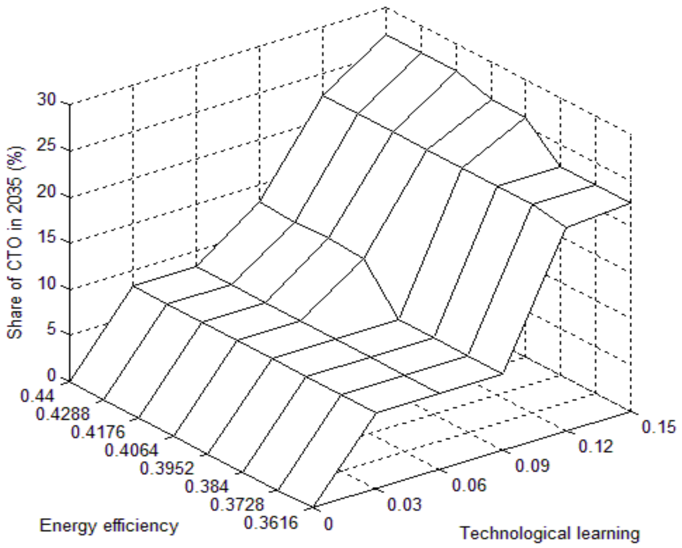

Fig. 5. Adoption of CTO in 2035 with different combinations of technology learning and energy efficiency in scenario A4.

We also carried out a sensitivity analysis of the discount rate for the four scenarios as illustrated in Table A5 in the appendix and we found changing the discount rate from 5% to 10% did not change the optimal results.

The results of the four scenarios show that CTO is competitive without considering carbon emissions in China's olefin industry, especially in scenario A2 and scenario A4. However, the expansion of the CTO capacity would imply high carbon emissions in this industry in China. In June 2015, China officially submitted its

Intended Nationally Determined Contribution (INDC) to the United Nations Framework Convention on Climate Change (UNFCCC), which added a target to the earlier pledge to peak CO_2 emissions by 2030 [57]. In this regard, CO_2 emissions might become a heavy burden on CTO technology. Two recent studies have provided insights into methods of reducing CO_2 emissions [6]. One study concluded that policies that promote investment in new and improved technologies (such as implementation of carbon capture and storage (CCS)) might be more effective for CO_2 emission reduction in the petrochemical industry than other policies, such as carbon taxes [59]. Another study argued that carrying out global carbon taxes (at $65–130/t CO_2) could lead to the widespread use of biomass-based routes and thereby could halve the total CO_2 emissions from the global petrochemicals production in their study period [60]. In the following section, we explore how a carbon tax and implementation of CCS to CTO change the optimal results of the four scenarios.

5. Impacts of a carbon tax and CTO with CCS

5.1. Impacts of a carbon tax

The configuration of the olefin industry is not only determined by the technological performance but also deeply influenced by the climate policy, such as carbon taxes. In the following study, a $20 per ton CO_2 tax is assumed to be imposed based on the four defined scenarios from the year 2021, which has been discussed by Nakata et al. [61], Xiong et al. [62] and Zhang [63].

Capacity configuration of different technologies with the carbon tax. We found that the carbon tax would induce a slight reduction of the capacity expansion of CTO in scenarios A2 and A4, with reductions of 2.05% and 2.99% respectively (see details of Table A6 and Table A7 in the appendix). Accordingly, OTO and PDH technologies will replace CTO partly in these two scenarios due to the lower emissions. Meanwhile, in scenarios A1 and A3, the imposed carbon tax does not change the optimal results. With the carbon tax, the adoption of CTO is 17.91% in 2035 in scenario A4, whereas it is 27.11% when there is no carbon tax (see details of Fig. A1 in the appendix). Therefore, the adoption of CTO in scenario A4 is 9.20% less than that without the carbon tax, indicating that the carbon tax will slow down the adoption of CTO and lead to the use of lower carbon technologies (i.e., OTO and PDH).

Accumulative total system costs and CO_2 emissions with the carbon tax.

After imposing the carbon tax, we found that the accumulative total system costs increased by 75.2 B US$ in scenario A1, 63.5 B US$ in scenario A2, 58.5 B US$ in scenario A3, and 63.2 B US$ in scenario A4 (see details in Table 4). Fig. 6 compares the annual CO_2 emissions of the four scenarios both with and without imposing the carbon tax, and the results show that in scenarios A2 and A4, imposing the carbon tax would increasingly reduce the CO_2 emissions from 2032 to 2035. Meanwhile, in scenarios A1 and A3, the carbon tax does not induce a reduction of CO_2 emissions because it does not change the capacity configuration of different technologies.

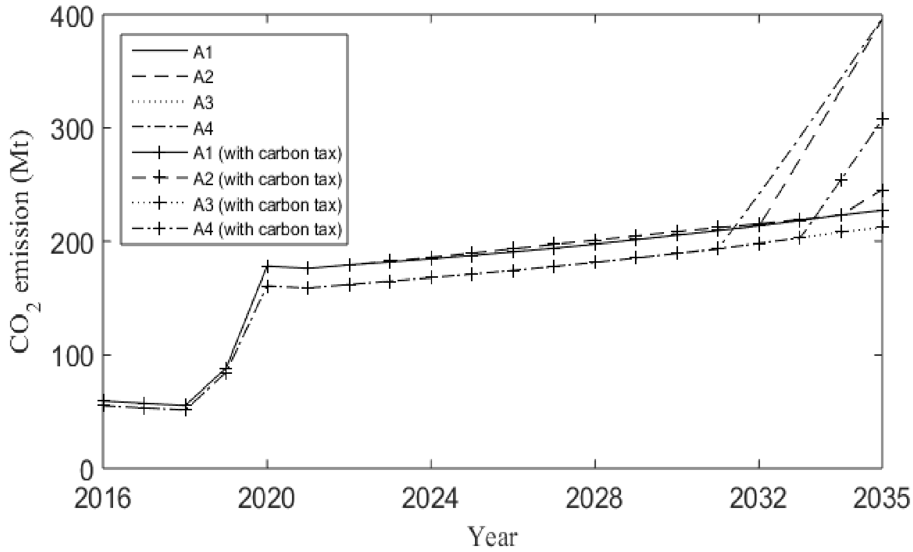

Fig. 6. CO_2 emissions in the olefin industry in the four scenarios both with and without imposing a carbon tax.

5. 2. Impacts of CTO with CCS

CCS might be a promising method of reducing the CO_2 emissions from CTO [5], although the production cost would be higher. According to Xiang et al.'s study [53], a CTO plant that achieves an 80% reduction of CO_2 emissions by implementing CCS is slightly less energy efficient (0.47%), has a total capital investment increase of 6%, and has an O&M cost increase of nearly 11% compared to the case without CCS, as shown in Table 3. Because the analysis presented in section 4 did not consider controlling the CO_2 emissions of China's olefin industry, CCS was not adopted in the system. In this section, we add an assumed regulation in the four scenarios, i.e., CTO must implement the CCS. In the following, we explore how such a regulation influences the capacity expansion of different olefin production technologies, total system costs, and CO_2 emissions of China's olefin industry.

Capacity configuration of different technologies with the CCS to CTO. We found that the cost of CCS would induce a slight reduction of the capacity expansion of CTO in scenarios A2 and A4 by 1.0% and 2.3%, respectively (see Table A8 and A9 in the appendix). Accordingly, OTO and PDH technologies will replace CTO partly in these two scenarios. Meanwhile, in scenarios A1 and A3, the implementation of CCS does not change the optimal results.

Accumulative total system costs and CO_2 emissions after implementing CCS to CTO. As shown in Table 4, we found that after implementing the CCS, the accumulative total system costs would increase by 64.2 B US$ in scenario A1, 68.6 B US$ in scenario A2, 56.3 B US$ in scenario A3, and 61.0 B US$ in scenario A4. We also found that the CCS will reduce CO_2 emissions by 1,257.3 Mt and 1,405.3 Mt in scenarios A2 and A4, respectively, which denote reductions of as much as 33.4% and 38.96%, respectively. In scenarios A1 and A3, the CCS will reduce CO_2 emissions by 992.6 Mt, which denotes reductions of as much as 28.93% and 31.47%, respectively.

Fig. 7 compares the annual CO_2 emissions of the four scenarios both with and without implementing the CCS, and it shows that for all four scenarios, the CCS would increasingly reduce CO_2 emissions up to 2035.

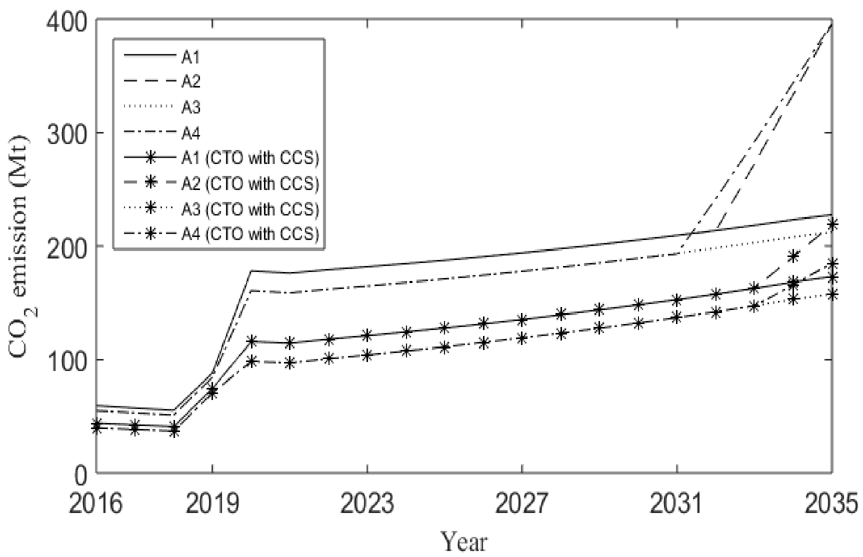

Fig. 7. CO_2 emissions in the olefin industry in the four scenarios both with and without CCS to CTO.

5. 3. Comparing the carbon tax with the CCS

Table 4 tabulates the changes of the accumulative total system costs and CO_2 emissions in the four scenarios either with the carbon tax or by implementing the CCS to CTO. We obtain average CO_2 reduction costs by dividing the increase in the accumulative total system cost by the accumulated CO_2 reductions, and the results are listed in the 4th column of Table 4. The results show that in terms of reducing CO_2 emissions, the CCS regulation is more efficient and cheaper than the carbon tax as shown in the third and fourth columns of Table 4. Of course, these results are based on the cost of implementing CCS to CTO following the study by Xiang et al. [53], and they ignore the uncertainties and risks of CCS that have been widely discussed (e.g., Rubin et al. [64]).

Table 4

Changes of the total system costs and CO_2 emissions after either imposing the carbon tax or implementing CCS to CTO in the four scenarios.

Scenarios	Total system cost (USD billion)	Total CO2 emission (Mt)	Percentage difference	CO2 reduction cost (US$/t)
A1 (with carbon tax)	75.2	0	0.00%	-
A2 (with carbon tax)	63.5	-289.6	-7.69%	219.3
A3 (with carbon tax)	58.5	0	0.00%	-
A4 (with carbon tax)	63.2	-311	-8.62%	203.2
A1 (CTO with CCS)	64.2	-992.6	-28.93%	64.7
A2 (CTO with CCS)	68.6	-1257.3	-33.41%	54.6
A3 (CTO with CCS)	56.3	-992.6	-31.47%	56.7
A4 (CTO with CCS)	61	-1405.3	-38.96%	43.4

6. Discussions

6.1 Model validation and verification

As mentioned in the introduction section, many studies have performed techno-economic analyses of different olefin production paths in China, whereas little work has focused on the perspective of system optimization to explore the optimal configuration of China’s olefin industry. Although the real setting of an industry does not have to be optimized in terms of the total cost, exploring the optimal configuration in this study can provide insights for developing appropriate strategies. Thus, the optimization model adopted in this study can inform decision-makers on the right strategy under different scenarios; however, it was not developed to perform future predictions. Based on this point of view, the model is not validated by comparing the model results with reality. Rather, we validate the model based on the following two aspects.

- First, the olefin production paths are consistent with real available paths and the techno-economic parameters of these paths were obtained from authorized studies, reports, and government documents. The greatest effort of this study was to guarantee that these parameters are consistent with reality by reviewing a number of published materials, and we further validate these parameters by interviewing people who work in the olefin production industry, such as people from the Shenhua Group. The optimization analysis framework adopted in our study has a long history of over 20 years and is still commonly used in energy system modeling, which provides some confidence for the methodology.
- Second, the results are consistent with insights drawn by other researchers who did not apply an optimization analysis framework. For example, we found that in all four scenarios, OTO will still dominate China's olefin industry in the next two decades, which is consistent with the results of Peng's study [58]. Moreover, our results suggest the CTO is competitive and will be significant in China's olefin production, which is consistent with China's official estimation [14]. In terms of reducing CO_2 emissions, the CCS regulation is more efficient and cheaper compared with the carbon tax, which is consistent with the findings of Xiang et al. [4], Van den Broek et al. [11], and Ruth et al. [59]. In short, the optimal solution of our model is consistent with other researchers' insights generated from their techno-economic analyses of different olefin production paths in China, which validate and verify our model and methodology. Compared with the qualitative insights in the available literature, the optimization model in our study can provide detailed optimal configurations of different olefin production paths.

6.2. Limitations

Of course, this study also has limitations. First, obtaining empirical data on the technological learning of CTO is difficult; therefore, the technological learning rate of CTO is estimated based on empirical research on other new technologies [34]. We conducted a sensitivity analysis on the technological learning rate of CTO to compensate for this limitation. Second, the future projections (e.g., demand, feedstock price, etc.) in this study are estimated via trends in historical data, although the former trend may not be consistent in the future. Third, real commercial applications of CCS have not been implemented and considerable debate on CCS remains. Finally, this research does not include revolutionary novel technologies. The readers of this paper should be cautioned about these limitations.

7. Conclusions

This study developed an optimization model to explore how China should configure its olefin industry by 2035 under four different scenarios of technological learning and energy efficiency improvement in the coal-to-olefin (CTO) process as well as with different environmental policies or regulations, i.e., either imposing a carbon tax or a regulation that CTO must be implemented with carbon capture and storage (CCS).

Our analysis showed that without considering controls on CO_2 emissions, because of its estimated technological learning potential, the CTO will be competitive and significant in China's olefin production, even when the oil price is as low as 48.71 US$/bbl. Although the improved energy efficiency of CTO does not necessarily promote the wide adoption of CTO, it can strengthen the effect of technological learning in terms of adopting more CTO. However, CO_2 emissions from the olefin industry would increase with the penetration of CTO technology.

Our analysis showed that after imposing a 20$/t carbon tax from the year 2021, CTO will also be competitive with the combination of technology learning and energy efficiency improvement. We also found that the adoption of CTO will be restrained and CO_2 emissions will be reduced in the fourth scenario. Our results showed that CCS regulation would restrain the expansion of the CTO capacity slightly, and in the fourth scenario with CCS regulation, the CTO still accounts for more than 10.29% of the production in China's olefin industry.

For policies-makers, our study implies that the development of CTO is not a wrong direction because it will be important in China's olefin production industry in the near future, especially in terms of reducing the dependency on crude oil since more than half of the crude oil consumed in China is imported. Our study also implies that the energy consumption reduction of CTO could contribute quite a lot towards reducing CO_2 emissions in China's olefin production technology; thus, it makes great sense to spend additional efforts on improving the energy efficiency of CTO by best practices as well as R&D.

Our study further implies that in terms of reducing CO_2 emissions, the CCS regulation might be a good choice if the cost of CCS could be as low as indicated in the study by Xiang et al.'s [53] cited here since it could reduce CO_2 emissions considerably at a relatively lower expense compared with that due to the 20$/t carbon tax. Of course, policymakers should be cautioned that a number of concerns about the uncertainties and risks of CCS remain to be addressed.

For private investors who are considering investing in China's olefin industry, our study provides insights into the technologies that could be competitive and worth investing in and the appropriate capacity configurations.

Acknowledgments

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Appendix

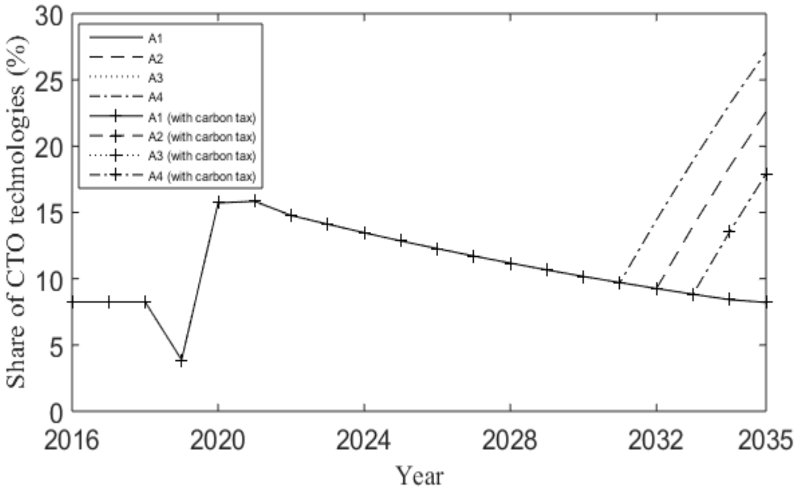

Fig. A1. Adoption of CTO in the four scenarios both with and without the carbon tax.

Table A1.

Under operation and planned CTO projects in China [51-52].

Investor project	Location	Capacity (Million tons/year)	Operational year
Shenhua Baotou (i)	Baotou, Inner Mongolia	0.6	2010
Shenhua Ningmei (i)	Yingchuan, Ningxia Province	0.5	2010
Yanchang China coal	Yulin, Shangxi Province	0.6	2011
Shanxi Pucheng	Pucheng, Shangxi Province	0.7	2011
Huating Meiye	Huating, Gangsu Province	0.2	2011
Datan Duolun	Duolun, Inner Mongolia	0.46	2012
China Coal yulin	Yulin, Shangxi Province	0.6	2014
Shenghua Ningmei (ii)	Yingchuan, Ningxia Province	0.6	2014
Ninxia Baofeng	Nindong, Ningxia Province	0.2	2014
Shenhua xiwang	Xiwan, Shangxi Province	0.3	2015
Zhongtian Hechuang	Erdos, Inner Mongolia	1.3	2016
Jiutai Energy	Erdos, Inner Mongolia	0.6	2016
China Coal Menda	Erdos, Inner Mongolia	0.5	2016
Ekuan Rongxin	Erdos, Inner Mongolia	0.6	2016
Shenhua Baotou (ii)	Baotou, Inner Mongolia	0.7	2016
Shenhua Wulumuqi	Wulumuqi, Xinjiang Province	0.68	2017
China Coal Yili	Yili, Xinjiang Province	0.6	2017
Qinghai Damei	Xinin, Qinghai Province	1.2	2017
Qinghai Kuanye	Haixi, Qinghai Province	1.2	2017
Qinghai Salt Lake	Yanhu, Qinghai Province	1	2017

Sanxi cooking coal	Taiyuan, Shangxi Province	0.6	2018
Datong Coal Mine	Sanxi, Shangxi Province	0.6	2019
Shenhua Yulin	Yulin, Shangxi Province	0.68	2019
Total		15.02	

Table A2.

Projected olefin demand in China for the period 2016–2035 [2].

Year	Olefin demand (ktoe)	Yearly growth in olefins demand from the base year 2015 (%)	Year	Olefin demand (ktoe)	Yearly growth in olefin demand from the base year 2015 (%)
2015	80,683	Base year	2026	125,522	55.57
2016	83,979	4.08	2027	130,690	61.98
2017	87,409	8.34	2028	136,074	68.65
2018	90,990	12.77	2029	141,684	75.60
2019	94,716	17.39	2030	147,529	82.85
2020	98,588	22.2	2031	153,620	90.40
2021	102,635	22.20	2032	159,966	98.26
2022	106,846	32.43	2033	166,579	106.46
2023	111,232	37.86	2034	173,471	115.00
2024	115,802	43.53	2035	180,653	123.90
2025	120,562	49.43			

Note: the average annual growth rate of olefin demand of China is approximately 4.12%.

Table A3

Accumulative olefin production with different technologies in the four scenarios.

Scenarios	OTO	CTO	PDH	MTO	Olefin imports
Scenario A1	69.76%	10.29%	11.75%	3.35%	4.84%
Scenario A2	68.59%	12.34%	11.03%	3.34%	4.70%
Scenario A3	69.76%	10.29%	11.75%	3.35%	4.84%
Scenario A4	67.73%	13.64%	10.60%	3.34%	4.69%

Table A4

Accumulative total system cost and CO2 emissions in the four scenarios.

Scenarios	Total system cost US$/billion	Percentage difference	Total CO2 emission Mt	Percentage difference
Scenario A1	1827.9	0	3430.8	0
Scenario A2	1823.5	-2.4%	3763.6	9.7%
Scenario A3	1821.7	-3.4%	3154.6	-8.05%
Scenario A4	1816.1	-6.5%	3607.1	5.14%

Table A5

Change of accumulative capacity expansion to discount rate increase from 5% to 10%.

Scenarios	OTO	CTO	PDH	MTO	Olefin imports
Scenario A1	0.00%	0.00%	0.00%	0.00%	0.00%
Scenario A2	0.00%	0.00%	0.00%	0.00%	0.00%
Scenario A3	0.00%	0.00%	0.00%	0.00%	0.00%
Scenario A4	0.00%	0.00%	0.00%	0.00%	0.00%

Table A6

Accumulated olefin production with different technologies in the four scenarios with the carbon tax.

Scenarios	OTO	CTO	PDH	MTO	Olefin imports
Scenario A1	69.76%	10.29%	11.75%	3.35%	4.84%
Scenario A2	69.76%	10.29%	11.75%	3.35%	4.84%
Scenario A3	69.76%	10.29%	11.75%	3.35%	4.84%
Scenario A4	69.73%	10.65%	11.57%	3.35%	4.71%

Table A7

Changes of accumulative capacity expansion in the four scenarios with the carbon tax.

Scenarios	OTO	CTO	PDH	MTO	Olefin Import
Scenario A1	0.00%	0.00%	0.00%	0.00%	0.00%
Scenario A2	1.17%	-2.05%	0.72%	0.01%	0.14%
Scenario A3	0.00%	0.00%	0.00%	0.00%	0.00%
Scenario A4	2.00%	-2.99%	0.97%	0.01%	0.02%

Table A8

Accumulated capacity configuration of different technologies in the four scenarios with CCS to CTO.

Scenarios	OTO	CTO (with CCS)	PDH	MTO	Olefin imports
Scenario A1	69.76%	10.29%	11.75%	3.35%	4.84%
Scenario A2	69.26%	11.34%	11.35%	3.35%	4.70%
Scenario A3	69.76%	10.29%	11.75%	3.35%	4.84%
Scenario A4	69.26%	11.34%	11.35%	3.35%	4.70%

Table A9

Changes of accumulative capacity expansion in the four scenarios with CCS to CTO.

Scenarios	OTO	CTO (with CCS)	PDH	MTO	Olefin imports
Scenario A1	0.00%	0.00%	0.00%	0.00%	0.00%
Scenario A2	0.67%	-1.00%	0.32%	0.01%	0.00%
Scenario A3	0.00%	0.00%	0.00%	0.00%	0.00%
Scenario A4	1.53%	-2.30%	0.75%	0.01%	0.01%

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Highlights

- This study develops an optimization model of China’s olefin industry until 2035.
- The results show that OTO will remain dominant in China’s olefin industry.
- And CTO is competitive in China and most likely its capacity will be expanded.
- The study suggests requiring CCS to CTO would be better than imposing a carbon tax.
- But policymakers should be cautioned about the uncertainties and risks of CCS.

Declaration of interests

☒ 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.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: