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Analysis of technology pathway of China's liquid fuel production with consideration of energy supply security and carbon price

Bingqing Ding[a], Marek Makowski[b,c], Jinyang Zhao[a], Hongtao Ren[a,b*], Behnam Zakeri[b], and Tieju Ma[a,b,*]

[a] East China University of Science and Technology, Meilong Road 130, Shanghai, 200237, China

[b] International Institute for Applied Systems Analysis, Schlossplatz 1, A-2361, Laxenburg, Austria

[c] Systems Research Institute, Polish Academy of Sciences, Newelska 6, 01-447 Warsaw, Poland

* Corresponding author: tjma@ecust.edu.cn; ren@ecust.edu.cn

Abstract

Efforts to provide alternative resources and technologies for producing liquid fuel have recently been intensified. Different levels of dependence on oil imports and carbon prices have a significant impact on the composition of the cost-minimizing portfolio of technologies. Considering such factors, how should China plan its future liquid fuel industry? The model for supporting the technology portfolio and capacity configuration that minimizes the total system cost until 2045 is described in this study. The results obtained for different carbon prices and levels of dependence on oil import indicate that the oil-to-liquid fuel (OTL) will remain dominant in China's liquid fuel industry over the next three decades. If the carbon price is low, the coal-to-liquid fuel (CTL) process is competitive. For a high carbon price, the biomass-to-liquid fuel (BTL) technology expands more rapidly. The results also reveal that developing the BTL and CTL can effectively reduce the oil-import dependency; moreover, a high carbon price can lead to the CTL being replaced with the low-carbon technology (e.g., BTL). Improvement in energy raw material conversion and application of CO_2 removal technologies are also effective methods to control carbon emissions for achieving the carbon emission goals and ultimately emission reduction targets.

Keywords: Liquid fuel production, system optimization model, energy supply security, carbon prices

1. Introduction

With the development of China's economy and people's living standards, the consumption of liquid fuel, diesel and gasoline has increased dramatically. As China has small domestic oil resources, it needs to import large amounts of crude oil to satisfy the ever-increasing demand for liquid fuel. In 2018, China imported more than 461 million tons of crude oil, accounting for 72% of its total crude oil consumption (National Bureau of Statistics of China, 2020). High oil-import dependency results in a fragile country energy structure and leads to low energy supply security (Song et al., 2019; Kong et al., 2019). Considering other liquid fuel production technologies is a feasible method for alleviating the high risks due to the oil supply caused by high oil-import dependency. In this avenue, biomass-to-liquid fuel (BTL), oil shale to liquid fuel (STL), and coal-to-liquid fuel (CTL) technologies can play prominent roles in China's energy sector. The diversity of China's energy structure can be improved by accelerating the development and utilization of alternative resources (biomass, oil shale, and coal) and the corresponding technologies (BTL, STL, and CTL) for the liquid fuel production can improve.

The analysis of OTL, BTL, STL, and CTL technologies has, to date, mainly concentrated on estimating the capital costs or on the techno-economic assessments of their production plants (Swanson et al., 2010; Mohajerani et al., 2018; Zhou et al., 2019). Swanson et al. (2010) adopted a comprehensive comparison between the capital and the production costs of two BTL production plants. Qin et al. (2018) conducted a techno-economic analysis of the CTL process with different entrained flow gasifiers. Focusing on technical, economic, and environmental analyses, Yang et al. (2020) compared the STL and oil-to-liquid fuel. Several techno-economic analyses have been performed for different liquid fuel production paths in China, resulting in recommendations on what kind of liquid fuel production technologies should be taken into account. However, these analyses did not focus on the configuration of the technology portfolio of the liquid fuel industry in the coming decades. Moreover, only a few studies exploring such questions can be found in the existing literature. To address this knowledge gap, the overall objective of the presented research is to advance methods for science-based decision-making support to address key problems in optimizing the technology portfolio of China's liquid fuel industry from a long-term perspective.

The current policy influences the liquid fuel industry development mainly due to the government's consideration of energy security (Mantripragada and Rubin, 2013; Xiang et al., 2014), economics (Xu et al., 2019, 2020; Ren et al., 2021a), and environmental issues (Rong and Victor, 2011). To satisfy the increasing demand for liquid fuel, China imports large amounts of crude oil. Energy security has become a focal topic from the political and scientific perspectives (Chen et al., 2018), and is thus an important factor in developing policies regarding the liquid fuel industry. Oil-import dependency is an important indicator in assessing energy supply security (Berndes and Hansson, 2007; Kong et al., 2019), which is why we choose oil-import dependency as a factor in our study. Considering the influences of reducing energy imports on primary energy supply, diversification of energy resources, and cost of imported fuels can assist the policymakers and stakeholders in the development of suitable energy policy for sustained economic development, but a limited number of studies have focused on it (Anwar, 2016). Therefore, the current study considers energy security as the key element of the optimization criterion.

The Chinese government has set a dual carbon emission reduction target (peaking emissions before 2030 and reaching carbon neutrality before 2060), and various emission reduction policies and measures will be implemented to reach these targets. The policies and measures are expected to impose extra costs for technologies with high carbon emissions, which would drive economic agents to adopt those with low carbon emissions (Lin and Xu, 2021; Ren et al., 2021; Best and Zhang, 2020). Many cases reveal substantial impacts of carbon-pricing schemes. For example, high carbon prices lead to the transition from coal to renewable energy (Murray and Maniloff, 2015; Bakhtiari, 2018; Best and Burke, 2018) and help to achieve climate commitments (Grottera et al., 2022). We adopt a bottom-up model with different technologies as elements chosen by economic agents (which is not explicitly modeled). We choose carbon prices because this can naturally represent the extra costs and thus economic drives of adopting different technology alternatives with different emission levels in such modeling practice. Balancing energy security with environmental sustainability has become a daunting task, for both developed and developing countries, especially those depending on fossil fuels (Shah et al., 2019). When considering both energy security and dynamic carbon prices, existing models seldom provide a comprehensive analysis of the composition of different liquid fuel technologies. To address this issue, we consider different carbon prices and the oil-import dependency levels as the breakthrough points for judging their impact on the liquid fuel production development.

To explore the impacts of the aforementioned issues on the configuration of the fuel production technologies, we develop a system optimization model. The model minimizes the accumulated total costs (composed of the investment cost, operation and maintenance cost, feedstock cost, and carbon emission cost) of China's liquid fuel industry until 2045 with a time step of 1 year, subject to meeting the given liquid fuel demand and the demand is exogenous. For exploring the relationship between the carbon prices, the oil-import dependency, and the technology portfolio of the liquid fuel industry, we constructed four different scenarios based on the oil-import dependency and the carbon prices.

While extensive research has focused on techno-economic analyses for different liquid fuel production paths, there remains a relative lack of analysis of China's optimal technology portfolio from a long-term perspective considering different levels of oil prices. Compared to these existing studies, the main contributions of this research in terms of methodology include the following: (1) Putting forward an optimization model to analyze the technology portfolio of China's liquid fuel industry from a long-term perspective. (2) Conducting scenario analysis considering different combinations of oil-import dependency and carbon prices with the developed optimization model.

The remainder of this paper is organized as follows. The technologies selected in this research are introduced in section 2. System optimization models of technology adoption with energy security and carbon price are presented in section 3. The initialization of parameters is discussed in section 4. A total of four different scenarios and the analysis of their results are provided in section 5. Finally, concluding remarks and policy implications are presented in section 6.

2. Technological options

China's domestic resources are characterized by a large amount of coal, sufficient oil shale and biomass, and scarce crude oil (Xie et al., 2010). The composition of the domestic resources implies that the liquid fuels produced in China from oil shale, biomass, and coal are likely to increase. China's oil refining industry is the second largest in the world and provides products to many sectors. Therefore, our model considers these four raw materials and the corresponding technologies.

The OTL technology was developed more than a century ago, and its capacities increased quickly, resulting in a well-established technology with unquestioned economic dominance. However, due to the volatile oil prices and continuing concern about energy security, attention has shifted to other energy supply technologies (Liu et al., 2013). Coal holds a large share in China's energy mix, so an efficient development of new coal chemical industry is of interest to China (Wang et al., 2011). The two basic approaches are direct and indirect coal liquefaction, which have the potential to produce liquid fuels from coal (Jiang and Bhattacharyya, 2015). Both direct and indirect CTL methods have been commercialized in China for a decade (Tennant, 2014). In general, CTL is a process that derives products from coal to replace and supplement conventional supplies of diesel and gasoline derived from crude oil (Mantripragada and Rubin, 2013). As it derives fuels from coal to replace or supplement conventional supplies of diesel and gasoline from crude oil, developing CTL technology has attracted increasing concentration in China (Mantripragada and Rubin, 2013).

To address aspects of energy security and future sustainable development, a series of policies have been established to accelerate the exploitation of unconventional oil resources, such as oil from oil shale pyrolysis and shale (NEA, 2012). As a promising alternative feedstock, the reserve of oil shale is 7.2×10^5 Mt, and the recoverable amount of shale oil pyrolyzed from oil shale in China is 4.76 Mt, twice China's crude oil reserves (Yang et al., 2016). The abovementioned resources are both non-renewable energy sources, and processes for converting these to liquid fuel are characterized by high energy input and large amounts of greenhouse gases (Zhou et al., 2016). As a renewable resource, biomass generates less carbon emissions during its conversion to liquid fuels in BTL processes and has thus attracted more attention. The first renewable fuel technologies were biomass to diesel and ethanol derived from corn (Fargione et al., 2008; Swanson et al., 2010). In the commercialization of the BTL industry, the greatest disadvantage is its lack of economic competitiveness in the energy market, especially due to its high capital costs, so this process has developed slowly.

In 2015, the liquid fuel production capacity from CTL, STL, and BTL in China reached 4.3 Mt, 1.4 Mt, and 0.68 Mt, respectively (National Energy Administration of China, 2017), and the predicted total capacity of CTL, STL, and BTL plants will be 20 Mt/y (Wang, 2014), 3 Mt/y (Gen et al., 2013), and 2 Mt/y (KAIDI Group Co., Ltd., 2013), respectively, by 2030. From the above discussion, the liquid fuels produced in China from biomass, oil shale, and coal appear promising. The proponents of these technologies argue that, to reduce its demand for imported energy, China should take advantage of its abundant reserves. It is conceivably the combination of economic and energy security considerations that has encouraged the development of this coal conversion technology in China. Thus, analysis of these four technologies will support the exploration of their diverse configurations that will depend on the diverse trade-offs between reaching competing economic, policy, and environmental goals.

3. System optimization model

3.1 Model framework

The model framework for China's liquid fuel industry contains three levels: resources (crude oil, biomass, oil shale, and coal), technologies, and products (see Fig. 1). The technologies (refinery, liquid fuel plants, etc.) are the links between different levels. The details of the three levels are outlined in the following paragraphs.

Resources level: Resources include biomass, oil shale, coal, and crude oil, and are either exploited domestically or imported from abroad. Technology level: This level includes liquid fuel converted from crude oil, biomass, oil shale, and coal-based on the relevant technologies (OTL, BTL, STL, and CTL, respectively).

Demand level: This level denotes the final products (diesel and gasoline) distributed to consumers and is identified via the demand for final products.

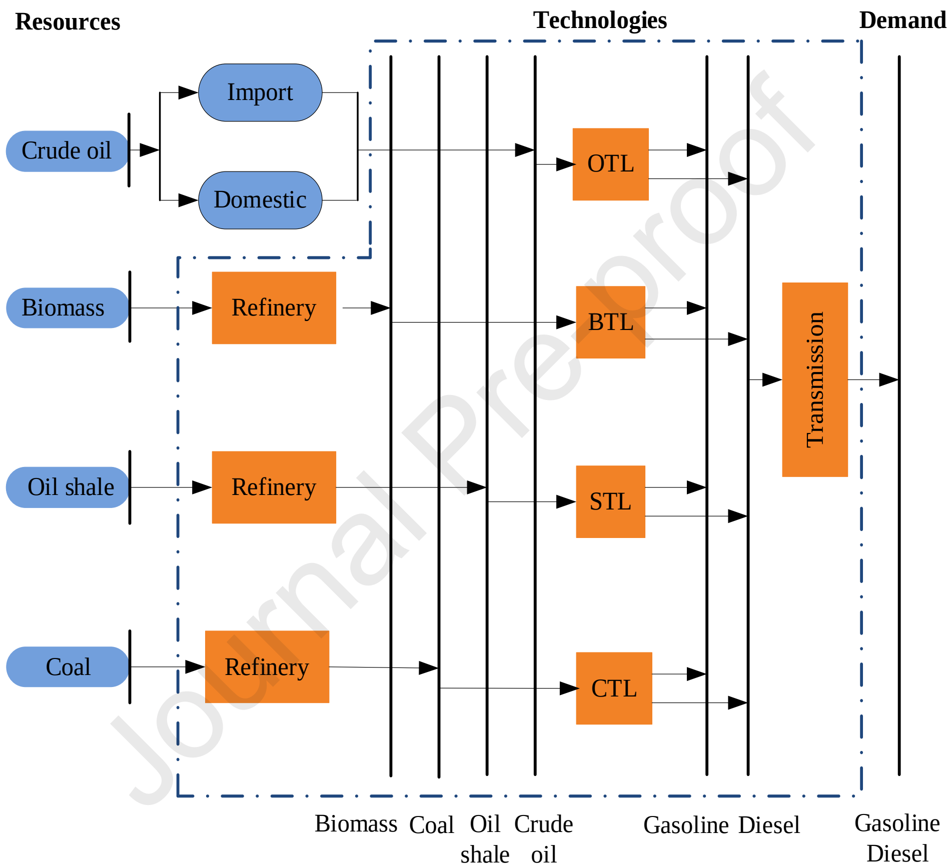


Fig. 1. Production chain for different liquid fuels

3.2. Model notations

The complete specification of the implemented model is summarized as follows.

Sets:

Indices and sets	Indices and sets definition
$i \in I$	Technologies (BTL, CTL, STL, and OTL)
$t \in T$	Time periods (years). The set $Tc \in T$ is composed of the oil import constraint periods

$k \in K$	Final products (diesel and gasoline)

Parameters:

Parameters	Parameter definition
cf_i^t	Investment cost
c_i^t	Installed capacity
$disc_t$	Capital recovery factor
τ_i	Plant lifetime
η_i	Efficiency
σ	Discount rate
α_k	Demand annual growth rate
com_i	Operation and maintenance cost of liquid fuel production
c_i	Initial installed capacity per year
cap_i	Initial cumulative installed capacity
pr_i	Price of the resource
pc	Carbon price
$emif_i$	Emission coefficient
f_i^t	Annual operation time percentage for technology
m	Oil-import dependency
d_k^t	Exogenous demand
$n_{i,k}$	The percent of final product k in the total output of technology i

Variables:

Variables	Variable definition
y_i^t	Newly installed capacity
$x_{i,k}^t$	Activity, representing the output of a certain technology, i.e., the product produced by a technology
tci	Total investment cost
tcr	Total raw material cost
$tcom$	Total operation and maintenance cost
tcc	Total carbon emission cost
r_i^t	The raw materials consumption amount
cap_i^t	The cumulative installed capacity of technology

3.3 Model specification

The model is formulated as follows. As shown in Eq. (1), the demand for diesel and gasoline is exogenous and increases over time. In Eq. (2), η_i is the ratio of product energy consumption to total energy consumption. Product energy contains the energy of gasoline and diesel, and total energy consumption contains that of feedstock, steam, and electricity. The energies of gasoline, diesel, and feedstock are calculated based on their lower heating values. The consumption amount is calculated in Eq. (2). The process for calculating the cumulative installed capacity of technology *i*, which equals the summation of installed capacity and the initial cumulative installed capacity of technology is illustrated in Eq. (3). The total installed capacity can be calculated as Eq. (4); $\frac{\tau_i - t}{\tau_i} c_i$ denotes the remaining initial installed capacity of technology *i*. The continuous decision variables $x_{i,k}^t$ and y_i^t are non-negative.

$$d_k^t = d_k^0 (1+\alpha_k)^t \ (k=1, 2) \tag{1}$$

$$r_i^t = \max_k \left(\frac{x_{i,k}^t}{n_{i,k}} \right) / \eta_i \tag{2}$$

$$cap_i^t = cap_i + \sum_{l=t-\tau_i}^{T} c_i^l \tag{3}$$

$$c_i^t = \begin{cases} \sum_1^T y_i^t + \dfrac{\tau_i - t}{\tau_i} c_i & t \le \tau_i \\ \sum_{l=t-\tau_i}^{T} y_i^l & t > \tau_i \end{cases} \tag{4}$$

Since it has no learning potential, the unit investment cost of the existing technology is fixed. The incremental and revolutionary technologies have learning potential, so their unit investment costs will decrease as the experience with them increases. Note that these are new technologies, and they have no initial cumulative experience, so their unit investment costs at time t=1 are equal to their initial unit investment costs, which means $cf_i^1 = cf_i^0$. 1-2^{-b_i} is technology i's learning rate, which means the percentage reduction in future investment cost for every doubled cumulative capacity; 2^{-b_i} is the progress ratio.

$$cf_i^t = \begin{cases} cf_i^0 & \text{If technologies without learning rate} \\ cf_i^0 \cdot \left(cap_i^{t-1}\right)^{-b_i} & \text{If technologies with learning rate} \end{cases} \tag{5}$$

The four cost components are defined in Eqs. (6)-(9). Eq. (6) represents the total capital investment cost (tci) and is the capital investment per unit of production capacity multiplied by newly installed production capacity. The cost of raw materials equals the resource consumption amount multiplied by the resource price and discounted by the discount rate to the current price. The detailed calculation process is presented in Eq. (7). The operations and maintenance (O&M) cost is determined by the activity of the system, shown in Eq. (8). The total carbon emission cost is calculated using Eq. (9), and is equal to the carbon price multiplied by the raw materials and the corresponding carbon emission factor. The outcome variable cost of our model, which includes investment cost (tci), raw material cost (tcr), O&M cost ($tcom$), and carbon emission cost (tcc), is presented in Eq. (10). All costs occur in the future and consider the financial needs and resources of the country, so the annual discount rate is assumed to be fixed.

$$tci = \sum_{i \in I} \sum_{t \in T} disc_t \cdot cf_i^t \cdot y_i^t \tag{6}$$

$$tcr = \sum_{t \in T} \sum_{i \in I} disc_t \cdot pr_i \cdot r_i^t \tag{7}$$

$$tcom = \sum_{i \in I} \sum_{t \in T} disc_t \cdot com_i^t \cdot \max_k \left(\frac{x_{i,k}^t}{n_{i,k}}\right) \tag{8}$$

$$tcc = \sum_{i \in I} \sum_{t \in T} disc_t \cdot pc \cdot emif_i \cdot \max_k \left(\frac{x_{i,k}^t}{n_{i,k}}\right) \tag{9}$$

Thus, the general form of the linear programming model is as follows. The objective function is defined by Eq. (10) and the constraints are defined by Eqs. (11)-(14):

$$\mathrm{Cos}t = tci + tcr + tcom + tcc \tag{10}$$

$$d_k^t - \sum_{i \in I} x_{i,k}^t \le 0, \quad \forall k, t \tag{11}$$

$$f_i^t \cdot c_i^t - \max_k \left(\frac{x_{i,k}^t}{n_{i,k}}\right) \ge 0, \quad \forall i, t \tag{12}$$

$$r_{OTL}^t - a \le m \times r_{OTL}^t, \quad \forall k, t \in Tc, 0 \le m \le 1 \tag{13}$$

$$x_{i,k}^t \ge 0, \quad \forall i, t, k \tag{14}$$

$$y_i^t \ge 0, \quad \forall i, t \tag{15}$$

The objective function represents the minimization of the accumulated total system cost defined by Eq. (10). In Eq. (11), the demand for the *k*-th final product must be satisfied by the total output of the different technologies. Constraint Eq. (12) ensures that the production amount should be no more than the installed capacity. Constraint Eq. (13) requires that the amount of import oil must represent less than m percent of total oil from 2036 to 2045. Constraint Eqs. (14)-(15) mean decision variables are non-negative.

4. Data used for the model parameters

Development plans in China are commonly made annually. We consider six consecutive five-year plans, from 2016 to 2045 with a time step of 1 year as the model planning horizon. We adopt 2015 as the base year; the annual discount rate is assumed to be 6% (sensitivity analysis of the discount rate is provided in section

5.2.1).

4.1. Demand trends of diesel and gasoline

From Fig. 2, we can obtain China's consumption of diesel and gasoline in the last 20 years: 175 Mtoe and 119 Mtoe, respectively, in 2015, with average respective growth rates in demand of 7.4% and 5.3% during the period from 2000 to 2017. According to the national policy in the 13th and 14th Five-Year Plans, the gasoline demand in China will continue to grow before 2030 then level off thereafter. Meanwhile, the diesel demand experience a period of decline then level off after 2030. Therefore, we assume that the model will meet increasing demand at the annual growth rates of 1.6% and - 2.0% for diesel and gasoline, respectively in 2016-2030, which will be 0.2% and - 0.3%, respectively in 2031-2045 (Xing and Luo, 2020).

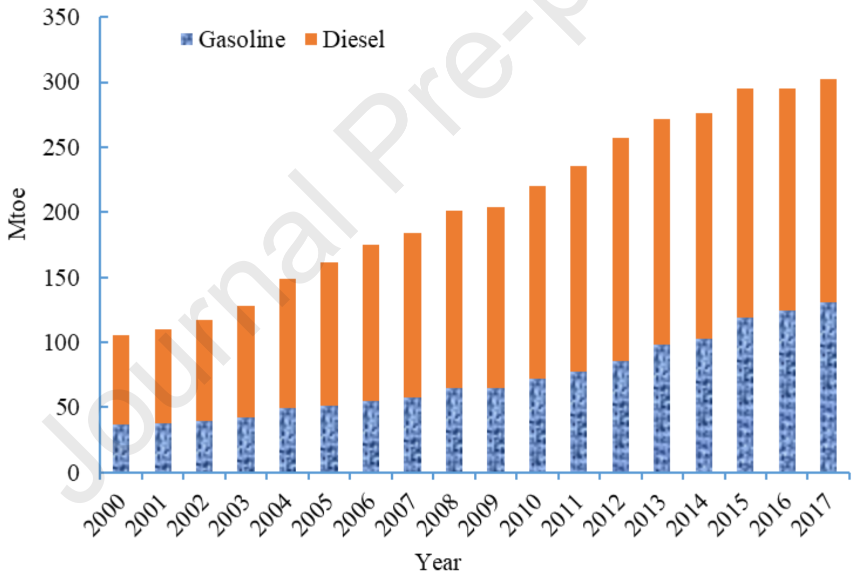


Fig. 2. Consumption of diesel and gasoline in China from 2000 to 2017

4.2. Feedstock prices in the base year

The prices of resources used to produce liquid fuels are presented in Table 1. These data were obtained from the National Bureau of Statistics of China and China Industry Research. As discussed in the introduction, this study focuses particularly on how China should compose raw materials and different production technologies to meet the given liquid fuel demand and objectives. For this purpose, we assume that the feedstock prices as inputs to these technologies will be constant.

Table 1. Feedstock prices in the base year

Year	Oil[a] US$/toe	Coal[b] US$/toe	Biomass[c] US$/toe	Oil shale[d] US$/toe
2015 (base year)	357	83	289	94

[a] Crude oil price is converted from the National Bureau of Statistics of China (NBSC, 2016).

[b] Coal price is converted from the National Bureau of Statistics of China (NBSC, 2016).

[c] Data on biomass are converted from Dimitriou et al. (2018).

[d] Data on biomass are converted from Zhou et al. (2016).

The capacities of the four technologies in 2015 and the new expansion capacity from 2016 to 2020 are shown in Table 2. From this, OTL dominated liquid fuel production in 2015 and accounted for approximately 99.4% of the total production, while CTL was the second most widely used liquid fuel production technology in 2015.

Table 2. Capacities of the four production technologies in 2015 and capacity expansion planned in 2016-2020

Technologies	Total capacity in 2015 (Mtoe)[a]	Share of technologies in 2015	Capacity expansion planned in 2016-2020 (Mtoe)[b]	Cumulative installed capacity in 2015 (Mtoe)[a]
BTL	0.6	0.09%	0.7	0.7
CTL	2.5	0.35%	9.5	3.0
STL	1.1	0.16%	2.0	1.4
OTL	700.0	99.4%	38.0	710

[a] BTL capacity data were taken from BP (2016), the CTL capacity data from Li (2017), the STL capacity data from the National Energy Administration of China (2017), and the OTL data from Zhou et al. (2019).

[b] These data were taken from the National Energy Administration of China (2017).

Following the optimization model framework, the liquid fuel technologies are characterized by their initial investment cost, O&M cost, energy efficiency, CO_2 emissions coefficient (i.e., total CO_2 emission per ton liquid fuel), capacity factor, construction time, and plant life. These techno-economic parameters are summarized in Table 3.

Table 3. Techno-economic parameters of the liquid fuel industry

Technology	BTL	CTL	STL	OTL
Feedstock	Biomass	Coal	Oil shale	Crude oil
Investment cost [a] (US$/toe)	1106	1397	532	509

C_{OM} cost [a] (US$/toe)	334	380	392	89
Efficiency [a] (%)	34	46	26	79
Total CO_2 emissions (t_{CO2}•t^{-1})	0.78	7.69	3.40	1.68
Capacity factor [a] (%)	80%	80%	80%	80%
Plant life [a] (yr)	20	20	15	20
Construction time[a] (yr)	3	4	2	3
Percent of gasoline [c]	0.34	0.25	0.16	0.37
Percent of diesel [c]	0.66	0.75	0.84	0.63

[a] 2018US$/¥ = 7. The CTL investment cost data were calculated from Zhou et al. (2018), the investment cost of OTL is from BP (2016), and the STL investment cost data are calculated from Zhou et al. (2019). The BTL investment cost was taken from Larson et al. (2010).

[b] These data were taken partly from a recent review by Zhou et al. (2018) and Zhang et al., (2019), the BTL emission data were assumed based on biomass cracking emissions from Yang et al. (2020) and Jouny et al. (2018).

[c] These data were taken partly from a recent review by Larson et al. (2010), and the BTL data are from Zhou et al. (2016).

4.3. Learning rate of the BTL technology

With the accumulating experience in new technologies, the costs of technologies tend to decline and such a process is known as technology learning (Ma, 2010). The technology learning rate and the learning curves can be used to predict the future cost of new technology development, for example, fuel cell electric vehicles (Ruffini and Wei, 2018), biomass direct combustion power generation (Tao et al., 2018), and renewable technologies (Newbery, 2018). Based on previous studies, we determined the technology learning rates of the considered new technologies to range from 15% to 5% (Zhou et al., 2018). Following McDonald and Schrattenholzer (2001) and Zhou et al. (2018), the technological learning of BTL is set to 10%.

5. Scenario analysis

The carbon price is an efficient method that can address the externalities of energy use, and oil-import dependency is an important factor in evaluating energy security. We, therefore, designed the following four scenarios for carbon prices and oil-import dependency, where the carbon price is obtained from the European Union emission trading system, and the current oil-import dependency is calculated based on the data collected from the National Bureau of Statistics.

5.1 Four scenarios

According to the National Bureau of Statistics, China's annual domestic crude oil production has not fluctuated substantially in the past ten years. Thus, we assume that the amount of domestic crude oil that is used to make liquid fuel will not change. In 2015, nearly 190 million tons in the total consumption of crude oil used to make liquid fuel was domestic crude oil (NBSC, 2020).

(Al) Scenario A1. This is the reference scenario in which the carbon price is 10 US$/ton and oil-import dependency is not considered. Between 2013 and 2014, China launched emissions trading system (ETS) pilots in five cities and two provinces. The seven pilots ETS combined to form the second largest carbon market in the world, after the European Union (EU) ETS. While China's carbon trading market is not fully developed, it is immature with weak carbon price fundamentals (Lin and Jia, 2019); thus, EU carbon trading prices may fit better. Before 2020, the carbon price is below 45 US$/ton and the predicted carbon prices is up to 55 US$/ton in 2035; thus, 55 US$/ton is set as a high price and 10 US$/ton as a low price.

(A2) Scenario A2. In this scenario, the carbon price increases to 55 US$/ton, while there is no consideration of oil-import dependency. This scenario represents the idea that the government wants to encourage energy conservation and emission reduction and promote the development of renewable energy.

(A3) Scenario A3. In this scenario, the oil-import dependency decreases to 50% (IEA, oil information overview 2019) after 2035, and the carbon price is 10 US$/ton. BP World Energy Outlook suggested that China's oil-import dependency will reach 76% by 2035 (BP, 2016), and such dependency in the reference scenario is up to 80% in 2035. The 50% oil-import ratio is generally regarded as a safety cordon for national energy security (IEA, oil information overview 2019). When the import ratio is higher than 50%, it indicates that China's oil security is facing high risks; when the import ratio is lower than 50%, it indicates that China's oil security is facing low risks. Thus, we choose 50% as a targeted oil-import ratio.

(A4) Scenario A4. In this scenario, following the China Economic Net (2019), the carbon price is 55 US$/ton, and oil-import dependency decreases to 50% after 2035.

The liquid fuel industry can reduce its carbon emissions and oil-import dependency by implementing the corresponding portfolio of technologies. In the following, we present and discuss the optimal results of these four scenarios. We then conduct a sensitivity analysis on carbon prices and oil-import dependency based on the four scenarios.

5.2 Results under the four scenarios

In this section, we present and discuss the optimal results of four scenarios, such as the capacity configuration of different technologies, the accumulated total system cost, and sensitivity analysis of carbon prices and oil-import dependency.

5.2.1 Capacity configuration of different technologies

The share contribution of diverse technologies for liquid fuel production in the four scenarios over the planning period (2016-2045) is given in Table 4. The results indicate that in some scenarios, OTL will remain the most significant over the next three decades, and CTL develops faster in Scenarios A1 and A3. For low carbon prices, approximately 9%-30% of China's liquid fuel production uses the CTL for its cheap feedstock price. The capacity of the BTL expands rapidly in three scenarios, especially Scenario A4. Because it uses renewable energy (biomass) and thus reduces carbon emissions in fuel production processes, the BTL technology can bring environmental benefits. Therefore, the higher the carbon price, the higher the percentage of BTL. In scenarios with tight constraints on oil-import dependency and with a high carbon price (e.g., in Scenario A4), BTL expands more rapidly than in other scenarios.

Table 4. Capacity shares of technologies in 2045 for each of the considered scenarios

Scenario	BTL	CTL	STL	OTL
A1	2.35%	8.66%	2.74%	86.25%
A2	12.42%	3.97%	2.35%	81.26%
A3	17.29%	30.29%	2.48%	49.94%
A4	29.48%	12.96%	7.95%	48.61%

From Fig. 3, we can see that in Scenario A1, the total expansion capacity reaches

89.74 Mtoe in 2030, consisting of approximately 0.86, 6.08, 2.36, and 80.44 Mtoe BTL, CTL, STL, and OTL, respectively. The liquid fuel production technology CTL capacity expands considerably until 2045. Despite their substantial learning rate, there is rather small capacity expansion of BTL. Accordingly, in the reference scenario, the contribution of CTL to the expansion capacity is more than 8%. In Scenario A1, the total accumulated expansion capacity of all technologies reaches 82.87 Mtoe until 2045. We set the capacity constraints of different technologies after 2016 in accordance with the development goals of the 13th Five-Year Plan, and these constraints led to the result that the share of some technologies changes very little. Moreover, in Scenarios A3 and A4, we set the constraints about oil-import dependency in 2035, which leads to the increase of some technologies (BTL, CTL, and STL) in the individual year.

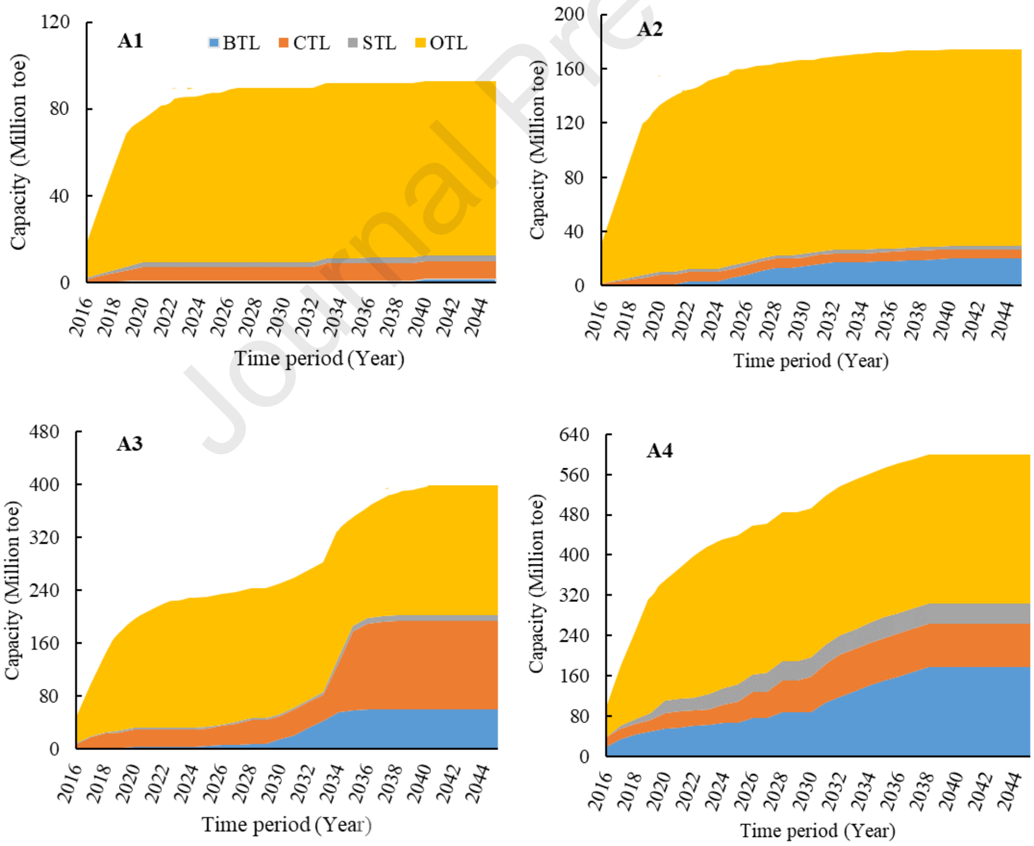


Fig. 3. Capacity expansion of different technologies over 2016-2045 in Scenarios A1, A2, A3, and A4

In Scenario A2, the total new capacity expansion will reach up to 168.45 Mtoe before 2030, consisting of approximately 14.20, 6.99, 2.37, and 144.19 Mtoe BTL, CTL, STL, and OTL, respectively. During 2021-2045, the capacity of BTL will expand considerably compared to that of CTL, accounting for approximately 12.42% of the total expansion capacity, while STL only exhibits a small capacity expansion within liquid fuel production technologies. From 2016 to 2045, the total accumulated capacity expansion amounts to 174.14 Mtoe, which is higher than the capacity in Scenario A1, and Scenario A2 has the same development trend; specifically, the capacity of the BTL in Scenario A2 is higher than in Scenario A1. The renewable and carbon-neutral nature of biomass leads to the BTL technology becoming the second most widely used liquid fuel production technology in Scenario A2. Under significant pressure to reduce CO_2 emissions, China has started to pursue low-carbon energies, which has increased investment in low-carbon technologies.

In Scenario A3, the total new capacity expansion will reach 249.63 Mtoe before 2030, consisting of approximately 13.36, 26.09, 3.12, and 197.05 Mtoe BTL, CTL, STL, and OTL, respectively. From Table 4, the total capacity of BTL and CTL will expand considerably, accounting for approximately 17.29% and 30.29% of the total expansion capacity, respectively, and STL has experienced a minor capacity expansion during the planning period. From 2016 to 2045, the accumulated capacity expansion will amount to 394 Mtoe, which is higher than the capacity in Scenarios A1 and A2. In scenario A3, we consider the technology portfolio of the liquid fuel industry from the perspective of reducing the oil-import dependency; the CTL obviously increases for its cheap raw material price and high energy conversion efficiency. The dominance of CTL in the liquid fuel industry results in vast quantities of CO_2 and other pollutants, the major cause of dire environmental dilemmas.

In Scenario A4, the expansion percentage of BTL is higher than that in the other scenarios. The total capacity expansion over the study period will amount to 607.64 Mtoe, which is higher than that in the other three scenarios. In Scenario A4, BTL accounts for 29.48% of the accumulated capacity expansion because it has lower carbon emissions. These results demonstrate that in high carbon price scenarios, BTL develops faster than other technologies for its feedstock can reduce fossil CO_2 emissions and replace non-renewable carbon resources. In scenarios considering reduction of import dependencies, the energy system will shift toward using biomass, coal, and oil shale; with its adequate supply and cheap price, coal in particular can prevent a shortage of depletable domestic oil resources.

As previously mentioned, the total system costs consist of the investment cost, feedstock cost, O&M cost, and carbon emission cost that are determined by the corresponding configurations of the technologies. In all scenarios, the feedstock cost constitutes the largest portion of the total system cost. In Scenario A1, the minimum total system cost for 30 years is 749.44 billion US$. In Scenarios A2, A3, and A4, the total system cost is approximately 1915.69, 2092.01, and 5131.18 billion US$, respectively. Accordingly, Scenario A2 shows the cost increase as compared with Scenario A1. The increase in the carbon price is the main reason for the rise in the total system cost; we note that carbon emissions in this scenario are lower than in Scenario A1. In Scenario A3, the constraint of oil-import dependency leads to the slow capacity expansion of OTL and the rapid capacity expansion of BTL and CTL, but the high adoption of new technologies needs much more investment cost and the low efficiency of new technologies needs to use more feedstock because the total system cost in Scenario A3 is higher than that in Scenario A1. Thus, with tight constraints on oil-import dependency and with a high carbon price in Scenario A4, the total costs are higher than that in other scenarios. In brief, the constraint of oil-import dependency and the increase in carbon price are reasons for the rise in the accumulative total system cost.

5.2.2 Sensitivity analysis of carbon price and oil-import dependency

In the aforementioned four scenarios, the carbon price (referred to as pc) and the oil-import dependency (referred to as m) drive the adoption of the technology portfolio. China's fossil fuel-dominated energy structure will still exist for the foreseeable future, and CO_2 is thus expected to increase, which places pressure on the Chinese government to mitigate climate change. Thus, a sensitivity analysis of the carbon prices focuses on comparing the adoptions of BTL and CTL under different carbon prices ranging from 0 to 100 US$/ton with an interval of 20 US$/ton, and the results are illustrated in Fig. 4.

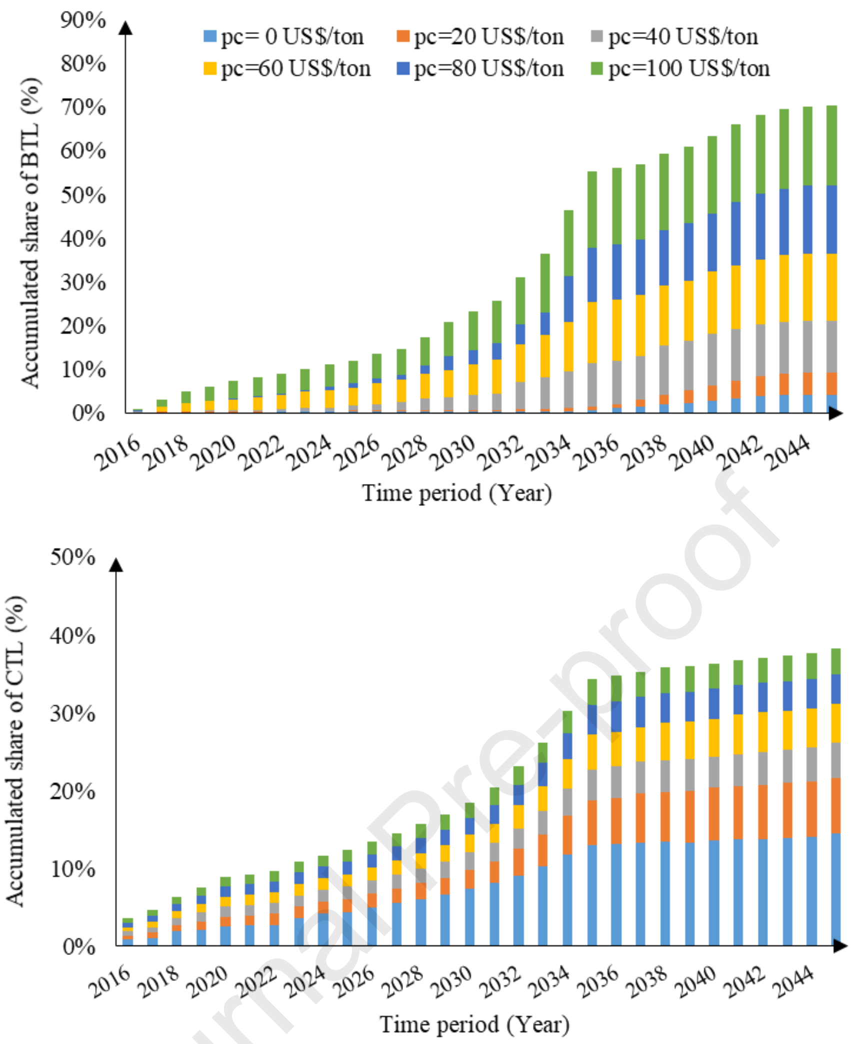
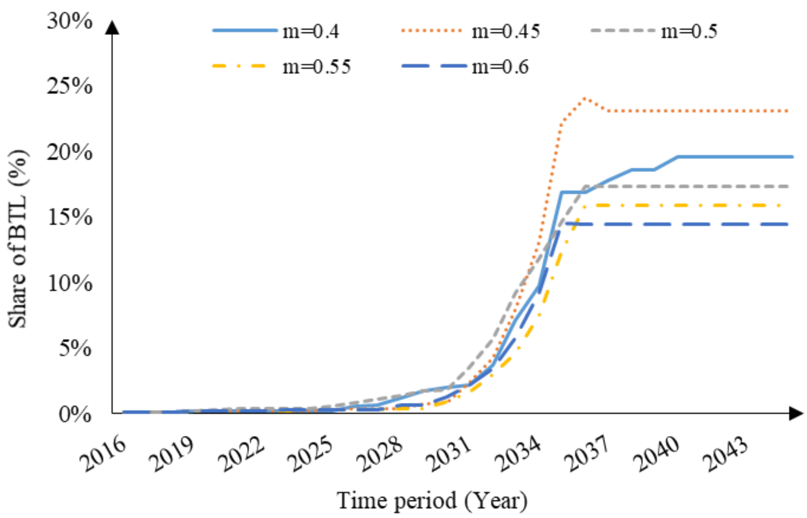


Fig. 4. Accumulated share of BTL and CTL with different carbon prices based on Scenario A2

The results indicate that implementing a high carbon price can significantly facilitate the development of low-carbon and renewable energy technologies (e.g., BTL). When the carbon price is 0 or 20 US$/ton, the percentage of BTL is almost 0% before 2030. The increase in carbon price leads to a rapid increase of the BTL share in the technology portfolio. For example, for the carbon price equal to 100 US$/ton, the share of BTL exhibits a quick increase from 2016. Since oil-import dependency is not considered in this scenario, the BTL technology benefits significantly from high carbon prices and takes a large share of the liquid fuel industry after 2030, and the annual shares will be up to 18% in 2045. Unlike BTL technology, the CTL has high carbon emissions; thus, the increase in carbon prices induces a sharp reduction of the CTL. Moreover, changing the carbon price from 80 to 100 US$/ton does not significantly affect the share of CTL, and the share is approximately 3% in 2045.

The model aims to minimize the total costs (composed of the investment, operation and maintenance, feedstock, and carbon emission costs) of China's liquid fuel industry. The carbon emission cost accounts for 10.9% when the carbon price is 10US$/ton, and the share of carbon emission cost increases with the increase of carbon prices. A high carbon price will drive the BTL to replace the CTL and thus reduce CO_2 emissions and improve China's energy structure.

Declining oil-import dependency is the improvement of energy security. The adoption of BTL and CTL technology with different levels of dependence on oil imports in Scenario A3 is illustrated in Fig. 5. The results describe that the share of CTL and BTL technology continuously increases during 2016-2045, while the share of OTL declines during this period with the constraints on oil-import dependency. The percentage of BTL is nearly 0% before 2030, and BTL develops faster; when we consider the oil-import dependency lower than 50% after 2035, the share of BTL is more than 20% in 2045. The CTL technology develops rapidly before 2035, then its development speed slows after 2040, but its share also exceeds 20% in 2045 and can be up to 30%. With a target of a 60% oil-import dependency, the total share of BTL and CTL during 2016-2045 increases by 35% compared to that in Scenario A1. This result suggests that domestic and renewable resources play important roles in China's liquid fuel production for reducing oil-import dependency.



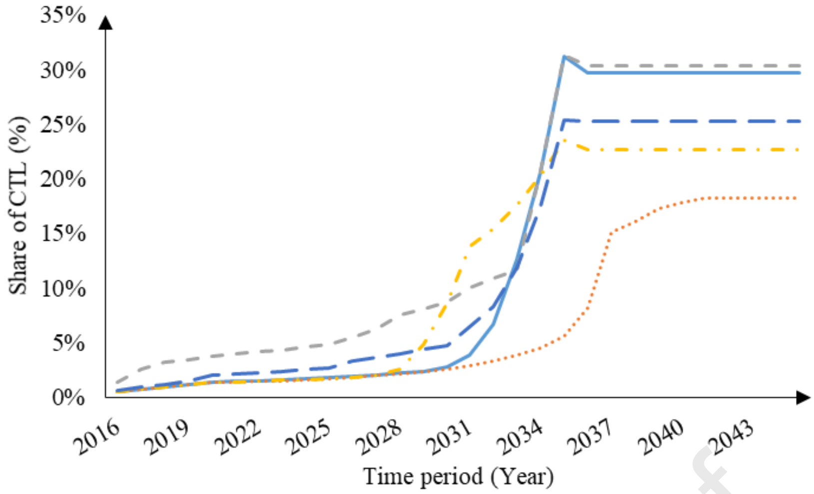


Fig. 5. Adoption of BTL and CTL with different oil-import dependencies based on Scenario A3

We also conducted a sensitivity analysis of the discount rate for all four scenarios, and found that changing the rate from 5% to 9% does not change the results significantly.

With Scenario A4, we experiment with different combinations of carbon prices and oil import dependencies. The adoption of BTL and CTL in 2045 with different combinations is illustrated in Fig. 6 and indicates that carbon prices and oil-import dependency will greatly influence their adoption. The results demonstrate that the CTL and BTL are competitive in terms of considering reducing oil-import dependency in China's liquid fuel industry, but an increase in the carbon price can lead to the latter replacing the former. These results suggest that increasing the use of renewable resources can not only eliminate dependence on oil imports, but also reduce CO_2 emissions, thus fighting climate change.

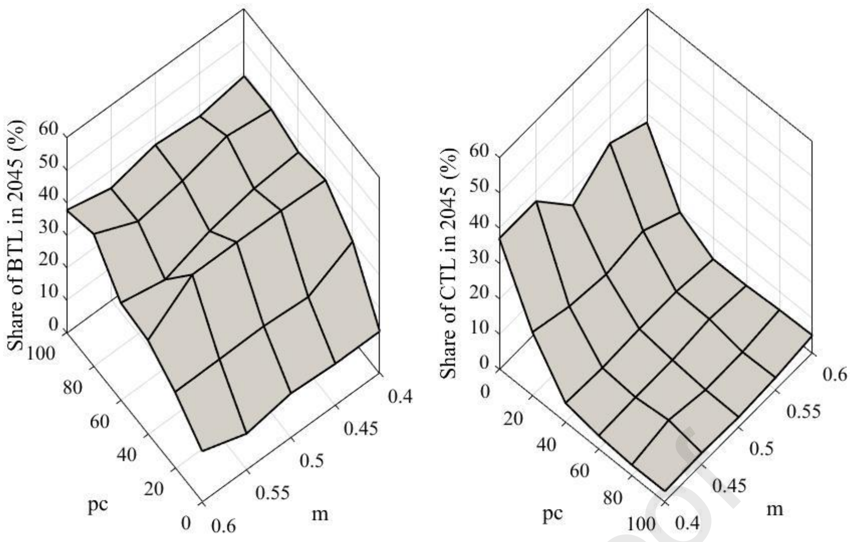


Fig. 6. Adoption of BTL and CTL in 2045 with different carbon prices and oil import dependencies based on Scenario A4

The learning rate is also important for the optimal solutions, and we consider that of BTL. Thus, we conducted a sensitivity analysis of the learning rate of BTL. Because Scenario A1 assumes a low carbon price (10US$/ton) and does not set constraints on oil-import dependency, the development of BTL technology will benefit mainly from its technological learning effect. Thus, a sensitivity analysis of BTL's learning rate is based on Scenario A1. We explored the adoption of BTL under different learning rates ranging from 5% to 15% (Zhou et al., 2018) with an interval of 2%, and the results are illustrated in Fig. 7. We can see that higher technological learning will result in more adoption of BTL technology, and the adoption of BTL technology is very sensitive to the learning rate when it increases from 11% to 13%. When the learning rate is more than 13%, the share of BTL changes little and the share of BTL is about 7.5% in 2045.

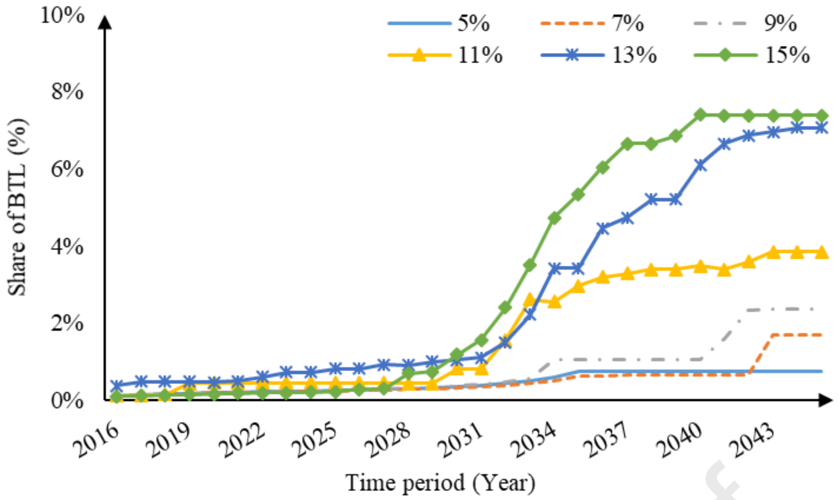


Fig. 7. Adoption of BTL with different learning rates based on Scenario A1

5.3 Model validation

Regarding the reliability or robustness of the bottom-up model, first, the bottom-up model shares the same methodology and framework of operational optimization energy system models that have been widely used to analyze energy systems for several decades; typical examples include the MESSAGE (Messner, 1994) and MARKAL models (Seebregts et al., 2001). Second, the parameters used in our model were obtained from government documents, authorized studies, and reports. Third, we compared the model results with those of other studies or the official plans, and these comparisons validated our model. For example, our results reveal that the CTL will be competitive and can relieve the excessive dependence on external oil, which is consistent with Zhang et al.'s (2021) results. Moreover, we suggest that increasing the use of renewable resources can not only reduce CO_2 emissions, but also eliminate dependence on oil imports, which is consistent with the 14th Five-Year Plan. Finally, to analyze the influences of different parameter values, we conducted sensitivity analysis of carbon prices, oil-import dependency, and technological learning rate.

6.Conclusions and policy implications

The model developed herein supports the analysis of China's liquid fuel industry configuration until 2045. The analysis focuses on four different scenarios for carbon prices and the levels of dependence on oil imports. In all four scenarios, the results reveal that the OTL will still be significant in the liquid fuel industry over the next three decades. In scenario A3, with tight constraints on oil-import dependency and with a low carbon price, the CTL will be competitive and play a significant role in liquid fuel production. In high carbon price scenarios, the share of the BTL is higher than that of CTL, especially in scenario A4. The share of CTL and BTL continuously increases during 2016-2045, while that of OTL declines during this period with the constraints on oil-import dependency.

For reducing oil-import dependency, domestic and renewable resources play important roles in China's liquid fuel production. The development of low-carbon technology can be incentivized by implementing a higher carbon price in the liquid fuel industry and accelerating the phase-out of technologies with high carbon emissions, and thus increase the share of low-carbon technology and consequently reduce carbon emissions. For achieving the carbon emission goals and ultimately emission reduction targets, improvement in energy raw material conversion and application of CO_2 removal technologies (such as carbon dioxide capture and use (CCU), carbon dioxide capture and storage (CCS), and biomass and carbon capture and storage (BECCS)) are needed.

This research primarily analyzed the optimal technology portfolio of China's liquid fuel industry in the long term by considering energy security and the reduction of carbon emissions; how specific industry policies influence the technological progress was not investigated. Policies such as subsidizing BTL, CTL, or clean utilization of coal will influence the technology development and China's liquid fuel production, which are worth exploring in future research.

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Declaration of interests

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