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Product-based Carbon Constraint Energy Planning with Pinch Analysis for Sustainable Methanol Industry in China

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For the purpose of greenhouse gas control in chemical industries, the industrial structure adjustment and low-carbon technology retrofit are the alternatives for policymakers and plants to simultaneously meet the energy demand and carbon emission limit. Considering the various technological sources and predictable product demand in methanol production industries, this paper presents the method of Product-based Carbon Constraint Energy Planning (PCEP) combined with improved GM(1,1) model to analyse the practical interaction between energy demand and carbon emission for methanol industry in 2020 in China. The results show that without any emission reduction measures, the total carbon emissions of methanol industry in 2020 would be 4.84 times larger than that of 2011. By enhancing the methanol production of biomass routing and conducting the project of CO_2 capture and storage (CCS) in all coal-to-methanol plants, the total carbon emissions would be 36.01 % less than the given carbon constraint. Besides, at least 65 % of coal-to-methanol plants should be retrofitted with CCS on the consideration of the current challenges of biofuel development in order to meet the carbon constraint. The energy structure of China and the inherent property with high carbon content in coal determine that the coal-to-methanol routing contributes the most of methanol supply but also the maximum carbon emissions in the methanol industry, even if policymakers and plants take measures to adjust the industrial structure and retrofit the existing plants with low-carbon technology.

1. Introduction

For chemical industries, the top-layer design of industrial structure and low-carbon technological retrofit are significant for both of the secure energy supply and carbon emission reduction. The carbon emission intensity of different technological routings greatly depends on the internal property of raw materials and the level of process system design. To match the diverse resources and carbon emission constraint in chemical industries, energy planning based on Pinch Analysis is the choice to address the issue of source-sink allocation.

Aiming to investigate the interaction between energy supply and carbon emission, Pinch Analysis has been widely extended in the fields of energy planning. Tan and Foo (2007) first extended the pinch method for preliminary energy planning with carbon emission constraint by graphical tools and focused on the static balance between CO_2 limit and energy demand. Carbon Emissions Pinch Analysis (CEPA) or Carbon Constraint Pinch Analysis (CCPA) was then proposed in different cases, especially the fields of power generation with/without CCS. The electricity generation sector in different countries, such as Ireland (Crilly and Zhelev, 2008), New Zealand (Walmsley et al., 2014) and China (Li et al., 2016), were taken as examples to account for the dynamic nature of electricity supply-demand, the optimal fuel mix, multi-dimensional environmental effects and the optimal storage site selection. Economic feasibility is a non-negligible factor in the practical engineering application. Walmsley et al. (2015) combined CEPA and Energy Return on Energy Invested (EROI) analysis methods to plan for the industrial process heat sectors in terms of energy sources and regional allocation. Considering both of CO_2 storage and CO_2 utilization, Mohd Nawi et al. (2015) proposed a new algebraic method and Total Site CO_2 Integration concept to target the optimum allocation of CO_2 capture, utilization and storage according to the purity of CO_2 headers. Additionally, Abdul Aziz et al. (2017) conducted a comprehensive Total Site Planning for low CO_2 industrial site planning by the integration of heat, electricity and hybrid renewable energy system, and systematically explored the minimum emissions by the CO_2 management hierarchy implementation.

The identification of emission constraint and energy demand is significant for the energy planning. Besides, most studies about CEPA focused on the field of power generation but few discussed about the industries of chemical production. Unlike the power generation sector, it would be difficult to obtain the data of product demand in some specific chemical industries due to the lack of relevant data sources. In this paper, focusing on the industry of chemical product production, we combined the improved GM(1,1) prediction model (Li et al., 2012) and Product-based Carbon Constraint Energy Planning (PCEP) to investigate the energy-emission planning for methanol production industry in China. Firstly, the methanol demand in 2020 is predicted by the improved GM(1,1) model. Compared with the basic scenario in 2011, the graphical representation method will be then used to analyse the effects of industrial structure adjustment and low-carbon retrofit on energy supply and carbon emissions by three scenarios: scenario of free development mode in 2020 (FDM), scenario of carbon constraint with only industrial structure adjustment in 2020 (ISA) and scenario of carbon constraint with both industrial structure adjustment and low-carbon technological retrofit in 2020 (ISATI). Finally, some suggestions are proposed for the low-carbon development of methanol production industry.

2. Methodology

In this section, we will elaborate the PCEP for methanol productions. Firstly, Section 2.1 will describe the overall procedure of graphical representation for the three scenarios. Then the detailed derivation of some important parameters, including carbon emissions and methanol demand, will be illustrated in Sections 2.2 and 2.3.

2.1 Graphical representation of PCEP

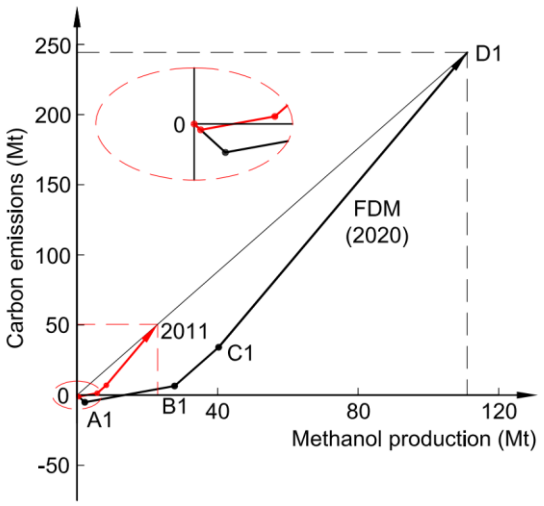

Figure 1: PCEP for Scenario FDM

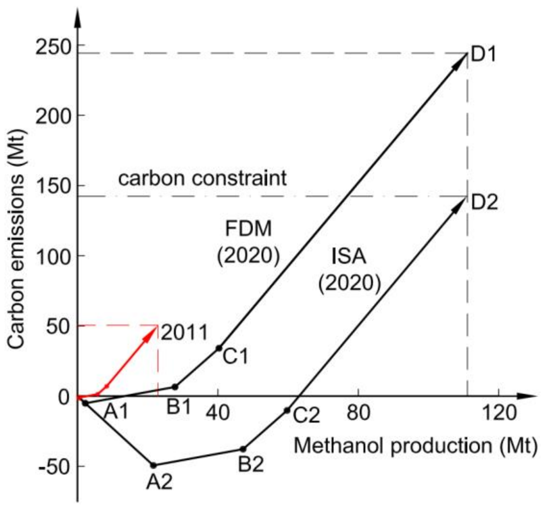

Figure 2: PCEP for Scenario ISA

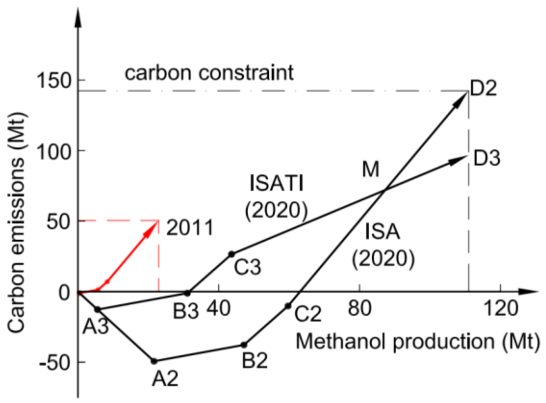

Figure 3: PCEP for Scenario ISATI

In the short and long term, coal, natural gas (NG) and coke-oven gas (COG) would be regarded as the major sources to produce methanol (Su et al., 2013), while the biomass accounts for a small part of raw materials but could be deemed as a promising way due to its low-carbon environmental effect in the life-cycle perspective. Coal, NG, COG and biomass are involved as the four resources to produce methanol.

Figures 1-3 show the interrelation between methanol production and carbon emissions for the three scenarios. The abscissa represents the methanol production while the ordinate stands for the carbon emission. Composite Curves with arrow, which are marked by OA1B1C1D1, OA2B2C2D2 and OA3B3C3D3 (O is the coordinate origin), represent the Scenarios FDM, ISA and ISATI in 2020. In each Composite Curve, four segments from left to right stand for the sources of biomass, NG, COG and coal. The segment slope depends on emission factor of the source. The straight line connecting the starting point and ending point of the Composite Curve delegates the average emission intensity of total methanol production industry. For the graphical method, the simultaneous magnification of the Composite Curve means that the four routings develop at a synchronous speed, while the decrease of the slope means that low-carbon technologies are employed in the corresponding routings.

In the case study, parameters including the emission factor and methanol production of the four routings in 2011 are known. The total methanol production in 2020 is predicted by the improved GM(1,1) model with the historical data from 2000 to 2015 (Liu, 2016). The emission factors of NG and COG are assumed to be constant in all scenarios.

In Figure 1, the Composite Curve of FDM is formed by stretching all segments of 2011 at the same rate, which means that the four routings increase the amount of methanol production at a synchronously speed but employ none of low-carbon measures. The average emission intensity in 2020 keeps constant with that of 2011. Based on Scenario FDM, Scenario ISA in Figure 2 indicates that when carbon constraint is set for the total methanol industry, parts of emissions caused by the high-emission coal routings (segment C1D1) should be cut down, and the industrial structure is adjusted to fulfil the methanol demand by extending the production of biomass routing (OA1→OA2). In Figure 1 and Figure 2, the slope of each segments for 2020 keep the same with that of 2011. Based on Scenarios ISA and ISATI, Figure 3 describes the coal routing is retrofitted with CCS (C2D2→C3D3, intersecting at point M) in order to maintain the share of biomass routing within a defined range (OA2→OA3). In this case, the slope of coal routing is smaller than that of the former cases.

2.2 Carbon emissions evaluation and carbon constraint

Carbon emissions of the four technological routings are evaluated by the corresponding emission factors and methanol production, where the annual methanol production is referred to the work of Liu (2016) and carbon emission factors are derived from the works of Qin et al. (2016), Renó et al. (2011) and later Bermúdez et al. (2013). In this paper, sugarcane bagasse based routing is chosen as the representative of biomass-methanol process and its carbon footprint was a negative value when considering the carbon fixation during the cultivation period (Renó et al., 2011).

Carbon emission constraint is generally set by the policy makers according to the evaluation of environmental burden and economic development. In this paper, we assume that the average emission intensity of methanol production industry in 2020 is approximately equal to the national carbon emission intensity which is characterized by the division of carbon emission by energy demand. Then the carbon constraint (CC) for methanol production industry could be calculated by

$$CC = \frac{NCE}{PED} \cdot MP \tag{1}$$

The three parameters in the right side of the equation are all prediction values in 2020. *NCE* and *PED*, which are estimated by the baseline scenario in the work of Yuan et al. (2014), represent the national carbon emission (kg CO_2) and primary energy demand (J). *MP* is the energy (J) provided by methanol product which is predicted by the improved GM(1,1) model in the following section.

2.3 GM(1,1) prediction model

Since the methanol demand is comprehensively affected by various factors such as population, economic growth, price, industrial structure and international trade, the forecasting results vary greatly with the selection of influencing factors. Moreover, the historical data of some factors is unavailable due to the missing statistics. The univariate GM(1,1) model, which was derived from grey system theory (GST), has been widely used for forecasting the energy consumption. In this paper, we use the improved GM(1,1) model (Li et al., 2012) with parameter correlation and weighted combination to predict the methanol production in 2020. The basic parameters needed are the historical methanol production from 2000 to 2015 (Liu, 2016). The calculating procedure of this model is depicted in Figure 4.

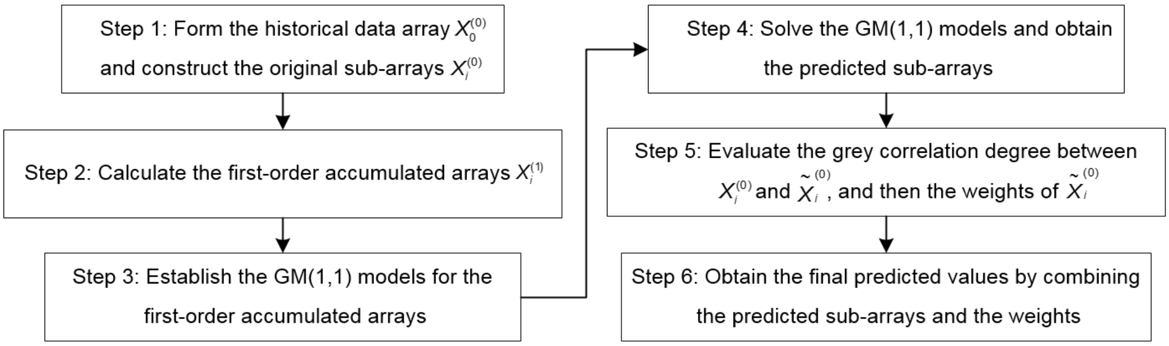

Figure 4: Procedure for the improved GM(1,1) model

In the first step, the sub-arrays are constructed, of which the array element depends on the number of the historical values. Secondary, the individual first-order accumulated array is obtained by the superposition of each sub-array before establishing the GM(1,1) models in the third step. Distinguished from the conventional model, the predicted value in the improved method is evaluated by the combination of multiple sub-arrays and their weights instead of single array. During the calculation of coefficients of the first-order differential equation in the third step, the background value $z^{(1)}(k)$ is optimized by iteratively changing the coefficient β until the deviation of β is within an acceptable level, as shown in Eq(2).

$$z^{(1)}(k) = \beta x^{(1)}(k-1) + (1-\beta)x^{(1)}(k) \tag{2}$$

where $x^{(1)}(k)$ is the element of the first-order accumulated arrays; the initial value of β is set as 0.5, and the iteration is calculated by

$$\beta(m+1) = \frac{1}{a(m)} - \frac{1}{e^{a(m)}-1} \tag{3}$$

where m is the number of iterations; a is the multiplier coefficient in the first-order differential equation. The main procedure of the iteration is shown as

$$\beta(0) \rightarrow z^{(1)}(0) \rightarrow a(0) \rightarrow \beta(1) \rightarrow z^{(1)}(1) \rightarrow a(1) \rightarrow \ldots \rightarrow \beta(m) \rightarrow z^{(1)}(m) \rightarrow a(m) \tag{4}$$

To predict the methanol demand in 2020, firstly, the statistic data of methanol production from 2000 to 2010 is used to calculate the predicted production from 2011 to 2015. Then the deviation of this model could be analysed by comparing with the historical data from 2011 to 2015. Finally, the methanol production in 2020 is forecasted by the historical trend from 2000 to 2015. Due to length limitations, more detailed information about the improved GM(1,1) model could be referred to the works of Li et al. (2012) and more recently Liu et al. (2014).

3. Results and discussion

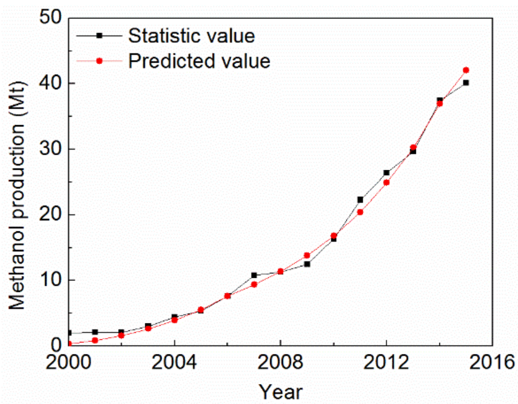

Figure 5: Verification of the improved GM(1,1) model for methanol production from 2011 to 2015

As shown in Figure 5, the average deviation of methanol production from 2011 to 2015 predicted by the historical data from 2000 to 2010 (Liu, 2016) is 0.2 %, which indicates the improved GM(1,1) model could manage the five-years prediction within an acceptable deviation. Compared with the basic case in 2011, the methanol production and carbon emission in 2020 of the three scenarios are shown in Figure 6 and Figure 7.

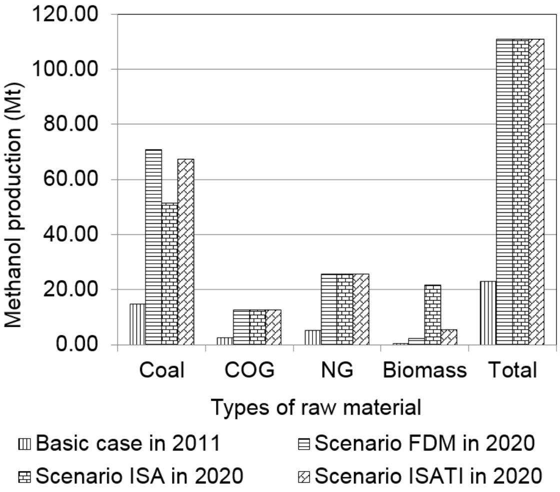

Figure 6: Methanol production profile

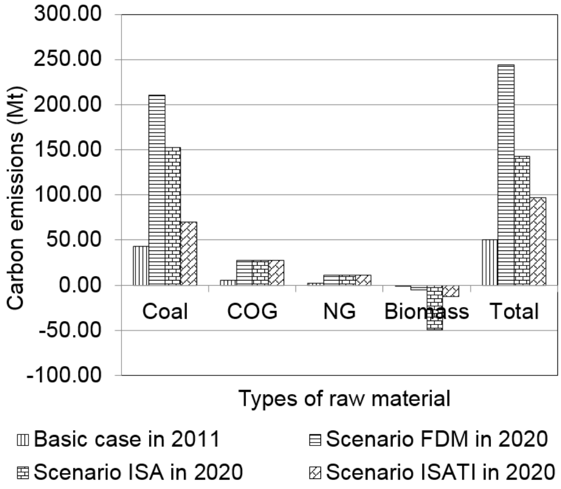

Figure 7: Carbon emission profile

3.1 Scenario FDM

In the free development scenario, four types of methanol production routing would purely enhance the amount of production without any industrial structure adjustment and low-carbon retrofit in plants. The methanol production and carbon emissions of each routing keep an average annual growth rate of 19.15 % from 2011 to 2020 to meet the predicted methanol demand (111.05 Mt). Both of the total production and carbon emissions in 2020 are 4.84 times larger than that of 2011.

3.2 Scenario ISA

For the purpose of greenhouse gas reduction, carbon emission constraint of 142.38 Mt CO_2, which is 41.72 % less than the emissions in Scenario FDM, is set for the whole methanol production industry. By increasing the methanol production of biomass routing and cutting down parts of the coal based source until the Composite Curve of scenario FDM intersects with the Pinch Point (intersection point D2 between methanol demand and carbon constraint in 2020), the results show that the production allocations of coal, COG, NG and biomass routings are 46.24 %, 11.30 %, 23.00 % and 19.46 %, while the emission contributions are 152.55, 27.61, 11.60 and -49. The negative emission of biomass routing is due to the consideration of carbon fixation during the cultivation period on the basis of life cycle assessment.

To form this industrial structure, from 2011 to 2020, the average annual methanol production of coal routing should increase at an annual growth rate of 14.98 %, while the annual production of biomass routing should enhance by 53.42 %. By the comparison with scenario FDM, it is seen that the coal routing would produce methanol at the lower growth rate, but the biomass routing should accelerate its production explosively.

3.3 Scenario ISATI

Considering the numerous challenges for the development of biofuels in China (Chang et al., 2012), the proportion of biomass routing in total methanol production in 2020 is assumed to set at 5 %. To satisfy the methanol demand and achieve the carbon constraint target, the emission factors of coal, COG and NG routings should be individually or simultaneously reduced. Considering the high carbon emission intensity of coal routing and the feasibility of CCS, the project of coal-to-methanol plants retrofitted with CCS is adopted in this scenario. Based on the previous study (Qin et al., 2016), the emission factor of coal-based methanol process would reduce from 2.971 to 1.043 tCO_2/tCH_3OH if the conventional methanol plant was retrofitted with CCS. The results show that if all the coal based plants adopt the CCS project, the total emission of methanol industry in this scenario would reduce to 96.83 Mt CO_2, and the carbon emission contributions of coal, COG, NG and biomass routings are 72.61 %, 28.51 %, 11.98 % and -13.10 %, respectively, which indicates 36.01 % share of the predicted carbon constraint (142.38 Mt CO_2) is left for the whole methanol industry. If 65 % of the coal based plants are retrofitted with CCS (segment MC3) and the rest 35 % maintain the status quo (segment MD2), the total emissions would just reach at the level of carbon constraint.

4. Conclusions

Energy planning in chemical industry provides an overall top-design for low-carbon development. In this paper, the Product-based Carbon Constraint Energy Planning (PCEP) combined with the improved GM(1,1) prediction model is proposed to investigate the energy demand and carbon emission of methanol production industry in 2020 in China. The results indicate that coal-to-methanol routing contributes the most methanol product due to the energy structure in China, and its contribution for carbon emission also occupies the most because of the inherent property with high C/H ratio of coal. It is suggested that the development pace of biomass routing and its share in methanol industry should be accelerated to offset the high emission of coal based routing. Meanwhile, 65 % of coal-to-methanol plants at least should be retrofitted with CCS on the consideration of the current challenges of biofuel development and the carbon constraint target.

Acknowledgments

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