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Synergy of air pollutants and greenhouse gas emissions of Chinese industries: A critical assessment of energy models

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ABSTRACT

In China, industrial energy use accounts for two thirds of total energy consumption, and this is expected to remain the same in the medium and long-term. China has embarked on a path towards more sustainable energy use to meet domestic (e.g. air quality) and global needs (e.g. climate change), and to sustain its economic welfare. However, most energy-economy models for China have shown limitations to evaluate policy instruments and technology diffusion in industries, in relation to the multiple policy goals. In this paper, the advantages and weaknesses of 19 current energy models for China are evaluated, including important co-benefits as reduced air pollutant emissions. Results show that the co-benefits of energy use and emission policies are rarely modeled on industrial level. Based on the critical assessment of the state-of-the-art energy models, we develop recommendations for modeling industrial energy use, with an emphasis on improved incorporation of (economic, environmental and energy) policy effects, technology representation, co-benefit modeling, and uncertainty analysis.

1. Introduction

Today, energy security, climate change, and air pollution are widely recognized as three challenging issues. China, as the largest developing country in the world, has achieved significant economic progress over the past decades, but it has now also become the world's largest energy consumer, source of GHGs (greenhouse gas emissions), and air pollution [1]. The increased demand for energy has mainly been provided by the increased combustion of fossil fuels, i.e. coal in industry and power generation, and oil products in transport. Because coal is the dominant energy source (accounting for 70.4% of final energy consumption) in China, the emissions of GHGs and air pollutants are comparatively higher than that for other countries [2].

Between 2000 and 2006, local governments often focused on economic development while neglecting to update environmental standards. Environmental policies were seldom implemented at a local level [3] and annual growth rate of China's energy consumption was 1.2 times higher than its economic growth. Fortunately, that was changed in the following five years (between 2006 and 2010) [4], when the government implemented a series of ambitious energy and air quality policies to curb energy use and reduce air pollutants. The "Top-1000" program, for example, which focused on the 1000 largest energy consuming enterprises in China, contributed to 21% of the national energy intensity target in the 11th Five Year Plan [5]. Likewise, SO_2 emissions from Chinese industry grew by 16%, while PM_{TSP} emissions fell by about 37%, from 2000 to 2010. This might be ascribed to the installation of air pollutant control options (e.g. Cyclone and Electrostatic Precipitation) [6]. During the 12th Five Year Plan (2011–2015), a new "Top-10000" program has been implemented, which covers two thirds of China's total primary energy consumption or 85% of energy use in industries. The target is to decrease coal consumption by 2.9% and CO_2 emissions from fossil fuels by 0.7%, from 2013 to 2014 [7]. The growth of energy use in China is aimed to slow down due to a series of policy instruments for energy efficiency improvement [8]. However, industrial final energy consumption in 2013 still accounted for 70% of total final energy consumption in China, and correspondingly, industrial CO_2 emissions contributed to 72% of total emissions [9].

There is mounting evidence that exposure to high levels of air pollution are associated with adverse health impact [10]. The latest results from the UNEP (United Nations Environment Programme) show that the death rate related to air pollution rose by 4% worldwide and 5% in China, between 2005 and 2010 [11]. In 2013

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an estimated 257 thousand premature death in 31 Chinese capital cities could be linked to $PM_{2.5}$ air pollution, which led to an increase in the mortality rate of 0.9‰. The study also found that if annual $PM_{2.5}$ concentration meets Air Quality Guidelines set by Chinese government standards, the mortality rate could be decreased by 0.41‰, compared to 2013 [12]. Hence, the increasing air quality problems have put a lot of pressure on the Chinese government, who is now pursuing aggressive policies to reduce air pollutant emissions by requiring more strict emissions standards, closing key emission sources (e.g. outdated power plants), updating fuel standards for automotive fuels, as well as introducing renewable energy sources as solar and wind energy. For example, the central government has pledged to spend $275 billion over the next five years to clean up the air [3]. However, the increase in the demand for energy services related to economic growth (albeit at a bit lower since the global financial crisis), is still being met with increased combustion of fossil fuels. Although the extra energy might be consumed though with an installation of air pollution control devices, in order to meet air pollution reduction targets.

Energy models are usually employed in policy making to forecast future energy consumption and emissions of GHGs and air pollutants, as well as the economic development and technology choices [13]. Several studies summarize the current bottom–up [14] and top–down [15] models that have been developed by Chinese modelers [16]. The detailed reviews of industrial bottom–up energy demand models have presented and provide suggestions for the current and next-generation policy model developments [17]. However, In modeling China's energy use and GHG emissions, most models rarely take into account a range of factors that could affect policy effects and efficiency [18]. The following weaknesses are still present in state-of-the-art energy models: 1) The failure to consider major changes, such as population peak, urbanization, industry development pathways and effects of market saturation, results in errors; 2) Estimating the effect of rapid changes in macro-economic drivers and policy impacts is still a challenge; 3) Potential synergies between energy use, climate change and air pollution mitigation are hardly evaluated in energy models [19]. Yet, all these factors need to be addressed to better estimate China's future energy consumption, and emissions of GHGs and air pollutants. Therefore, the relationship between energy consumption and GHGs emissions as well as air pollution deserves special attention in this context. The aim of this paper is to address this gap and understand the limits of commonly used models and approaches through comparing the current models. Specifically, we first critically assess model methodology, scenario construction, and uncertainty in existing models used in energy, GHG and air pollutant emissions and policy assessment. We identify the opportunities to strengthen modeling efforts in China to include air pollutants and GHGs in projecting future energy use. We focus on the industrial sector, as these represent 70% of energy use and emissions in China, and are often weakly represented in models. Two main questions are explored in this paper:

1. What are the strengths and limitations of models that have been applied to forecast future energy consumption and emissions of GHGs and air pollutants for Chinese industry?
2. To what extent and how do these models evaluate co-benefits of energy efficiency, GHG emissions and air pollution policies?

The structure of this paper is as follows. Section 2 describes the methodological aspects used for comparing the 19 energy models or tools. Based on the methodology, a comprehensive literature review of bottom–up, top–down and integrated models is given in Section 3. We further assess these models by a detailed evaluation on national and industry-sector level. Scenario construction, basic assumptions, technology diffusion, policy impacts and uncertainty analyses incorporated in the energy-economy models are discussed in Section 4. The recommendations for improving these state-of-the-art models are presented in Section 5. Finally, the conclusion is given in Section 6.

2. Methodology

Four steps were carried out to evaluate 19 selected energy models or tools that have been used to evaluate future energy use and associated GHG and air pollutant emissions. Model selection (see Table 1) was based on having a wide coverage of different types of models (bottom–up, top–down, hybrid, and global versus national and industrial level) that are used in China. While we acknowledge that these models are different and developed for different goals, they are all used to estimate future energy use in China.

As a first step, we conduct a comprehensive assessment of the selected models in Section 3. In this step, key characteristics, strengths and weaknesses of the models are analyzed. In the second step (in Section 4), the modeling approaches and structures, scenario construction and basic assumptions are reviewed. Next, we discussed how representative technologies, their diffusion and barriers for implementation are included in the model. We also provide a detailed evaluation of how policy instruments and impacts are modeled in this step, followed by a discussion on uncertainty analyses used. In a third step (in Section 5), we attempt to provide constructive suggestions to improve the accuracy of energy-economy models specifically to improve the modeling of the interactions between energy use and emissions policies.

3. Energy models used for energy consumption, GHGs emission and air pollution policies

In recent decades, several models (e.g. bottom–up, top–down, and hybrid models) have seen a rapid improvement in the possibility to analyze the interaction between energy consumption and GHG emissions on global, national, and industry levels, such as (e.g., the CIMS (Canadian Integrated Modeling System) [20], China End-Use Energy Model [21], and the LEAP (Long-range Energy Alternatives Planning System) [22], C-REM (China Regional Energy Model) [23], C-GEM (China-in-Global Energy Model) [24], GAINS-AIM/CGE (Greenhouse Gas and Air Pollution Interactions and Synergies-Asia Pacific Integrated Assessment Model/Computational General Equilibrium) [25], and GAINS-ECSC (GAINS-Energy Conservation Supply Curves) [26]). Many of these models have been used in China or include China. As shown in Table 1, the key features of 19 current energy models or tools used to evaluate energy consumption, as well as the emissions of GHGs and air pollutants in China were summarized.

Many Bottom–Up models have been develop to assess the interaction of energy consumption and low carbon emission trajectories to meet China's mid-term and long-term goals on a national level [21] and industry level [27]. The bottom–up China End-Use Energy model, for example, was adopted to assess the potential for China to reduce energy demand and emissions, and used two scenarios to assess this, i.e. CIS (Continued Improvement Scenario) and AIS (Accelerated Improvement Scenario). The key feature of this model is the use of end use technologies to model energy demand on a sector level. Technological development, equipment efficiency, and saturation effects were included in the CIS and AIS scenarios. The main finding was that China's CO_2 emissions will not likely continue to grow as rapidly, as demand for a selection of energy services will saturate around 2030. Unlike other countries, the industrial development path, especially the energy intensive

Table 1
Included models or tools for assessing energy efficiency, GHG and air pollutant emissions.

Item	Reference	Model name	Model type	Geography	Sectors included
Energy efficiency and GHG emission	[57,21,58]	China End Use energy model	Bottom–Up	China	All sectors
	[31]	Decomposition analysis	LMDI method	China	Manufacturing
	[20,50,69,86]	CIMS model	Integrated	Canada, US, China	All sectors
	[40]	MARKAL-MACRO energy system model	Top–Down	UK	All sectors
	[33,34]	Hybrid IO model	RAS, Input–Output, SDA	China	All sectors
	[27,30,29]	LEAP model	Bottom–Up	China	Electricity, iron and steel, cement, pulp and paper, transport
	[41,53]	WITCH model	Integrated	Global	All sectors
	[24,36]	C-GEM model	Top–Down	Global, China	All sectors
	[23,37]	C-REM model	Top–Down	China	All sectors
	[35,59,62,66,87]	EPPA model	Top–Down	Global	All sectors
GHG emission and air pollution	[52]	MARKAL model-AIM/ENDUSE	Integrated	India	All sectors
	[39]	WorldScan	Integrated	EU	All sectors
	[44]	Haiku model	Integrated	US	Electricity
	[25]	GAINS-AIM/CGE	Integrated	China	All sectors
Energy efficiency, GHG emission, air pollution	[54,56,71,88,89]	GAINS	Integrated	EU, Asia	All sectors
	[19]	GAINS-MESSAGE	Integrated	Global	All sectors
	[26,42,43]	GAINS-ECSC	Integrated	China	Iron and steel, cement
	[45–47]	MERGE	Integrated	EU	All sectors
	[51]	MARKAL	Integrated	Shanghai	All sectors

industry, dominates China's total energy consumption and GHGs emission [28]. The LEAP model was employed by Wang et al. and Cai et al. to project future energy consumption of China's five major (industrial) sectors [27] (i.e. electricity [29], iron & steel [30], cement, pulp & paper, transport) using three scenarios. The results of these studies provide potential development pathways for energy use of China's energy intensive industries. The studies found that GHG mitigation policies for the electricity, transport and cement sectors have more co-benefits than two other sectors (i.e., iron & steel and pulp & paper) in reducing emissions of other air pollutants. In these models, the benefits of energy use, climate change and air pollution are studied separately. Yet, these issues are closely related. Only Cai et al. mentions that GHG mitigation policies have notable co-benefits by reducing air pollutant emissions [27].

To better understand the industrial development pathways, and improved modeling to forecast future trends of energy consumption and carbon emissions on a national level, a retrospective and prospective decomposition analysis was conducted for China's 18 industry subsectors under three scenarios [31]. Not surprisingly, this study found that three factors (i.e. industrial output, structural change, and energy intensity change) have a large impact on future trends. There are many cost-effective opportunities to improve energy efficiency and decreasing GHG and air pollutant emissions that are not (fully) implemented. A bottom–up analysis method was adopted to estimate the ancillary benefits of emissions mitigation of CO_2 and air pollutants, but not at the same level of detail as for developed countries [32].

To compare bottom–up models to top–down models, The MRIO (multi-regional input–output) model was employed to project energy requirements and CO_2 emissions in China [33]. In the model, China is divided into eight regions and four sectors including agriculture, manufacturing, construction and services. The results show that improvement in energy end-use efficiency for each region could generate different energy savings up to 2020. For example, the central of China has the highest energy savings, followed by those in eastern and northeast regions. Regional emissions in the model may differ from actual emissions. Hybrid IO (Hybrid energy input–output) models (Input–Output model, decomposition analysis, and modified iterative proportional method) were applied to decompose drivers (i.e. energy input mix, industry structure, and technology improvement) to identify how these factors impact changes in energy intensity [34]. Energy requirements were projected for a BAU (Business-as-Usual) scenario and alternative scenarios. The main findings were that energy demand in China will continue to increase rapidly to 138 EJ (4.7 billion tonne of coal equivalent (tce)) and CO_2 will reach 11.47 billion tons by 2020 in the BAU scenario.

The EPPA model was employed to evaluate the potential synergy between air pollution and CO_2 emissions in China up to 2050 [35]. The main finding was that CO_2 abatement measures have strong effects on air pollution reduction, and vice versa. C-GEM, a similar model framework incorporating the EPPA model, was used to analyze China's energy consumption, CO_2 emissions and economic activity [36]. In line with the study, an improved version of C-GEM was developed to simulate future CO_2 emission trajectories and evaluate the effects of new policy directives of the Chinese government by 2050 under different scenarios [24]. Main findings were that a modest CO_2 price would reduce CO_2 emissions significantly. Considering the regional heterogeneity across China, C-REM was used [37] to assess the efficiency and distributional implications of alternative coal and fossil energy cap policies. The main results were that the fossil energy cap policy on national level is more cost effective than regional coal cap policy because of large welfare losses in some provinces (i.e. Guangdong and Jiangsu). Afterwards, in line with the study, an improved version of C-REM [23] was employed to further analyze migration effects on energy consumption and energy intensity, as well as economic activity. This study showed that migration has fewer impacts on energy consumption and economic consumption on national level than provincial changes. In addition, the provincial energy intensity targets with lower cost would be more efficient than provincial energy caps under the changes of migration.

The CGE (computable general equilibrium model) [38] were used to analyze the impact of end of pipe options for air pollutants on GHG emissions in the EU. The model only included interactions of CO_2 and air pollutants in stationary energy sources. Subsequently, in line with this study, the extended CGE model WorldScan, a global coverage model, were employed to analyze interactions between EU's air pollution and climate change policies [39]. The main result of this study is that changes in energy use (i.e. fuel switching, efficiency improvements, and structural change) will contribute at least 50% to the required air pollution emission reduction. The study also found that the cost of GHGs mitigation policies will decrease when air pollution control is included, e.g. if the air pollution emission target exceeds 40% reduction, carbon prices could drop to zero. This study only evaluates interactions of air pollution and climate changes policies in the EU regions, and did not consider China. The authors also mentioned that the interactions of CO_2 and air pollutants in China will investigate in future.

To solve the limitations of bottom–up models and top–down models, hybrid models were developed to compensate for the limitations of both types of models. Generally, hybrid models can be classified into three broad types [40]. First, independently developed bottom–up and top–down models are combined together through soft linked (e.g. MARKAL-MACRO energy system model) and hard linked (e.g. the WITCH (World Induced Technical Change Hybrid model) [41], GAINS-AIM/CGE [25], and GAINS-ECSC [42]). The GAINS-AIM/CGE model has been used to pursue CO_2 and air pollutant emission trajectories and related co-benefit in China under four alternative scenarios featuring different levels of carbon mitigation policies and air pollution control technologies [25]. It was found that if both policies were implemented the CO_2 intensity and SO_2 emissions could be reduced by 41% in 2020 and 20% in 2030, compared to 2005 level. Developed regions were found to have usually more co-benefits than developing regions, but the latter is more cost effective.

Similarly, the GAINS-ECSC was used to assess the co-benefits of energy efficiency measures and air pollution control options that jointly reduce GHGs emissions and air pollutants, as well as energy consumption in China's cement and steel industries up to 2030 [43]. The main result was that the energy consumption and emissions of CO_2 and air pollutants in cement and steel industries will increase quickly until they peak in 2020. Both studies found that energy efficiency measures will result in significant reduction in air pollution during the study period. Second, one model type (either bottom–up or top–down) uses reduced form representations of the other (e.g. WorldScan and Haiku). For example, the Haiku model [44] has been used in the US to simulate electricity generation, consumption, air pollution and GHG emissions. In that study, electricity demand, electricity prices, air pollutants and health effects were modeled using various scenarios to simulate air quality policy. This resulted in the incomplete modeling of emissions (i.e. only the power sector) and health effects [44]. The third approach provides an integrated platform (CIMS, GAINS and GAINS-MESSAGE). The GAINS model, for example, has been used to evaluate synergies of climate and air quality impacts of changing energy use in various regions of the world [57]. The studies recognize that reducing GHG emissions can lead to a simultaneous decrease of air pollutants. The MERGE (Model for Evaluating the Regional and Global Effects of GHG emission reduction policies) [45], for example, as one of the early models that was used for cost-benefit analyses of climate change policy, ecological damage, valuation and discounting. In a study by Bollen et al. [46], climate change policy proposals were evaluated in light of air pollution and corresponding health damages using MERGE [46]. However, the study had important limitations in analyzing emission abatement costs. An extended MERGE model [47] was developed for a cost-benefit analysis of GCC (global climate change), LAP (local air pollution) and energy security based on three different policy scenarios. The main finding was that the combined implementation can generate additional benefits that each area individually does not. Specifically, global climate change policy not only reduces CO_2 emission, but also generates a net decline of PM emissions. Synergies of GCC and LAP policies can further reduce CO_2 emission by 15% in Western Europe and 20% in China, respectively. LAP policies reduced PM emissions with a large effect on CO_2 emissions. Inversely, GCC policies produced negligible impacts on improved air quality in the short-term. The main reason is that while fossil fuel use is reduced, increased biomass use will increase air pollutant emissions.

The main findings from this literature review include: various scenarios in selected models have been made to analyze mid-term and long-term patterns of China's energy use, which also included projecting expected policy results [48]. The results found in these studies indicate that China's energy consumption and emission trends are poorly understood and hard to predict with current energy economic models, because of rapid economic growth and new energy policies (i.e. top 10,000 program), which leads to distortions in most models when forecasting China's future developments [18]. The models (e.g. China End Use energy model, LEAP model and Hybrid IO model) have been developed by Chinese modelers to mostly study energy efficiency, greenhouse gas emissions and air pollution separately. There have little attention to evaluate the synergies of energy use and emissions of GHGs and air pollutants in China, compared to developed countries (e.g. US and EU). In particular, the evaluation of the synergies between energy efficiency, climate change and air pollution policies on the level of industrial sectors has received little attention. Yet, these sectors are not only the engine of economic growth; they are the key energy user and source of emissions. The co-benefits in developing countries would be higher than developed countries, based on a survey of 37 studies [49]. Therefore, the integrated analysis of those benefits on an industrial level is essential. Other models (e.g. WITCH and WorldScan, and GAINS-AIM/CGE) provide lessons on analyzing co-benefits of energy efficiency, GHG emission and air pollution policies, but have no or limited sub sector detail.

4. Lessons from energy economy models and integrated assessment models

4.1. Model construction and scenarios assumption

Table 2 summarizes the key features of the models for scenario construction and basic assumptions. A clear definition of a baseline or alternative scenario is critical for scenario construction. The baseline (reference) scenario assumptions include mainly the level of macro-economic activities, energy and products demand, population growth, structural change effects, technology representation (including diffusion, spillovers), policy instruments, and uncertainty and sensitivity analysis.

Different modeling methodologies have a variety of assumptions to define baseline scenarios. The baseline scenario can be treated as the status quo or reflect current expectations or continuation of present government policies. In terms of macro-economic assumptions, many models assume key drivers (e.g. GDP growth, per capita income, structural effects, population and urbanization) through general economic assumptions [50], combining literature [51], government expectations [52] and expert judgment [31]. For example, most Top–Down models use a Ramsey type neoclassical optimal growth and neo-classical recursive dynamic framework to determine macro-economic drivers in the baseline scenario, e.g. WITCH model [53], WorldScan model [39], EEPA model, C-GEM, C-REM, and MERGE model [47]. This approach may lead to distortions when meeting irregular phenomena, which means that future development pathways might have a higher uncertainty level if macro-economic factors, energy use and intensity change drastically. It is necessary to assess these uncertainties and calibrate key drivers based on latest historical data, government expectations and literature [39]. Hence, the question can be raised if these approaches provide reliable results for the Chinese economic conditions. The China End-Use Energy Model [21], a typical bottom–up model, uses a conservative assumption for activity and economic drivers (e.g., population peak,

Table 2
Key drivers.

Item		Population drivers			Marco-economic drivers		Energy drivers			Structure effects	Production drivers	
		Population	Urbanization	Migration	GDP	Value added	Intermediate energy consumption	Energy/ electricity trading	Fuel/ electricity price		Production	Intermediate product consumption
Energy efficiency and GHG emission policies	China End Use energy	▲	▲	–	▲	–	–	–	–	▲	▲	–
	Decomposition analysis	–	–	–	▲	▲	–	–	–	▲	▲	–
	CIMS	▲	▲	–	▲	–	–	–	▲	–	▲	–
	MARKAL-MACRO energy system	▲	▲	–	▲	▲	▲	–	▲	▲	▲	–
	Hybrid IO	▲	▲	–	▲	▲	▲	–	▲	▲	▲	▲
	LEAP	▲	▲	–	▲	–	–	–	–	–	▲	–
	WITCH	▲	▲	–	▲	–	▲	–	▲	▲	▲	▲
	C-GEM	▲	▲	–	▲	▲	▲	–	▲	▲	▲	▲
	C-REM	▲	▲	▲	▲	▲	▲	▲	▲	▲	▲	▲
	EEPA	▲	▲	–	▲	–	▲	–	▲	▲	▲	▲
GHG emission and air pollution policies	MARKAL model-AIM/ENDUSE	▲	–	–	▲	▲	▲	–	▲	▲	▲	–
	WorldScan	▲	–	–	▲	▲	▲	–	▲	▲	▲	▲
	Haiku	▲	–	–	▲	–	–	▲	▲	–	▲	–
	GAINS-AIM/CGE	▲	–	–	▲	–	–	–	▲	–	▲	–
Energy efficiency, GHG emission and air pollution policies	GAINS	▲		–	▲		–		▲	–	▲	–
	GAINS-MESSAGE	▲	–	–	▲	–	–	–	▲	–	▲	–
	GAINS-ECSC	▲	▲	–	▲	–	–	–	▲	–	▲	–
	MERGE	▲	–	–	▲	▲	▲	–	▲	▲	▲	▲
	MARKAL	▲	–	–	▲	▲	–	–	▲	▲	▲	▲

Table 3
Technology representation.

Item		Technology representation		
		Fuel technology	Electricity technology	Air pollution control technology
Energy efficiency and GHG emission policies	China End Use energy	▲	▲	–
	Decomposition analysis	–	–	–
	CIMS	▲	▲	–
	MARKAL-MACRO energy system	▲	▲	–
	Hybrid IO	–	–	–
	LEAP	▲	▲	–
	WITCH	▲	▲	–
	C-GEM	▲	▲	–
	C-REM	–	–	–
	EEPA	–	–	–
GHG emission and air pollution policies	MARKAL model-AIM/ENDUSE	▲	▲	–
	WorldScan	–	–	▲
	Haiku	▲	▲	–
	GAINS-AIM/CGE	–	–	▲
Energy efficiency, GHG emission and air pollution policies	GAINS	–	–	▲
	GAINS-MESSAGE	▲	–	▲
	GAINS-ECSC	▲	▲	▲
	MERGE	▲	–	▲
	MARKAL	▲	▲	–

urbanization rate, and saturation effects) to evaluate the influence of these drivers on future energy use and carbon emissions. This leads to future primary energy consumption and carbon emission results that are lower than those forecasted by e.g. McKinsey, CEACER and IEA. Furthermore, activity projections of future economic development was used as a baseline projection in the GAINS model [54]. For China, they use the baseline projection, developed by the ERI (Energy Research Institute), as a reference scenario. In line with this study, a new method was developed to link mid-term emission interactions of air pollutants and GHG derived by GAINS with long-term projections that are developed for MESSAGE to expand the original baseline scenario [19]. In this model, GDP growth, population growth, and technological development are derived from literature. This approach provided a new direction to forecast mid-term and long-term baseline emissions of air pollutants and GHGs.

Structural changes by shifting from higher energy intensive and polluting industries to less energy intensive economic activities, whether inter-sectorial [55] or intra-pectoral [31], in the economy are a major driver affecting emissions and energy use. During the period 2000–2005, structural changes caused an increase in manufacturing energy use, mainly due to an increasing share of energy intensive industries. A retrospective and prospective decomposition analysis was used to estimate the extent of energy savings that can be obtained by structural changes in Chinese manufacturing during the periods 1995–2020 [31]. They conclude that the structural effect is vital to decrease overall energy consumption, both in the past and for the future in three different scenarios. Many models incorporate structural changes to construct scenarios. However, in alternative scenarios, the economic structure is usually assumed to be similar to the baseline. This is not correct, especially if there are large differences between the scenarios. The MRIO (multi-regional input–output) model assumes using the same growth rate for future industries development for each region in China [33].

The WorldScan model [39] were employed to provide a better understanding to what extent emission reduction can be obtained by structural changes in the EU, the marginal abatement cost curves

Table 4
Policy instruments and economic feedbacks.

Item		Policy instruments		Economic feedbacks
		Technology policy	Economic policy	
Energy efficiency and GHG emission policies	China End Use energy	–	▲	–
	Decomposition analysis	–	▲	–
	CIMS	▲	▲	▲
	MARKAL-MACRO energy system	▲	▲	▲
	Hybrid IO	–	▲	▲
	LEAP	–	▲	–
	WITCH	–	▲	▲
	C-GEM	–	▲	▲
	C-REM	–	▲	▲
	EEPA	–	▲	▲
GHG emission and air pollution policies	MARKAL model-AIM/ENDUSE	–	▲	–
	WorldScan	–	▲	▲
	Haiku	–	▲	▲
	GAINS-AIM/CGE	▲	▲	–
Energy efficiency, GHG emission and air pollution policies	GAINS	–	▲	–
	GAINS-MESSAGE	▲	▲	–
	GAINS-ECSC	▲	–	–
	MERGE	–	▲	▲
	MARKAL	▲	▲	–

was used to find largest co-benefits between GHGs mitigation and air pollutants reduction with minimized cost. In the expanded WorldScan model, time series were used to calibrate the BAU (Business-as-Usual) scenario. They also analyzed the indirect impact of GHGs mitigation induced structural changes and air pollution policies. The potential role of structural change was explored to identify cost-effective measures to reduce the emissions of air pollutants and GHGs in the GAINS optimization tool. However, GAINS does not consider non-technical behavior changes [56].

Compared with modeling other macro-economic drivers, representing current technologies and accurate forecasting of future technologies is more difficult. Technologies are divided into end-use energy demand and supply technologies, and air pollution control technologies (see Table 3). Technological explicit models are most represented by bottom–up models. Only current technology was used in several bottom–up models to simulate policy impact and optimize strategies, such as the China End Use energy model, MARKAL, GAINS, and GAINS-MESSAGE. The China End Use energy model contains information on current end-use technologies [21], current international best practices [57] and emerging technologies (including CCS (Carbon Capture and Storage)) [58] projected energy intensity trends and industrial production growth under scenarios representing different technology implementation rates. In contrast, top–down models generally apply constant-elasticity-of-substitution functions to represent production technologies, with no detailed technology representation, such as the C-REM, C-GEM, EPPA, and WITCH model. Technological learning effects and R&D investments are combined to capture the dynamics of technological change in these models [53]. Note that C-GEM not only uses AEEIs (autonomous energy efficiency improvement) to represent current energy technology diffusion within China, but also includes 11 advanced energy technologies that are not yet commercial [36]. Most of the other integrated models link bottom–up models or combine CES production functions (e.g., WITCH model, WorldScan, MERGE, MARKAL model-AIM/ENDUSE and MARKAL-MACRO energy system model, and GAINS-AIM/CGE model). The WorldScan model links end of pipe technology and emission data derived from GAINS to extend the evaluation of air pollution and GHG emission policy and to what extent technological and structural change contribute to emission reduction [39]. The energy efficiency technologies and air pollution control options are combined together in the GAINS-ECSC to evaluate the co-benefits between energy savings and emissions mitigation in Chinese industry [43]. The use of aggregated AEEIs and ESUB (elasticity of substitution) to represent current energy technology diffusion in the CIMS model, resulted in useless outcomes for Chinese policy-makers seeking policy advise to meet energy intensity and GHGs emission targets, as in reality AEEIs and ESUB differ widely by sector [50] (see Table 4).

The diversity of policy instruments plays an important role in technology diffusion. Several energy modelers have modeled policies aimed at specific technologies (e.g. technology procurement and best practice dissemination) and general policies (e.g. regulation, standards, pricing and taxation, subsidies, energy and emission trading, voluntary programs) [13]. Only general policy instruments are adopted by Top–Down models (e.g. Hybrid IO, EEPA, C-GEM, and C-REM). In contrast, most Bottom–Up models (e.g. China End Use energy model) and hybrid models (e.g. MARKAL-MACRO, CIMS, MERGE, WITCH, WorldScan, C-GEM, C-REM, GAINS, and GAINS-AIM/CGE model) often employ both type of policy instruments together. For example, the China End Use energy model and GAINS-ECSC use (extensions of) current and future policies and best practice dissemination, to model baseline and alternative scenarios.

Economic feedbacks may be incorporated to assess the impacts of energy, climate change and air pollution policies. In most Bottom–Up models (e.g. China End Use energy model and GAINS-ECSC), these feedbacks are ignored. However, in most Top–Down models, typically iteration is used to calculate the feedback and optimize the results. For example, technology improvement, population growth, and trade coefficients had main impacts on national energy use and CO_2 emissions in the Hybrid IO model [33]. Aggregated energy demand responses were adopted to calculate macro-economic impacts in the MARKAL-MACRO energy system model [40]. Similarly, climate change damages were taken into account through feedback from an integrated climate module in the WITCH model [53]. The extended MERGE model used penalty functions and other parameters to simulate interactions between climate change damage, premature deaths, and the economy [47].

Table 5
Technology representation, technology learning and their barriers.

Item		Technology representation		Technology learning	Technology diffusion barriers
		Endogenous technical change	Exogenous technical change		
Energy efficiency and GHG emission policies	China End Use energy	–	▲	–	▲
	Decomposition analysis	–	–	–	–
	CIMS	▲	▲	▲	▲
	MARKAL-MACRO energy system	–	▲	▲	▲
	Hybrid IO	–	–	–	–
	LEAP	–	▲	▲	▲
	WITCH	▲	–	▲	▲
	C-GEM	▲	–	▲	▲
	C-REM	▲	–	▲	▲
	EPPA	▲	▲	▲	▲
GHG emission and air pollution policies	MARKAL-AIM/ENDUSE	–	▲	▲	▲
	WorldScan	–	▲	▲	▲
	Haiku	▲	–	–	▲
Energy efficiency, GHG emission and air pollution policies	GAINS	▲	▲	▲	▲
	GAINS-MESSAGE	–	▲	▲	▲
	GAINS-AIM/CGE	▲	–	▲	▲
	GAINS-ECSC	–	▲	▲	▲
	MERGE	▲	–	▲	▲
	MARKAL	▲	–	▲	▲

Table 6
Policy and instruments.

Item			Policymakers and consumers behavior	Implementation of policies instruments			Cost and benefit	
				Tax/price policies	Cap/target for emissions and consumption policies	Technology specific policies	Conventional benefits	Co-benefits
Policies instruments and evaluation	Energy efficiency and GHG emission policies	China End Use energy	–	–	▲	▲	–	–
		Decomposition analysis	–	–	▲	–	–	–
		CIMS	▲	▲	▲	▲	▲	–
		MARKAL-MACRO energy system	▲	▲	▲	–	–	–
		Hybrid IO	–	▲	–	▲	–	–
		LEAP	–	–	▲	▲	–	–
		WITCH	▲	▲	▲	–	–	–
		C-GEM	–	▲	▲	▲	▲	–
		C-REM	–	▲	▲	–	▲	–
		EPPA	–	▲	▲	–	▲	–
	GHG emission and air pollution policies	MARKAL-AIM/ENDUSE	–	▲	–	–	–	–
		WorldScan	▲	▲	▲	–	▲	▲
		Haiku	▲	▲	▲	–	▲	▲
	Energy efficiency, GHG emission and air pollution policies	GAINS	–	–	▲	▲	▲	▲
		GAINS-MESSAGE	–	–	▲	▲	–	–
		GAINS-AIM/CEG	–	▲	▲	▲	▲	▲
		GAINS-ECSC	–	–	▲	▲	▲	▲
		MERGE		▲	–	–		
		MARKAL	–	▲	–	–	▲	▲

In addition, the impact of tax policy on the economy were analyzed through adjusting carbon prices and the willingness-to-pay in WorldScan [39]. The modelers of C-GEM and C-REM evaluated the robustness of energy and emission cap policies on the energy and environmental targets by changing prices and taxes [37].

As demonstrated above, each modeling approach has advantages and limitations. The strengths of traditional bottom–up energy economy models (e.g. China End-Use energy model and LEAP) include more detailed information (e.g. technology representation) to forecast interactions of energy use and energy related carbon emissions on industrial sector level (see Table 5). However, these models hardly quantify the co-benefits of energy use, GHG emission, and air quality policies. The traditional top–down models (e.g. EPPA, C-GEM, and C-REM) usually use neo-classical recursive dynamic approach forecasting macro-economic drivers to build scenarios. The top–down models still dominate in the discussion as they can assess both economic impacts and behavioral factors. However, detailed industrial (sub-) sector-level representation is lacking, while this information is needed for policy making. Some extended models (e.g. MERGE, WorldScan, GAINS-AIM/CGE, GAINS-ECSC, MARKAL-MACRO, and WITCH) and new integrated models (e.g. GAINS, MARKAL, CIMS, and GAINS-MESSAGE) are developed to overcome these limitations. However, those models typically still do not cover all drivers (e.g. technological learning, non-price policy effects, non-energy benefits) of industrial energy use and emissions. Hence, Model improvements have to be developed to improve the discussed aspects in these models at the level of individual (sub-) sectors to come to modeling tools that have policy relevance (see Table 6).

4.2. Technology representation, diffusion and its barriers

The methodology to model technological change is widely considered as the vital determinant for realistic modeling results for energy, climate and air quality policies. The current models mostly focus on the potential of technology diffusion, but technology change is ignored [59]. As shown in Table 5, endogenous or exogenous mechanism was adopted to represent technological change in the energy-environment-economy models [60]. Table 5 shows that the bottom–up models are better in representing technology options depending on technological learning (although primarily focused on the energy sector) and associated costs. For example, to achieve national targets, energy efficiency policies and programs were designed in the China End Use energy model to simulate technological change through exogenous mechanism. Conversely, the top–down models are better in modeling technology penetration based on endogenous mechanism [61]. Both types of mechanisms have their advantages and limitations. There has been no single mechanism (neither exogenous nor endogenous) that dominates modeling of technology diffusion and technology options. To overcome the gap between both mechanisms, several approaches are developed to represent technology options and diffusion in the state-of-the-art models. A typical method for better modeling technology representation and diffusion is constructing a link for different models. The WorldScan and incorporates end of pipe options (derived from GAINS) [39] were used to analyze the interaction of air pollution and climate change policies. The cost of air pollution control options from GAINS was input as an exogenous factor in the EPPA model to assess the potential synergy between pollution and carbon emissions [35]. The results from ECSC containing energy technology diffusion was input into GAINS to represent the diffusion of air pollution control options to assess co-benefits of energy efficiency and air pollution [42]. Similarly, AIM/CGE models, which simulate production technologies in an endogenous way, were combined with GAINS, in order to evaluate the co-benefits of CO_2 emissions and air pollution [25]. The other methodology is one type (either exogenous approach or endogenous approach) can use reduced form representations of the other. For example, the learning curves that affect prices of new vintages of capital and R&D investments were an endogenous input into the WITCH model to represent technological progress [53]. The exogenous factors of AEEI and CES production function that endogenously represent technology change and penetration were both adopted in EEPA, C-GEM, and C-REM models. In these models, the technology-specific factor was adopted to operate the backstop technology that have not been implemented yet at commercial scale [62]. The third approach is an integrated methodology based on theoretical and practical developments of solution algorithms. For example, the mixtures of equations and inequalities combined with MCPs (mixed complementarity problems) were used in CIMS, C-GEM, C-GEM, GAINS and GAINS-MESSAGE, who attempted to forecast rates of technical implementation. In CIMS [50], the financial and social discount rate were replaced by behavioral parameters to simulate technology penetration. In addition cross-cutting technologies (e.g. motor systems, lighting, utilities) combined with specific other technologies will generate more energy saving in energy intensive industries [63]. The cross-cutting technologies and different plant type's technologies in the industry sector were included in the GAINS database.

Many studies demonstrate that costs of new technologies will decrease due to technological learning. Technological learning assumes that a technology's performance improves as experience with the technology accumulates. The experience curve is incorporated in many energy-economy-environment models [55]. Learning rates of future technologies have been included in MARKAL-MACRO for future supply technologies based on the published literature. Similarly, the WITCH model incorporates learning by doing effects in the electricity sector [53]. In that study, it is assumed that mature technology spillovers and constant learning rates are used in all countries. The extended WorldScan model uses induced technological change to analyze mitigation policies under emission targets [39]. The feedback between supply side technologies and macroeconomic impacts are typically embodied through technological change, induced by prices. The bottom–up models (e.g. China End-Use Energy Model) excludes endogenous technological learning and economics, as it assumes that best practice technology will be fully implemented in different scenarios. The impacts of technology R&D and non-technical behavior were considered, but exogenously in the model inputs. A relatively high CCS (carbon capture and sequestration) utilization rate was assumed in coal fired power plants and other industries by 2030 in China [64]. In contrast, the LBNL (Lawrence Berkeley National Laboratory) and ERI (Energy Research Institute) of China scenarios do not expect CCS to play a major role in the power sector [65].

MAC (Marginal abatement cost) curves are a typical approach to estimate the abatement potential of GHG emission. It has frequently been used in many energy economy models [66], using either smooth functions or step functions [67]. In practice, the bottom–up models generate larger cost-effective potentials than top–down models. The MAC curves depict the abatement cost for a single point in time, which may lead to inaccuracies. Carbon prices (exogenously) combined with mitigation measures were used to generate MAC (marginal abatement cost) curves in the GAINS model. In the MAC curves, the co-benefits of GHG emission and air pollutant reductions were included. However, other limitations, e.g. economic feedbacks [68], interaction of behavioral aspects, economy, and abatement measures [69] are still a challenge.

Barriers for technology diffusion have been widely discussed, and are also included in some of the models [59], including imperfect information, hidden costs (WorldScan, WITCH), capital constraints, high observed discount rates and low price elasticities (Haiku, MARKAL-MACRO, GAINS and GAINS-MESSAGE, CIMS, and MERGE). These factors reduce the implementation level of many cost-effective measures [70]. Generic technology constraints are generally applied in energy models (e.g. to limit application rates). An upper limit on the application rate and hidden costs for technologies was employed to identify potentials for improving air quality and decreasing GHG emissions [71]. In GAINS, technology constraints are distinguished into four categories, i.e. generic constraints, sector-specific constraints, context-related constraints and transition constraints. Compared with other models, low implementation rates were assumed for selected technologies in alternative policy scenarios. This might lead to under estimating the co-benefits of GHG emission and air pollution policies in the future [72].

Summarizing, we found that models with detailed technology representation can provide more accurate results than other models without technology representation. Technology representation is also necessary to assess the co-benefits of GHG emission and air pollution policies (see Table 5). The bottom–up models often result in larger mitigation potentials of energy use and emissions than the top–down models. Technological learning is included in a few models, but often limited to supply-side technologies only [41]. Barriers limiting the uptake of mitigation options are included in some models. However, the modeling of barriers is still indirect and has large uncertainties. In addition, the interaction between energy technologies and air pollution control options are failed to be considered. Modeling barriers for technology diffusion and related issues (e.g. integration of co-benefits in decision making, behavioral parameters) are challenges that need to be addressed in model development.

4.3. Policy development and their implications

Evaluating policy is an important issue for models to come to realistic ex-ante estimates of policy impacts. Several studies modeled policy instruments to assess the economic, environmental and energy impacts, including regulation, standards, pricing and taxation, subsidies, emission trading, voluntary programs, and technology best practices [73]. The China End Use energy model mainly uses energy efficiency standards, enforcement of sector-specific energy intensity targets, and mandated closure of inefficient plants to simulate policy in the scenarios. They found that the largest potential to decrease energy use and carbon emission is in the energy industry sector in the short-term, and in the buildings sector in the long-term [74]. The GAINS model also extrapolate current legislation in the baseline and alternative scenarios to forecast future energy use and emissions in China [55]. Carbon and fuel prices were also introduced to develop alternative scenarios (e.g. MARKAL-MACRO energy system model, EPPA, C-GEM, C-REM, and CIMS). In MERGE [47] and WorldScan [39], the impacts of policy were estimated through technology learning curves and mitigation cost curves. Pricing and taxation for fuel and electricity were introduced to mimic policy impacts in C-GEM and C-REM [24]. An exogenous method was used to evaluate policy effects in LEAP [27], GAINS [55] and GAINS-MESSAGE [19]. Also, government expectations and expert judgments are often used to simulate Chinese industry development pathways under different scenarios [31].

The understanding of the behavior of policy and decision makers is crucial accurately model energy use, GHG and air pollutant emissions. Behavior is still indirectly included in the models. The China End-Use Energy Model only qualitatively describes consumer preferences [21]. Similarly, GAINS excludes non-technical factors [71]. In contrast, the CIMS model uses a logit function to simulate market shares. In this function, the preference of decision makers, intangible cost, and heterogeneity in the market were estimated by stated preference surveys [50]. MARKAL-MACRO, WITCH, and Haiku considered decision behavior, free-riding behavior and market heterogeneity (however often exogenously). A so-called progress ratio was used to reduce the costs of new technologies depending on their market penetration in some models [40]. Free-riding behavior was used to estimate technology spillovers in the WITCH-model, which will lead to more realistic estimates of the cost-effectiveness of policy [53].

Cost-benefit or cost-effectiveness analysis is an important modeling aspect. Co-benefits play an important role in understanding the cost-effectiveness. However, inclusion of co-benefits is still limited. In this discussion we focus especially on the interaction of GHGs emissions and air pollution in energy models. Many literature sources demonstrate that strategies for decreasing air pollution also reduce GHGs emissions, and vice versa, and also found that this co-benefit is higher in developing countries [49]. Previous analysis of ancillary benefits of carbon policies yielded higher estimates due to incomplete modeling of emission and policy baselines [56]. Similarly, the actual co-benefits (both implementing CO_2 mitigation measures and air pollution control options) usually were much higher than when only applying CO_2 mitigation measures [25]. Increased use of biomass can mitigate CO_2 emissions, but at the same time, biomass is a source of particulate matter emissions [75]. Hence, the impacts of GHGs policy will depend strongly on the strategy selected. The carbon price (emission trading system) may fall or even drop to zero when more severe air pollution policies implemented [39]. The average marginal costs of energy efficiency measures will decrease by 20% if the co-benefits of air pollution are taken into account [42]. Furthermore, each percent reduction of CO_2 emissions, particulate matter emissions will also fall by 1% [55]. The extended MERGE model [47] and the GAINS model [54] were used to present an integrated assessment of energy use, climate change and air pollution policies, both studies notice that synergetic policies can produce multiple benefits that each individually cannot bring about. Understanding the co-benefits may help policymakers and decision makers to design and implement better policies.

This above analysis show that most models simulate policies by modifying energy price; but the non-price influence is often ignored in models for China [21]. This confirms earlier findings [13]. In reality, various (non-price) policies are implemented simultaneously, and synergistic or inhibitory relationships of the individual policies within the mix, are also not well understood. The top–-down and integrated models have currently more advantages than bottom–up models to simulate behavior as these are generally presumed to have a better understanding of economic aspects and feedbacks. However, the model inputs are based on historic statistical analyses, and often for industrialized countries. It is questionable, if these models provide correct results for a country like China, and it is not sure if the past relationships hold for the future. The integrated models (e.g. GAINS, and WorldScan) do provide a better opportunity to evaluate the synergies of policies on energy use, climate change and air pollution [39]. Although the co-benefits are much higher in developing countries, the inhibitory effect of policy mixes has not been considered so far. It is necessary to expand the state-of-the-art models to assess the co-benefits of different policy instruments.

4.4. Uncertainty and sensitivity analysis

Uncertainty and sensitivity analyses are important because all energy models cannot predict the future with precision. In energy modeling literature, uncertainty may be classified into two types, i.e. model structural uncertainty (including model solution algorithms) and parameter uncertainty resulting from imperfect knowledge of the parameter values [76]. The structural uncertainty can be further divided into conceptual model structure (caused by lack of understanding of the modeled system) and technical model structure (caused by simplifications, and errors in software and hardware) [77]. Several approaches (e.g. approximate dynamic programming, stochastic programming, stochastic mixed integer liner programming, Monte Carlo sampling, and regret theory etc.) combined with future projections of key drivers were adopted when performing uncertainty analyses of energy models. In most of Bottom–Up energy models, simplified approaches are adopted to examine the effects of changes in a single parameter and assuming no changes in all the other factors. For example, simplified uncertainty analyses were adopted to compare the results of different studies in China End Use energy [21] and CIMS [50], respectively. Different lower economic growth assumptions were adopted in the LEAP model to track energy demand and supply patterns, as well as greenhouse gas emissions under different scenarios [78]. In contrast, prices and taxes for energy and CO_2 emissions were employed in most Top–Down models (e.g. EPPA, C-GEM, and C-REM) through PDFs (Probability Distribution Functions). For example, the AEEI and substitution elasticity between energy and capital-labor bundles, as important input parameters, were tested in C-GEM and results showed the effects on energy consumption and CO_2 emissions [36]. Some uncertainties can be reduced by calibrating input data. The China's official database (China's 2007 national input–output table, China's 2007 energy balance table, and China's industrial energy consumption table) were used to replace the GTAP (Global Trade Analysis Project) database in C-GEM to reduce the input data error [36]. The main sources of uncertainty in CO_2 emissions and prices derived from GDP growth, AEEI, and elasticity of substitution between energy and non-energy inputs [62]. In a similar way, the uncertainty of key parameters (e.g. market shares, emissions, and costs) together was estimated in CIMS models by PDFs [79]. The other hybrid models (e.g. extend MERGE [46] and WorldScan [39]) tend to use optimization approaches to quantify uncertainties or errors. Activity drivers and varying assumptions were extensively described in these models to analyze the effects on modeling outcomes. For example, the calculation of how the costs and benefits of policies for global climate change and local air pollution vary by changing behavior and scaling factors [47]. The GAINS-ECSC was employed to assess the changes of energy saving potential and emissions mitigation under different assumptions (e.g. production, discount rate, substitution of different energy) [42]. Further, market structure, fuel prices, environmental regulations, new air pollutant standards, and health epidemiology are included in the Haiku model to simulate ancillary benefits between air pollution policies and GHGs mitigation policies in the electricity sector. Previous estimated large ancillary benefits due to incomplete modeling was identified [44], demonstrating the risk of large uncertainties.

As demonstrated above, uncertainty in many energy models, especially developed by Chinese modelers, has only received limited attention. Several source of uncertainty in energy models are mainly derived from uncertain estimates of model parameter values. Most analyzed sources of uncertainty focused on key parameters, but the structural model uncertain is ignored. The behavioral sources of uncertainty from policymakers and end users are hardly considered in energy models. In addition, the interaction between uncertain variables is not captured in the models [80]. Therefore, a transparent model should involve elements to address uncertainties in items like input parameters, model structure, and solution algorithms. This is especially important for countries like China, as the changes in the economy can be fast and relatively large.

5. Recommendations

Although valuable results have been found using energy-economy models, many challenges and problems still exist, especially for models for China. As for the model itself, especially the industrial model, the framework, approaches, and uncertainty

Table 7
Advantages and weaknesses.

Item			China end-use energy	Decomposition analysis	CIMS	MARKAL-MACRO energy system	Hybrid IO	LEAP	WITCH	C-GEM	E-REM	EEPA	MARKAL-AIM/ENDUSE	WorldScan	Haiku model	GAINS	GAINS-MESSAGE	GAINS-AIM/CGE	GAINS-ECSC	MERGE	MARKAL
Definition of business as usual and scenario construction	Key drivers assumption		+	+	0	+	−	0	0	+	+	0	+	+	0	+	+	+	+	+	0
	Choice of available technology		+	−	+	+	−	+	−	0	0	0	+	+	+	+	+	0	+	+	+
	Implementation of policy instruments		0	−	0	−	−	0	0	+	+	0	−	0	−	0	0	+	0	+	−
	Economic feedbacks		+	−	+	+	0	−	+	+	+	+	0	+	0	−	+	−	−	+	−
Technology and opportunity representation	Technology representation	Endogenous technical change	−	−	+	−	−	−	+	+	+	+	−	−	0	−	0	−	−	−	−
		Exogenous technical change	−	−	+	+	−	+	+	−	−	−	0	+	−	+	+	+	+	+	−
	Technology learning		0	−	+	+	−	0	+	0	0	0	0	+	0	+	+	0	+	+	0
	Technology adoption and diffusion barriers		0	−	+	+	−	0	+	+	+	+	0	0	+	0	0	0	0	0	−
Policies and instruments	Policymakers and consumers behavior		−	−	+	+	−	−	+	−	−	−	0	+	+	−	−	−	−	+	−
	Implementation of policies instruments		+	0	0	−	+	+	0	+	+	+	−	+	+	+	0	0	0	−	+
	Cost and benefit		−	−	+	+	−	−	+	0	0	0	0	+	+	+	0	+	+	0	+
Sensitivity (uncertainty) analysis	Parameter uncertainty		+	−	+	+	0	0	+	+	+	0	+	+	+	+	+	0	+	+	−
	Model uncertainty		0	−	+	+	−	−	+	+	+	0	0	+	+	+	+	0	0	0	−

The meanings of the symbols used are as follows: + = strength of model, 0 = average, − = weak point of model.

analysis can be improved. In addition, the co-benefits of energy uses and emissions policies are rarely reported on industrial level, yet, they are very important for developing countries. In this section, some constructive suggestions to improve the accuracy of energy-economy models for analyzing the interactions of energy use and emissions policies is given (see Table 7). As shown in Table 7, the symbol of '+ =' represent the elements that is are included in the model. Inversely, the '− =' symbol insinuates the element in the energy model that needs to be improved in the future.

5.1. *Better use of model construction and scenarios assumption*

Each model has its own structure and methodology, often based on basic economic approaches, and patterns and relationships based on historic statistics from industrialized countries. Some other mechanisms are still not well understood (e.g. barriers, policy effectiveness, potential rebound effect), limiting the reliability of the results. For other determinant missing drivers, especially non-linearity in key drivers, other models or tools are needed. In many Chinese industries, non-linearity has been observed [81]. The saturation effects (e.g. population peak, urbanization rate and demand saturation per person) should be considered when modeling Chinese development pathways. Some of the drivers in other sectors may produce large impacts on industry activity, e.g. as the population and urbanization rate would start to decrease over the next decades, the building floor space will saturate and relevant industrial activities (e.g. iron and steel, cement, and aluminum) would be reduced [57]. Similar relationships are discussed in other studies [21]. Furthermore, energy intensive industries may affect each other, though there are still no convincing approaches to quantify these impacts, other than government expectation and expert judgment. Hence, it is difficult to model the non-linear drivers in scenario construction, and this is why some models forecasting Chinese future energy use and related carbon emissions result in apparent deviations [18]. All these factors make it complicated to simulate future energy use and emissions. Unlike for other developed countries and regions (e.g. US and EU), a detailed assessment of the synergies between energy efficiency, GHGs emissions, and air pollution policies at industrial level in China has not been implemented in the state-of-the-art energy models. To improve the results of energy models for Chinese industry, the following aspects need to be considered:

- *Including industrial sub-sectors*. Although most models include some industrial sub-sectors, quantifying the relationship within industry and across industries is still a challenge. For example, how to quantify the relationship between raw material demand in the buildings and transportation sector and production activity level for cement and iron and steel. If confined by constraints (model costs, software, and hardware, computational feasibility etc.) which limit the inclusion of sub-sectors. The exogenous approach might be used to build a link between different models, such as GAINS-AIM/CGE model.
- *Data availability and quality*. Reliable data is an essential element for any model. Currently, different data sets are used in models for China. Different data sources have different qualities, necessitating sensitivity analysis. More analysis into the validity of the different Chinese energy and production statistics is also warranted.
- The *non-linear development patterns* of industries in rapidly changing countries like China need special attention. Current modeling approaches cannot fully include the effects of these rapid changes in industrial production and production structures. Some energy models use non-linear functions to forecast

future trends of production and macro growth. However, the outputs of these models are still inefficient to predict future pathways in China due to inconsistent of input data. In other latest models with calibrated input data (such as C-GEM) the linear function is still adopted when forecast future energy consumption and Co_2 emissions. The results of these models might have large uncertainty.

- *Synergy effects of energy use and emissions policies* are required to expand to better model energy use at the industry sector level. The co-benefits between energy efficiency and policies for GHGs emissions, air quality, and health impacts have been included in some models. Developing countries, including China, appear to gain higher co-benefits than developed countries. However, there has not been a detailed evaluation at industrial level yet. This is especially important as air quality may be a key driver for (energy) policy in China for years to come. There have been overestimations of the co-benefits because of incomplete considerations and other assumptions. Hence, integration of better understanding of the co-benefits is necessary in the models to accurately calculate the impacts on energy use and emissions for industries.

5.2. Better use of technology representation and diffusion

Technology availability and diffusion is another essential element. It has been widely discussed in the literature how to better characterize technological change and diffusion in the energy economy models [82]. According to our evaluation (see Section 4.2), most of the models, especially developed by Chinese modelers, hardly take into account synergies of technologies and policy instruments, which lead to under estimating the co-benefits. In addition, the ancillary benefits of abated air pollutants and emissions mitigation of GHGs can be overestimated because of potential overlaps due to different sector classifications. The following directions should be considered by modelers:

- Extending and improving the model framework for uncertainty analysis. The uncertainty in model structure should be considered a process error, a functional error, a resolution error, a model-fix error or a numerical error, depending on the status and purpose of the model. The uncertainty parameters in the models should assess the influence of variations in key model parameters and their influence on model output.
- Technology rich models seem to better at grasping the synergies of mitigation options. Enriching models by better representing current commercial technologies and new technologies is an important step to improve modeling.
- The impacts of multiple technologies should be considered in models. It is necessary to add technologies for energy efficiency improvement when estimating co-benefits of emissions mitigation of GHGs and air pollutants. Developing a new approach to avoid double counting should also be considered. Specifically, energy efficiency technologies are used to improve energy efficiency and thereby reduce GHGs emissions and air pollution. In contrast, air pollution control options only abate certain emissions, while consuming extra energy.
- Capturing the trajectories of technology diffusion if large policy changes appear. Considering the implementation of a large policy package, such as top 1000 energy programme, it is necessary to improve the approach to forecast China's future energy consumption and emissions of GHGs and air pollutants.
- Forecasting future trends of technology needs caution. Excess capacity exists in several energy intensive industries and products in China (cement, iron and steel) because of excessive dependence on capital investment in the past decades [83]. For example, the Chinese cement industry, especially for the NSP (new suspension preheater/precalciner) kilns, has seen rapid developments in the last decade and shows excess capacity phenomena [42]. This means that the technology diffusion of Chinese cement industry is non-linear. Hence, the potential application of advanced technologies might be lower than before.
- Enriching the parameters to *estimate MAC curves* needs to be considered. The hidden costs (e.g. market barriers, economic feedbacks, behavioral and inter-sectorial interactions) may affect the MAC curves when analyzing technology adoption and resulting impacts.

5.3. Better modeling policy development

Although a series of policy instruments have been developed and modeled by government and policymakers, most rely on changing cost factors. Choosing an appropriate modeling method for policy impacts remains challenging. Several approaches were used to exogenously model and affect non-price barriers in models that incorporated diffusion of specific technologies. There are still many challenges to better represent non-price policies in energy-economy models. These policies are as heterogeneous as the barriers (e.g. decision-making behavior, free-riding, intangible cost, imperfect information, and market heterogeneity) addressed. In addition, information policy instruments are hardly considered in models. To allow improved modeling, evaluation of previous policies is vital. Ex-post assessment of energy policies, including decomposition analysis, Top–Down combined with Bottom–Up approaches, can provide better understanding and lead to new methods to incorporate non-price barriers and policies in the models [84]. Therefore, the following aspects should be considered by modelers:

- Capturing the effects of non-price policies in energy models: non-price policies are not considered in most models, especially for Top–Down model, because of data limitation. It might be possible to improve representation of non-price policy instruments through e.g. accelerating information diffusion to increase the technological application rate. For example, the CIMS and Haiku models provide interesting directions to improve the estimation of non-price policies barriers in models.
- Considering that crucial interactions exist between energy and air quality policies. Most studies indicate that policy interaction and coordination need to be considered in the future based on ex-post assessment of different policies [84]. Hence, It is necessary simulate the interactions between energy efficiency, climate change, and air pollution policies through coupling of energy and air quality models (e.g. GAINS-TM5) [85].

5.4. Improving uncertainties in models

Unlike other model elements, uncertainty analysis is part of the whole process from input parameters calibration, model structure determining, and policies planning. Compared to other components of the model, uncertainties are given little attention by many modelers. Specially, empirical analysis and expert judgment are often used to estimate the uncertainty of the model structure. Yet, uncertainties resulting from technology and policy instruments have limited assessment. Several energy modelers only focus on uncertainty related to input parameters. As mentioned above, some traditional bottom–up models, such as China End Use energy model, only compare to other studies to assess the uncertainties [21]. In this model, detailed technology and related policy instruments were introduced, but the uncertainty factors (e.g. technology risk, behavioral aspects, and market distortions) that affect technology application rate are hardly considered. On the other hand, in many other models the price elasticities are usually used to assess policy instrument impacts and technology cost. As a typical example, WorldScan analyses co-benefits of air pollution and GHG emission policies through adjusting the carbon price. They found that if government would implement more stringent air pollution policy, the resulting carbon price could be zero [39]. Hence, these synergies do affect the elasticities used, but are often not well understood. Furthermore, assumptions of uncertain parameters also influence the baseline results. As noted before [13], the choice of an appropriate baseline is key to understanding the results of policy modeling. In the GAINS model, it is noticed that the cost-optimal baseline scenario was used to replace a baseline scenario. This not only overcame several shortcomings (e.g. the uncertainty of input data and application status of current technology and policy) in baseline scenario, but also the modeling results were found to be more realistic [71]. Hence, the uncertainty analysis in energy models should not only estimate how much model outputs (future energy consumption and emissions) are affected by changes in uncertain key parameters, but should also assess structural model uncertainty. In addition, it is necessary to provide detailed information addressing the significance and interactions among different policies or technologies. To improve the accuracy and reliability in energy models, the interactions between different parameters should be considered because changing parameters simultaneously can have a large effects on results compared to changing them separately. For example, the outputs of energy consumption and CO_2 emissions in EPPA were estimated through adjusting the parameters of energy and CO_2 emission prices. However, the interaction between the two was ignored, in spite of energy prices having an (in)-direct effect on CO_2 prices. Furthermore, it is necessary to consider uncertainties related to technology diffusion and behavior of policymakers, producers, and end users.

6. Conclusion

Many different energy models are used to project China's future energy consumption and emissions of GHGs and air pollutants. However, many factors (e.g. market saturation, multiple effects of different technologies, synergies between energy use, climate change and air pollution mitigation etc.) pose large challenges for modeling. The aim of this paper is to evaluate the modeling of these challenges through assessing 19 selected models. These models include the most frequently used models to simulate China's future energy consumption, as well as emissions of GHGs and air pollutants on different levels (e.g. national versus industrial level).

A critical assessment is done of the 19 models, taking into account model structure, scenario assumptions, features of technology representation, and development of energy and air policy instruments. It is found that these models have a number of limitations to project China's future energy consumption and emissions of GHGs and air pollution, as well as economic development, especially on sub-sector level. Some main limitations are difficulty to represent new technologies, difficulty to represent interactions of different policy instruments, insufficiently developed to represent non-linearities for technology diffusion, and limitation of model uncertainty estimates.

Based on the assessment we provided several key recommendations to improve the accuracy of energy models for projecting future energy consumption, and emissions of GHGs and air pollutants, as well as the interaction of different policies and their co-benefits. For example, uncertainties of model structure and of key input parameters will become more important especially when capturing the trajectories of technology diffusion, effects of non-price policies, and synergies between energy consumption and emissions of GHGs and air pollutants. These are important to be addressed when extending/incorporating new modeling approaches. Finally, the approach in this paper can be a guidance for future studies that compare energy models.

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