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The potential of industrial electricity savings to reduce air pollution from coal-fired power generation in China

Hui Yue [a, b, *], Ernst Worrell [b], Wina Crijns-Graus [b], Shaohui Zhang [c, d]

[a] Center for Energy, Environment & Economy Research, Zhengzhou University, Science Avenue 100, 450001, Zhengzhou, China
[b] Copernicus Institute of Sustainable Development, Utrecht University, Princetonlaan 8a, 3584 CB, Utrecht, the Netherlands
[c] School of Economics and Management, Beihang University, Xueyuan Road 37, 100191, Beijing, China
[d] International Institute for Applied Systems Analysis (IIASA), Schlossplatz 1, A-2361, Laxenburg, Austria

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ABSTRACT

Coal-intensive power supply systems, along with a fast-growing electricity demand driven by industry has caused serious air pollution and health concerns. These concerns are particularly prominent in countries where electricity use is likewise dominated by industry and heavily dependent on coal-based electricity. A more efficient industry and coal-free electricity systems are the core components of the United Nations 2030 Agenda for Sustainable Development. Previous studies rarely reflect on the impacts of the electricity savings of industrial consumers on the electricity supply sector with respect to future air emission changes, and also neglect the potential benefits of reducing investments in new generation capacity. Here, a comprehensive modeling framework is newly developed to quantify the connections of electricity savings, coal-based electricity systems, air pollutant emissions, and control investments in China, a country exposed to poor air quality. The modeling framework includes 175 energy efficiency technologies (covering multiple industrial sectors) and detailed information of power generation units (thermal efficiency, environmental performance, and lifespan), and allows for unit-by-unit assessment. We find that industrial efficiency improvements can significantly decrease the dependence on coal-fired power generation, particularly the most polluting power fleet. Efficient use of electricity in industry can drive all small high-polluting coal generation units (i.e. units below 300 MW, in total 753 units) to be phased out and effectively curb less efficient coal-fired plants to come online in China. Meanwhile, the air pollutant emissions can be significantly avoided because of the closed coal-fired power units. Developed cost portfolios demonstrate that improving industrial energy efficiency is more cost-effective than installing flue gas controls in coal-fired plants. We further reveal that a sustainable industry could contribute to climate change mitigation even if less remarkable than air quality improvement, while enabling the expansion of intermittent renewable power supply.

1. Introduction

This study conducts an in-depth analysis of electricity saving potentials and cost-benefits of power-related emission mitigation due to scaling up energy efficiency in industries. The research background, motivation, objective, and contributions are introduced in this section. The background, which provides an overview of the industrial electricity demand, installed coal power capacity, and the environmental impacts of a coal-dominated electricity generation sector, is presented in Section 1.1 to highlight the research significance. Section 1.2 critically reviews existing studies for two aspects (i.e. air pollution and energy efficiency) to identify the knowledge gap and emphasize the novelty of our research. Based on the background and literature review, the research contributions and objective are summarized in Section 1.3.

1.1. Background

In light of transitioning to a sustainable energy system, more efficient use of electricity in industries is an effective way to displace emissions of air pollutants and greenhouse gas (GHG) from

* Corresponding author. Copernicus Institute of Sustainable Development, Utrecht University, Princetonlaan 8a, 3584 CB, Utrecht, the Netherlands
E-mail addresses: H.Yue@uu.nl (H. Yue), E.Worrell@uu.nl (E. Worrell), W.H.J.Graus@uu.nl (W. Crijns-Graus), S_Zhang@buaa.edu.cn (S. Zhang).

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Nomenclature

Abbreviations

BAU	business-as-usual scenario
CCS	carbon capture and storage
CO_2	carbon dioxide
DSM	demand-side management
ECSC	electricity conservation supply curve
EEI	energy-efficiency improvement
EIA	U.S. Energy Information Administration
EoPC	end-of-pipe control scenario
EPA	U.S. Environmental Protection Agency
ERI	Energy Research Institute of China
GAINS	Greenhouse gas - Air pollution Interactions and Synergies model
GEM	Global Energy Monitor
GHG	greenhouse gas
IEA	International Energy Agency
IGCC	integrated gasification combined cycle
IIASA	International Institute for Applied Systems Analysis
IRP	integrated resource planning
NDRC	National Development and Reform Commission of China
NO_x	nitrogen oxides
PM	particulate matter
$PM_{2.5}$	fine particulate matter with diameters less than 2.5 μm
RAINS	Regional Air Pollution Information and Simulation model
SDGs	Sustainable Development Goals
SO_2	sulfur dioxide
UNFCCC	United Nations Framework Convention on Climate Change
WEPP	World Electric Power Plants database

Symbols

A	amount of coal consumption
ACC	annualized capital cost
AEC	abated emission concentration
AF	annuity factor
C	capacity size of power unit
CC	capital cost of energy efficiency technology
CCE	cost of conserved energy for a technology
CF	capacity factor
E	emission level
EF	emission factor
ES	annual electricity saving
FC	annual fuel consumption
FS	annual fuel saving
G	amount of electricity generation
H	lower calorific value
Mol	molar mass
OM^{fix}	annual fixed operating costs
OM^{var}	annual variable operating costs
OR	oxidation rate of coal
P_{ele}	electricity price
P_{fuel}	fuel price
TES	annual total energy saving
UAC	unit abatement cost by air pollutant
uef	unabated emission factor
β	theoretical flue gas rate
γ	carbon content of coal
η	thermal efficiency of power unit
o	capacities controlled factor
λ	air pollutant removal efficiency of control technology

Subscripts

$coal$, e	coal-fired power fleet, emission type
f, g	fuel type, air pollutant species
i, k	industrial sector, pollution control technology
n, m	existing power unit, newly-built power unit
t, y	energy efficiency technology type, year

Units

GJ	gigajoules
GW, GWh	gigawatts, gigawatt-hours
kt	kilotonnes
Mt	megatonnes
MW, MWh	megawatts, megawatt-hours
TWh	terawatt-hours

electricity production, and to limit investments in new power generation capacity (IEA, 2018a). The demand of electricity to support industrial development has surged in the world, particularly in developing economies, during the past five decades (IEA, 2018b). Fossil power plant fleets have expanded rapidly (with an annual growth rate of ~4% since 1997) to meet the surging demand, emitting vast amounts of air pollutants (~36%, ~15%, and ~6% of global anthropogenic emissions of SO_2, NO_x, and fine particulate matter ($PM_{2.5}$), respectively, in 2016) (IEA, 2018c), thereby increasing human health risks (Gao et al., 2018; Oberschelp et al., 2019). Linking the supply-side (power sector) to the demand-side (industry) is therefore particularly relevant for several Sustainable Development Goals (SDGs): good health (SDG 3), energy access (SDG 7), sustainable industry (SDG 9), climate action (SDG 13) (Nerini et al., 2018). As emphasized by the United Nations, treating the complex linkages between the industry and power sectors from a cost performance perspective is critical to coordinate energy efficiency improvement and power plants deployment in an energy system (Rashid, 2019) that also benefits to achieve energy savings, air quality improvement, and climate change mitigation simultaneously.

As a rapidly developing country, China is currently facing the dual tasks of achieving industrialization (MIIT, 2017) while mitigating the costly burden of high energy use and environmental impacts (World Bank, 2016). Industry in China consumes ~40% of global industrial electricity demand (~63% of China's total electricity demand), which is larger than the total power consumption of the European Union (IEA, 2018b). With an annual growth rate of ~10%, electricity is the strongest growing energy carrier in China's industrial energy use between 2000 and 2016, constituting ~33% of the growth in end-use energy (IEA, 2018b). Electrification policies can lead to even stronger growth in industrial electricity use in China (NDRC, 2016) and potentially exacerbate the deployment of new power capacity (Wang et al., 2019a). Moreover, inefficient industrial processes, due to outdated technology and less efficient equipment (MIIT, 2014), lead to large electrical energy losses, thereby increasing net electricity demand (ERI & NREC, 2018). At the same time, the supply of the rising electricity demand is heavily dependent on a coal-intensive power plant fleet in China (~70% of total electricity generation), which in turn increases air pollutant emissions from power plants that significantly deteriorate local air quality (Peng et al., 2018).

As shown in Fig. 1, the coal power additions in China are much higher than the decommissioned coal capacities since 2000, confounding the movement against the most polluting fossil fuel. The newly-built coal-fired plants would lock-in the energy infrastructure in a pollution-intensive pathway for at least the next 40 years, thus has detrimental implications for not only air quality but also climate change. The trend of installed coal power capacity in the world is highly similar to that in China. This indicates that China's power sector plays a pivotal role in moving the global energy system on a course towards sustainable development. China's poor air quality has posed a serious threat to public health. Annually 1.0–1.4 million people die prematurely in China as a result of exposure to high concentrations of total particulate matter (PM), while power generation is estimated to contribute to 5–39% of mortality (Cohen et al., 2017; Gao et al., 2018; Lelieveld et al., 2015; Reddington et al., 2019). Therefore, it is urgent to seek a sustainable pathway for the globally largest manufacturer and emitter, China, while at the same time managing its existing power generation fleet and curbing future additions.

1.2. Literature review

Various studies have indicated the adverse ambient air impacts of a coal-intensive power sector. Tong et al. (2018a) estimated that air pollutant emissions from fossil power plants in service as of 2010 in China emitted the most because of the big coal-fired power plant fleet. Besides air quality concerns, Cui et al. (2019) showed that the growing expansion of coal-fired power plants around the world, particularly in Developing Asia, will result in failing to reach global climate change targets. Oberschelp et al. (2019) presented an emission inventory for global coal-fired power plants in the year 2012, and assumed that shutting down 10% of the most polluting coal capacity can significantly reduce air pollution-related health impacts and avoid 16% of coal power GHG emissions. Managing electricity requirements in end-users to reduce coal generation unit deployment (e.g. driving coal units into early retirement) is an important option to co-control air quality and electricity savings, while generating additional GHG mitigation benefits and is economically competitive (Fleischman et al., 2013). This study explores the impacts of actions to improve electricity use efficiency in industries on the evolution of coal-intensive electricity systems by 2040 and the emission changes of air pollutants.

Retrofitting power plants with end-of-pipe treatment devices can also reduce air pollutant emissions from electricity generation. The emission control measures are widely applied to large-size coal-fired power units but rarely to small-size units (e.g. installed capacity below 100 MW) because the retrofits come at the expense of high capital expenditures (Li and Patiño-Echeverri, 2017). Moreover, the air pollution control systems increase the auxiliary electricity use (Yang et al., 2018) and cause an energy penalty in power plants (Graus and Worrell, 2007), thus resulting in secondary environmental impacts (Cui et al., 2018). In this study, the portfolio costs of air pollution reductions, both by installing flue gas controls in power plants and promoting efficient electricity use in industries, are modeled to identify the most cost-effective way.

As energy efficiency continues to gain attention as a key resource for economic and social development across all economies, understanding its real value is increasingly important (IEA, 2018a). This is becoming more urgent for emerging economies and developing countries as they seek to optimize their resource base to reduce poverty and support sustainable growth (Wang et al., 2019b). Previous studies, adopting aggregated exogenous parameters (e.g. production elasticity coefficient and labor index), made useful attempts to identify the potentials of energy efficiency improvement in China, with a focus on the industry. For example, Shi et al. (2010) assessed the maximum room for industrial efficiency improvements across China's regions by applying a popular top-down model, i.e. data envelopment analysis. Xiao et al. (2017) examined the electricity consumption performance by industrial subsector across all China's regions via employing input-output framework, and the results point out that chemical and metal smelting industries have great efficiency improvement potentials. Furthermore, the logarithmic mean Divisia index method (Liu et al., 2018; Ma et al., 2017) and computable general equilibrium model (Xiao et al., 2020) are widely used by energy scholars to investigate the driving factors impacting the growth of energy consumption and provide valuable insights in understanding the energy savings and emission reductions. However, most of these top-down studies

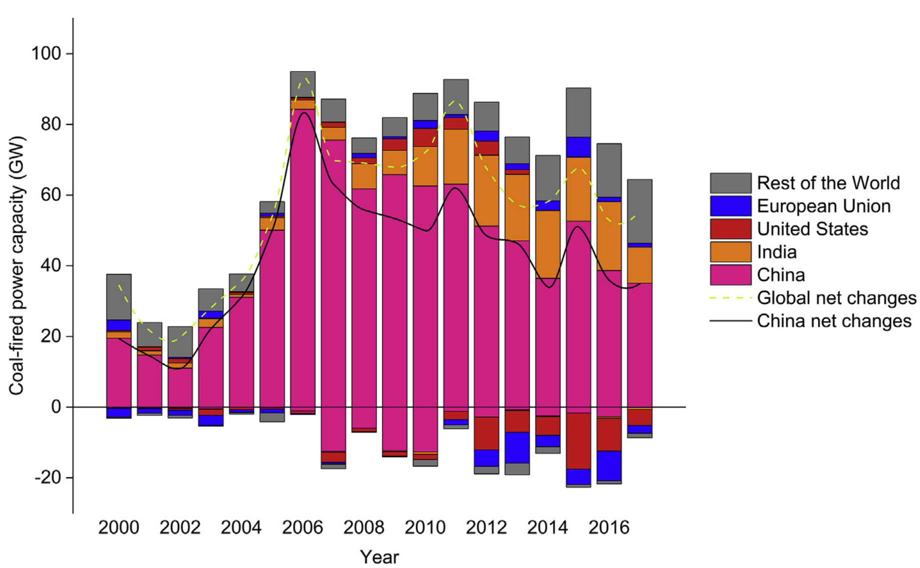

Fig. 1. The bars represent additional and retired coal-fired power capacity by country or region from 2000 to 2017. The curves represent the net changes of coal-fired capacity Globally and in China. Source: calculated from (China Electric Power Yearbook, 2018; Global Energy Monitor, 2019; S&P Global Platts, 2018).

are limited to macro-economic analyses on a country or sector level and fail to capture the available potentials of energy savings at technology level.

Actions to improve energy efficiency are frequently portrayed as the lowest-cost strategies available because the reduced energy bills can recover capital investments. A growing body of evidence shows that efficiency improvements can deliver substantial value through a broad range of economic and social impacts beyond the traditional focus on energy demand reduction (EPA, 2015). The additional impacts produced by efficiency improvements are also called co-benefits or multiple benefits (IEA, 2018a), such as enhancing the sustainability of the energy system, avoiding multiple detrimental air emissions, reducing air pollution-related health impacts, and raising living standards. These high-value benefits have attracted much attention from both researchers and policy-makers. Zhang et al. (2015, 2019) measured the air quality benefits of energy saving potentials in China's iron & steel and cement industries, and suggested that the efficient production technologies play a win-win role in fulfilling both energy and air quality regulations. Zhou et al. (2018) and Langevin et al. (2019) estimated the potential impact of efficiency improvements on CO_2 emissions in the buildings sector of China and the United States, respectively. They revealed that boosting building efficiency can significantly reduce CO_2 emissions by 2050. Talaei et al. (2019) used the long-range energy alternative planning model to evaluate the potentials of energy savings and associated GHG mitigation in Canada's cement industry. Most existing studies, using a bottom-up or integrated model, outlined a cost-effective way for mining energy saving potentials and promoting environmental goals (e.g. climate change mitigation or local air quality) for a specific sector with single element (e.g. cement (Zuberi and Patel, 2017), aluminum (Kermeli et al., 2015), and steel (Zhang et al., 2018a)). Few studies extended the scope to the sectors with complex production systems such as the chemical industry (Talaei et al., 2018; Yue et al., 2018). Nevertheless, studies to date rarely reflect on the impacts of the electricity savings of industrial users on the electricity supply sector with respect to future emission changes of air pollutants, and also neglect the potential benefits of reducing investments in new generation units. The latter has been the focus of demand-side management (DSM) and integrated resource planning (IRP) in the 1990s in regulated power markets, but has achieved limited attention since, due to deregulation of most power markets around the world. Although Reyna and Chester (2017) pointed that promoting energy efficiency to reduce residential electricity demand can potentially avoid the installation of additional power capacity, a qualitative assessment of the relationship between electricity savings and the evolution of power systems is missing.

1.3. Knowledge gap and research objective

China promoted proactively the implementation of energy efficiency measures across industrial processes (NDRC, 2019), but the synergies due to demand-side electricity savings have rarely been incorporated into the assessment of national sustainable development policies, nor in power system planning or air pollutant emissions management. A major barrier to the integration of electricity and air quality planning is the difficulty in fully quantifying the potential mutual benefits existing for both industrial consumers and electricity generators. To fill the knowledge gap, a technology-rich and multi-sectoral framework is developed to model the potential for electricity savings in China's largest industries to reduce the deployment of specific coal generation units (those that are most polluting) in order to avoid air pollutant emissions, and compare this to the alternative of flue gas control systems in terms of emission abatement and costs. In order to better understand the research object, the knowledge gap is further decomposed into four key questions, i.e. (1) how much electricity can be saved in China's energy-intensive industries; (2) how much polluting capacity can be offset by the reduced electricity demand; (3) how much air pollutant emissions can be avoided due to the displaced coal generation capacity; (4) which investment portfolio is the most cost performance option between improving industrial efficiency and retrofitting power plants with pollution control technologies, under the pre-condition of reducing the same air pollutant emissions. These questions are explored in turn in our research.

We begin with developing an industrial efficiency improvements scenario that models electricity saving potentials by implementing energy efficiency technologies in China's energy-intensive industries (including iron & steel, cement, chemical, aluminum and paper) up to 2040. In order to estimate the impact of these electricity savings on the electricity supply sector, this study compiles exhaustive unit-level information of the power plant fleet (e.g. commissioning year, fuel type used, generation efficiency, and flue gas concentrations), relying on various reliable sources. The future evolution of power supply, demand, and capacity is simulated under a reference scenario. Next, we integrate the electricity load reductions resulted by industrial efficiency improvements into future alternative pathways for the development of the power plant fleet, in order to reduce air pollutant emissions (e.g. by retiring less efficient coal-fired power plants). Finally, cost-effective portfolios are determined to tackle air pollution from electricity generation by electricity savings and end-of-pipe retrofits pathway.

The main scientific contribution of this study lies in the integration of different datasets and modeling approaches to provide a cohesive view of the role of electrical energy efficiency improvements in China's industries with electricity savings, coal phase-out, air pollution reductions, and technology costs as key policy-relevant analysis indicators. What's more, revealing the relationship would be helpful towards a high-efficiency industry and clean electricity systems, thus mitigating climate change and improving air quality. This integration is novel and potentially quite useful for replication in other regions (e.g. Australia, Germany, and India), where electricity supply heavily depends on a coal-intensive power sector. The multi-sectoral modeling framework and comprehensive databases presented in this paper provide analysis capabilities at finer levels of technology and spatial resolution than previously available (which enables more specific policy analysis), and the case studies chosen provided interesting new insights into how China's industry and power sector can synergistically transform to deliver GHG and human health benefits in an economically efficient way. This paper adds to previous studies that 1) use implicit technology representation to aggregate energy saving potentials (Lin and Xu, 2015; Lin and Zheng, 2017; Xu et al., 2012), 2) tend to focus on only one demand-side sector (Fleiter et al., 2012; Wen et al., 2014; Zhang et al., 2021), 3) develop assessment framework based on proprietary (Stehfest et al., 2014; Tong et al., 2018b) or outdated basic data (Oberschelp et al., 2019; Williams et al., 2012). To the authors' knowledge, none of the studies has modeled the technology-driven potentials of electricity savings across China's industries and its impacts on taking coal power plants off the grid network, thereby generating benefits on cleaning the air. Therefore, this paper extends the application of model-based assessment and provides a comprehensive understanding of the pivotal role of industrial efficiency improvements, which is critical for China to achieve a more sustainable industry and moving towards a coal-free electricity supply system. Quantifying the multiple benefits also promotes the penetration of high-efficiency technologies and allows investors to adopt the most cost-effective technologies.

Besides, the databases (i.e. industrial efficiency technologies and power plants) with mass information compiled in this study provides a latest and openly-available underlying data, which greatly improve the modeling data existing in previous work.

The remainder of this paper is structured as follows. Section 2 describes the approaches used to compose the modeling framework and details the scenario designs. The results of industrial electricity savings, avoided high-polluting capacity, emission reductions, and abatement costs are presented in Section 3. Section 4 analyzes the key factors affecting the research results and discusses the research limitations and directions. Meanwhile, the main conclusions of this research are drawn.

2. Methods

Different datasets and modeling approaches are integrated into an internally-consistent analysis framework that provides technology details and energy, costs, GHG emissions, and air pollution combined. Section 2.1 presents the modeling structure, which consists of four modules. The electricity saving module, which contains hundreds of energy efficiency technologies, is described in Section 2.2. Section 2.3 deduces the deployment of the power plant fleet in China during the period of 2016–2040. The emission module is proposed in Section 2.4 to calculate the unit-level emissions of air pollutants and CO_2. In Section 2.5, the GAINS model is employed to estimate the abatement costs of end-of-pipe measures. Section 2.6 details the storylines of the different emission scenarios.

2.1. Modeling framework

An integrated assessment framework integrating four modules (i.e. electricity demand in industries, the evolution of power plant fleet, the changes in air emissions from electricity generation, and economic assessment of air pollution abatement) is developed in this research to measure the pivotal role of targeting industry efficiency to strategically scale down the coal-fired power plant fleet (unit-by-unit) to curb air pollutant emissions from electricity systems. Fig. 2 presents a brief overview of the modeling structure design for this study. In this framework, we organically combine inhouse and externally hosted methods in formally-defined ways to ensure consistency in the building of scenarios for quantifying the nexus of electricity savings, emissions, and abatement costs. The implementation steps can be organized as follows.

We first develop two comprehensive databases, i.e. energy efficiency technologies and China's power stations, which contain detailed measured parameters for each efficiency technology and power generator. Secondly, the underlying data is input into the industrial demand-side and electricity supply-side modules, respectively, to conduct analysis of the technology-driven electricity savings (Section 2.2) and the unit-based evolution of coal-intensive power systems (Section 2.3). Thirdly, the air emission module is introduced to estimate the emission changes due to the closed high-polluting power plants (Section 2.4). Fourthly, the GAINS (Greenhouse gas - Air pollution Interactions and Synergies) model is employed to model the costs of air pollutant reductions due to deploying end-of-pipe treatment measures by calling the ECLIPSE V5a dataset (Section 2.5). Finally, the cost-benefits module is used to compare the abatement costs of both efficiency improvements in industries and flue gas treatments in coal power plants when avoiding the same level of air pollutant emissions.

We run the modeling framework for China for the end of 2016, the most up-to-date year available at the time of the study. The target year is 2040, which is consistent with the World Energy Outlook. The cost parameters are processed to 2017 constant prices in US$ (2017 $). Essential energy consumption data by industrial sector at national level and macro-economic parameters (e.g. fossil fuel price and capital investments per generation technology) in China are assumed, based on the Current Policies Scenario (World Energy Outlook, 2018 edition (IEA, 2018c)) developed by the International Energy Agency (IEA). Other key parameters, such as output projections by industrial products, lifespan by power plants, and thermal efficiency by generators, are provided in the Supplementary Information.

2.2. Electricity saving module

We construct an exhaustive database of energy efficiency measures for specific production processes in industries to determine bottom-up potentials for electricity savings (see Appendix A). This database covers hundreds of commercially available technologies with detailed technical characterization that reflects the current knowledge of performance in terms of energy savings and costs. The detailed parameters of each efficiency technology (e.g. electricity saving, fuel saving (if possible), capital investment, and lifetime) are obtained from published research articles, technical books and government official documents while taking into account their reliability. Based on new to be installed capacity and the retirement of some of the existing capacity, implementation rates up to 2040 are determined for each technology, assuming linear deployment (Dai et al., 2013; Yue et al., 2018). The implementation rates follow four criteria: (1) the diffusion rate of each technology should be up to 100% by 2040, except for certain technologies with limited application conditions (e.g. oxygen depolarized cathodes can only be applied to caustic soda from ionic membrane rather than diaphragm device); (2) if several technologies with similar roles (conflicting technologies) are used in a production line, the total implementation rate of these technologies should not be beyond 100% (e.g. a fully graphitized cathode and the competing TiB2/C composite cathode); (3) advanced technologies are given preference so that the diffusion rate of conflicting technologies can be lower than its initial value in 2016; (4) the implementation rate of cost-effective technologies with great energy performance is higher than that of similar technologies by 2040.

Electricity conservation supply curves (ECSCs) are built to capture the technology-driven electricity savings in the industries from both economic and engineering perspectives. The ECSC developed in this study is derived from the supply curve of conserved energy, which is first introduced by the Lawrence Berkeley National Laboratory (Meier, 1982) to assess the economic trade-off between efficiency investments and conserved energy costs (Worrell et al., 2003). As a bottom-up modeling approach, the supply curve is widely used by energy analysts to explore the cost-effective opportunities of energy conservation and emission mitigation for an energy system on different scales (e.g. a single factory, a group of plants, or an economic sector). By far, the modeling results of conservation supply curves have provided important information on designing energy efficiency and emission reduction policies for various countries or regions. Zuberi and Patel (2017) developed energy efficiency supply curves for the cement industry in Switzerland, and found that around 80% of total energy saving potentials can be accessed by implementing cost-effective efficiency technologies. They furthermore indicated that low energy price and carbon tax are the key economic barriers to boost energy efficiency. Zhang et al. (2018b) constructed city-level supply curves to assess the air quality benefits of actions to improve energy efficiency for a group of cement plants located in China's Jiangsu province, and indicated the NO_x and PM can be substantially declined due to the energy savings. Ma et al. (2016) investigated the impacts of carbon tax policy on screening cost-effective mitigation

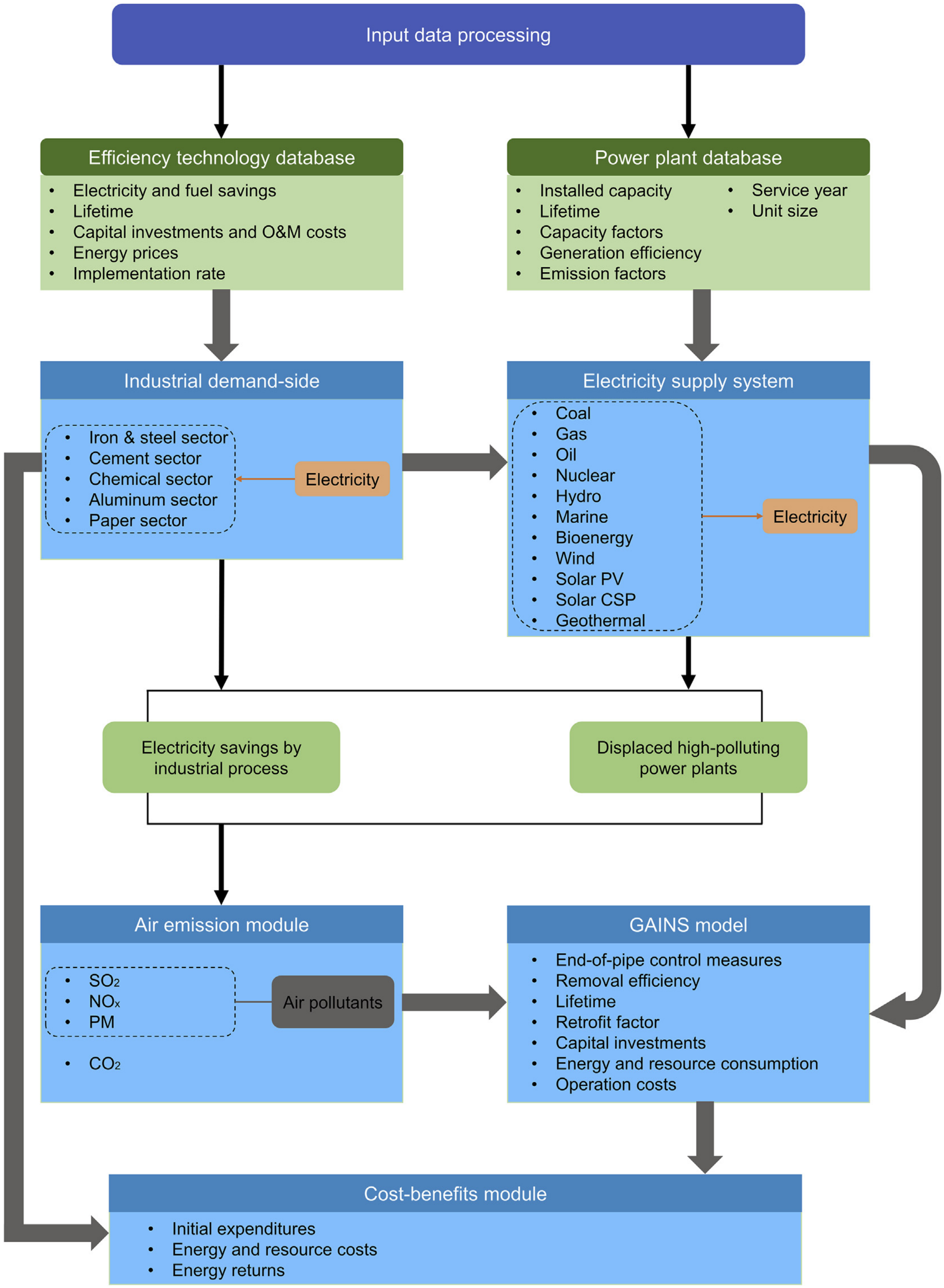

Fig. 2. Overview of the integrated assessment structure.

measures in the Chinese steel sector by incorporating carbon prices into the abatement supply curves. Morrow et al. (2014) employed the conservation supply curves to analyze the energy saving potentials for the cement and steel industry in India, respectively. Through an intensive review on the application of the supply curve model, we found that previous studies tend to focus on only one demand-side sector, particularly the cement and iron & steel sector. Little attention has been devoted to quantifying the multiple benefits of technology-driven electricity savings for multi-sectoral industrial systems.

The key step in constructing an ECSC is to calculate the cost of conserved energy per electricity saving technology, as presented in formula (1), which is deduced from the research of co-authors (Yue et al., 2018; Zhang et al., 2021). The equation is described as the total cost of conserved final energy divided by the total energy savings. Because some energy efficiency measures reduce both electricity and fossil fuels, the marginal cost of conservation includes not only the conserved electricity cost but also the reduced fossil fuel cost.

$$CCE_{t,i} = \frac{CC_{t,i}*AF_{t,i} + \Delta O\&M_{t,i} - \left(ES_{t,i}*P_{ele} + FS_{t,i}*P_{fuel}\right)}{TES_{t,i}} \;\forall\; t,i \tag{1}$$

where t and i represent the energy efficiency technology type and industrial sector, respectively; *CCE* represents the cost of conserved energy for an efficient technology in US$/GJ; *CC* represents the capital cost of the technology in US$; *AF* represents the annuity factor; *ΔO&M* is the annual change in operation and maintenance cost in US$; *ES* is the annual electricity saving for a technology in kWh; P_{ele} is the electricity price in US$/kWh; *FS* represents the annual fuel saving (GJ) in equation (1); P_{fuel} represents the fuel price in US$/GJ; and *TES* indicates the annual total energy saving of a technology in GJ.

2.3. Deployment of power plant fleet

We begin by using the World Electric Power Plants (WEPP) database (which is the September 2017 version) (S&P Global Platts, 2018) to compile unit-level information of the power generation fleet in operation in 2016, in China. The historical data of installed capacity reported by the WEPP database is also employed by the IEA to project the power generation capacity by fuel type up to 2040. Thus, the WEPP database is used as the basis for this study to ensure consistency with the data published by the IEA in the World Energy Outlook. The in total 31 types of primary energy included in the WEPP database are coded into 11 categories (e.g. coal, gas, oil, nuclear, and wind) based on the fuel definition (IEA, 2018b). We combine this with data of installed capacity per category from the World Energy Outlook (IEA, 2018c) and proceed with an appropriate adjustment to the WEPP data. The WEPP database provides information on unit size, primary feedstock, commissioning year, physical location, and generation technology. But data on energy and environmental performance (e.g. thermal efficiency and stack concentration in flue gas) are missing. We fill this data by cross-checking unit-based information provided by China Electricity Council (CEC, 2018), U.S. Environmental Protection Agency (EPA, 2018), U.S. Energy Information Administration (EIA, 2018), and Tang et al. (2019). General values of thermal efficiency and emission factor for each generation technology distinguished by capacity size are summarized in Supplementary Information.

Next, we design a retirement pathway for existing power capacity by considering both lifespan and commissioning year of individual units, following the convention of eliminating older facilities first (Ackerman and Fisher, 2013). For example, the decommissioning age of coal power generator practically peaks around 40 years considering the capacity availability, operation costs, and maintenance costs (Farfan and Breyer, 2017). Detailed information on the lifetime of power plants can be found in Supplementary Table S2. For around 20 GW (accounting for 1.5% of total installed capacity) or 618 units in the WEPP database, commissioning year information is lacking. We fill this data gap by cross-checking various reliable power plant databases (e.g. the Global Power Plant Database (Byers et al., 2019), the Global Energy Monitor (GEM, 2019), the Worldwide Industrial Information (IndustryAbout, 2019), the Clean Development Mechanism Database (UNFCCC, 2019), and the Almanac of China's Water Power). For 181 small hydropower units (in total 0.85 GW), the same assumptions on vintage year are used as Davis and Socolow (2014).

Finally, we simulate the evolution of installed capacity per category over the 2016–2040 period by coupling the decommissioned capacity from WEPP with the future capacity projections from the World Energy Outlook (IEA, 2018c). We further divide the 11 power plant categories into 25 subcategories based on both generation technology and installed capacity by unit (e.g. coal capacity is divided into four technologies and four unit size levels; Supplementary Table S1). The future installed capacity per subcategory is determined by the share of the generation technology in new capacity and the units still in existence after the decommissioning of existing units at the end of their lifetime. The newly constructed capacity is estimated by tracking newly proposed projects (power plants recorded in WEPP as planned and under construction), China's policy planning, and the Renewable Energy Outlook (ERI & NREC, 2018).

In addition, we collect the exact latitudes and longitudes information for the total of 10,159 units in China by either coupling WEPP with databases (Byers et al., 2019; Davis et al., 2015; GEM, 2019; IndustryAbout, 2019; Ummel, 2012; UNFCCC, 2019) that include geographical coordinates or using the Google Maps to infer geocoordinates on the basis of available physical address information provided by WEPP (e.g. company, street, county, city, and province information). Google Earth has been used to assist the maps to accurately determine the coordinates of individual power plants through capturing 3D satellite imagery with high resolution identifying power plant characteristics (e.g. power houses, dam, photovoltaic array, and wind turbine). This coordinated information can greatly support researchers to characterize the spatial distribution of fossil fuel and renewable power plants.

2.4. Emission levels of air pollutants and CO_2

In this study, the reduced electricity load due to efficiency improvements in industries is assumed to displace coal capacity. Removing of coal-fired units plays a pivotal role in the deep reduction of air pollutant emissions (Zhai, 2019), largely because the emission intensities for generation units fueled by coal are significantly higher than those by natural gas (Tang et al., 2019; Tong et al., 2018a). Therefore, we prioritize that the electricity saved by industries is taken from the coal generation fleet. We do this by identifying the less efficient and most polluting power stations (see Supplementary Tables S1 and S4). The emission levels of air pollutants and CO_2 for the coal-fired power generation fleet are estimated by equation (2):

$$E_{coal,e,y} = \sum_{n}^{exi}\left(EF_{n,e,y} * C_{n,y} * 8760 * CF_y\right) + \sum_{m}^{new}\left(EF_{m,e,y} * C_{m,y} * 8760 * CF_y\right) \;\forall\; e,y \tag{2}$$

where *coal*, *e*, and *y* indicate the coal-fired power fleet, emission type (that is, SO_2, NO_x, PM, and CO_2), and year, respectively; and E represents the emission level in kg. Indices n and m indicate the existing and newly-built coal power unit, respectively; *EF* represents the emission factor in kg/MWh; C is the capacity size in MW; the number 8760 is the full-load hours per year; and *CF* represents the capacity factor in %.

The emission factors of SO_2, NO_x, and PM at unit-level are estimated using equation (3) on the basis of operation and emission parameters (e.g. stack gas concentration, control devices, and removal efficiency). In total data from 2500 units is obtained from China Electricity Council (unit size ranging from 100 to 1050 MW) and from Tang et al. (2019) (unit size < 100 MW), matching ~65% of the existing coal capacity in service as of 2016 in the WEPP database.

$$EF_{g,y} = \frac{AEC_{g,y} * \beta_y * A_y}{G_y} \ \forall \ g, y \tag{3}$$

where g represents the air pollutant species (i.e. SO_2, NO_x, and PM); *AEC* represents the abated emission concentration from power station stacks in g/Nm^3; β is the theoretical flue gas rate (Chinese Research Academy of Environmental Sciences, 2010) in Nm^3/tonne-coal; *A* is the amount of coal consumption in tonnes; and *G* is the amount of electricity generation in kWh. The emission factors for specific generation technologies at unit-level (Karplus et al., 2018) are deduced based on the individual units, and the results are cross-checked with practical experience of coal power plants from the Energy Technology Systems Analysis Program (IEA-ETSAP). Furthermore, we use these unit-based emission factors to fill the missing data in the remaining 35% capacity.

The CO_2 emission factors at unit-level are estimated based on coal generation efficiency and carbon content as follows (Graus and Worrell, 2011).

$$EF_{CO_2,y} = \frac{\gamma * OR * H * Mol_{CO_2} / Mol_c}{\eta_y} \tag{4}$$

where γ represents the carbon content of coal in g/MJ; *OR* is the oxidation rate of coal in %; *H* is the lower calorific value for electricity in MJ/kWh; Mol_{CO_2} is the molar mass of CO_2 (44.01 g/mol); Mol_c is the molar mass of carbon (12.01 g/mol); and η is the thermal efficiency of power unit in % (see Supplementary Information).

2.5. Investment budgets for achieving air pollutants reductions

Investments in efficiency improvements for the industrial sectors (iron & steel, cement, chemical, aluminum, and paper) are calculated based on individual efficiency technologies. The cost parameters for the specific technologies are shown in Appendix A. Unlike the efficiency measures, flue gas control devices do not bring additional benefits of reducing energy bills, but consume electricity and resources, emit solid waste and thereby increase the operation costs (Abel et al., 2019). Based on the ECLIPSE V5a database that includes 3500 measures for reducing air pollutants (IIASA, 2015), the GAINS-China module is employed to measure the unit cost per tonne air pollutant removed by end-of-pipe measures from China's coal power plants.

The GAINS-China module, incorporating the specific characteristics of China, is a regional part of the GAINS model which was launched by the IIASA (International Institute for Applied Systems Analysis) as an extension to the RAINS (Regional Air Pollution Information and Simulation) model (Kanada et al., 2013). The GAINS model integrates cross-subject information into an internally-consistent analysis framework to provide the assessment of alternative strategies that reduce air emissions (including six air pollutants and six GHGs) at least costs, and minimize emission-related effects on air quality, human health, climate change, and acid deposition (IIASA, 2018). Users can set emission abatement scenarios in the GAINS model by introducing exogenous indicators or assumptions (e.g. economic activity, power generation, and energy consumption) (Purohit et al., 2019; Qin et al., 2017) to examine the costs of abatement measure portfolios on addressing detrimental air emissions. The GAINS model characterizing by the together data and flexibility plays an important role in estimating emission reduction potentials (Liu et al., 2013), health impacts (Tian et al., 2018), and emission control costs (Amann et al., 2011) on various scales (e.g. global, national, and regional levels). This model has been employed by the European Union to conduct scenario-based analysis on the emission reduction potentials for the Member States, thus provided guidelines on formulating policy for combating air pollution and climate change for (European Commission, 2019). The IEA also used the integrated analytical tool to analyze the air quality across the world by projecting the air pollutant emissions by 2040, which are presented in the World Energy Outlook (IEA, 2018c).

The GAINS model estimates the unit abatement costs for each of the air pollutants following equation (5). Details on the technology-based methodology in the GAINS model are described in the studies (Cofala and Syri, 1998a, 1998b; Klimont et al., 2002).

$$UAC_{k,f,g} = \left(\frac{ACC_{k,f,g} + OM^{fix}_{k,f,g}}{FC_f} + OM^{var}_{k,f,g} \right) \Big/ \left(uef_{f,g} * \lambda_{k,f,g} * o_{k,f,g} \right) \quad \forall \ k, f, g \tag{5}$$

where k and f represent the pollution control technology and fuel type, respectively; *UAC* is the unit abatement cost by air pollutant in US$/tonne; *ACC* is the annualized capital cost in US$; OM^{fix} is the annual fixed operating costs in US$; OM^{var} is the variable operating costs in US$/PJ; *FC* is the annual fuel consumption in PJ; o is the capacities controlled factor in %; λ is the air pollutant removal efficiency of control technology in %; and *uef* is the unabated emission factor of air pollutant in tonne/PJ.

2.6. Emission scenarios

This study establishes four emission scenarios, which are described in the following paragraphs, to explore the interconnections of a high-efficiency industry and electricity supply system to realize the synergies of addressing air pollution cost effectiveness.

Based on currently implemented policies and standards, a business-as-usual (BAU) scenario is introduced as a reference case. The key parameters and projections in the BAU scenario, such as installed capacity, electricity generation, and socio-economic assumptions, are consistent with the Current Policies Scenario developed by the IEA. This scenario provides a benchmark against which the impact of alternative scenarios can be measured. The energy-efficiency improvement (EEI) scenario services as an alternative representing the implementation of efficiency technologies (e.g. direct current arc furnaces, zero electrode-distance membrane electrolyzer, and anodic steel claw of aluminum-steel composite structure) in China's industries to achieve more efficient use of electricity towards the world best practice levels. The electricity saving potentials are measured in the EEI scenario via plausibly implementing 175 specific technologies in five energy-intensive industries (i.e. iron & steel, cement, chemical, aluminum, and paper industrial sectors). Meanwhile, the multiple benefits of the reduced electricity demand on displacing the high emissions, low efficiency power plants to reduce air pollutant emissions from electricity generation are analyzed in this alternative.

The end-of-pipe control (EoPC) scenario is developed in the GAINS model to explore the costs of installing air pollution abatement measures in coal-fired power fleet to achieve the same emission reductions as in the EEI scenario. The EoPC scenario builds on the BAU scenario, but additionally incorporates the flue gas control strategies which are derived from the ECLIPSE V5a database (see Section 2.5). Different from the demand-side improvements, the EoPC scenario represents the transformation on electricity supply-side and is used to measure the most cost-effective strategy by comparing the investments and benefits between retrofitting power plants with pollution control systems and managing electricity use in industries (EEI scenario). Finally, a joint scenario

(EEI + EoPC), including both efficiency improvements in industries and pollution control retrofits in coal power plants, is constructed. The joint scenario is optional and provides an understanding of the joint impacts on the emission changes of air pollutants from electricity generation processes. The joint scenario starts from the EoPC-based air pollution control strategies, but incorporates the same assumptions as the EEI scenario in terms of the reduced electricity demand in China's industries by 2040. Based on the storyline definition, the investments of the joint scenario are equal to the total expenditure of the EEI and EoPC scenarios. Detailed analysis on the joint scenario can be found in Supplementary Discussion.

3. Results

Four key subtargets are proposed to address the knowledge gap on assessing the multiple benefits of industrial demand-side measures on scaling down the coal-based power plant fleet with the purpose of air quality improvement. In this section, the modeling results are organized in three subchapters in turn to answer the four key questions. The electricity saving potentials by sector are presented in Section 3.1 to answer the first question "how much electricity can be saved in China's energy-intensive industries". Section 3.2 answers questions 2 and 3 by drawing the impacts of the reduced electricity load on offsetting the most polluting power capacity and associated changes of air pollutant emissions from electricity generation. Finally, the comparison results of different pollution abatement strategies in terms of costs to achieve the same impact are provided in Section 3.3.

3.1. Electricity saving potentials in China's industries

We estimate potential reductions in electricity demand (compared to the BAU scenario) of numerous commercially available energy efficiency technologies for five key electricity-intensive industries during the period of 2016–2040. Fig. 3 shows the results for the specific savings per industrial subsectors by year.

Total electricity demand for the included sectors is driven by increasing requirements of raw materials (e.g. nitrogenous fertilizer, aluminum, and polyvinyl chloride) for downstream sectors (such as agriculture, construction, and packaging sectors). Without efficiency improvements a substantial growth of 40% is observed in the 2016–2040 period (see Fig. 3). In contrast, aggressive promotion of high-efficiency measures keeps the electricity use growth negligible and markedly reduces electricity demand compared to BAU levels by 185 TWh in 2025 and 506 TWh in 2040 (equal to 24% of electricity use in the BAU scenario). This indicates that significant room remains to save electricity in China's industry, in addition to savings already realized since 2000 (IEA, 2018a). The reason for these potentials might be that efficient technologies implemented to date are primarily aimed at reducing direct fossil fuel use, but ignored electricity so far.

From the industrial subsectors, the iron & steel sector has the potential to reduce the total electricity consumption by 9.3% in 2040, which contributes to the largest share of the reduction (197 TWh). The aluminum and chemical sectors are expected to avoid 229 TWh of electricity demand by 2040, which is equivalent to 10.8% of the annual electricity consumption, followed by the cement sector that contributes 53 TWh of electricity savings. Lastly, the paper industry provides the smallest contribution, which potentially reduces the annual electricity demand by 1.3% (equaling 27 TWh of the reduction). These correspond to great improvements of 47%, 13%, 19%, 38%, and 27% in electric efficiency, respectively, compared to the BAU scenario. Progress on sectoral efficiency improvements drives the electricity use per unit production in China towards the world best practice level (Worrell et al., 2007). For instance, the electricity use per tonne crude steel in the EEI scenario, following an average annual decline of 2.6%, effectively decreases electricity use to 344 kWh/tonne in 2040, while the best level in the world (Worrell et al., 2007) is 227 kWh/tonne. An

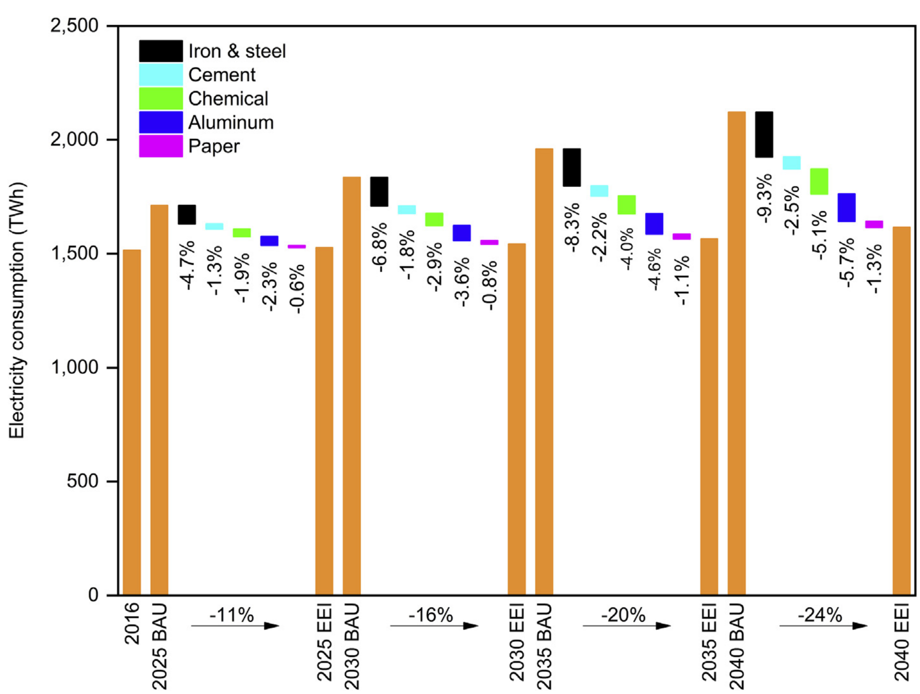

Fig. 3. Total electricity consumption levels and electricity savings for key industries with energy efficiency improvements for the 2016–2040 period. The orange bars indicate the estimated annual electricity use under the BAU and EEI scenarios. The floated bars represent the electricity savings of the studied industrial sectors. Note: Section 2.2 describes the data collection and Appendix A provides the details of data sources.

important finding is that cost-effective opportunities represent more than 98% of the identified potentials in iron & steel, 87% in cement, 85% in chemicals, 96% in aluminum, and 84% in paper (i.e. the annualized costs of these measures are lower than or equal to the annual benefits of the realized electricity savings; see Fig. 4). This clearly suggests that, economically, investing in equipment upgrades, with its high share of cost-effective technologies, would be preferable to increasing electricity generation and expanding power supply and transport infrastructure with high investment costs to meet the surging demand.

We decompose the annual reductions of electricity demand by production process for each sector, and critically compare the contribution of individual processes to highlight specific opportunities. As shown in Supplementary Fig. S2, the highest reduction potential in the iron & steel industry is found in the process of casting, rolling, and finishing (representing 52% of the annual reductions from the steel sector). An important measure is the replacement of traditional casting in service for finishing mills with thin slab casting (see Supplementary Fig. S2). Similarly, a substantial reduction of 106 TWh in 2040 (greater than UK's total industrial electricity use in 2016) is found in the process of aluminum electrolysis, which is close to the potential savings in the chemical industry. Retrofitting or replacing outdated cell technology (e.g. with low-temperature and low-voltage cells) is the key to unleash the electricity saving potentials. Considering the process characteristics, the results reveal a rapid and deep improvement option to access significant reductions in the short run through supporting efforts to boost energy efficiency in the key areas within a sector, while a large part of the investments is highly cost effective (see Appendix B).

3.2. High-value benefits of industrial efficiency improvements on polluting units phase-out and air pollutant abatement

In the BAU scenario, coal-fired power plants continue to dominate the fleet in 2040 (accounting for 38% and 51% of the total installed capacity and electricity generation, respectively), even though 911 coal units (in total 162 GW) will be decommissioned after an average lifespan of 40 years. The capacity of coal-fired power plants that came online before 2016 is still 784 GW in 2040, and the capacity of newly constructed coal power plants is 447 GW. Subcritical units, which operate under comparatively low pressures and temperatures, have a lower energy efficiency than supercritical units. This is especially the case for small units below 100 MW. Furthermore, these have typically less air pollution controls implemented and combined with the lower efficiencies have significantly higher specific air pollutant emissions (Tang et al., 2019; Tong et al., 2018a). We find that subcritical power plants are still an important part of the coal capacity in 2040 (31%), of which small units account for 3%. These small units tend to be even less efficient and heavily polluting, and it is often unprofitable for them to comply with environmental regulations. Therefore, these small units are interesting candidates for early retirement, thereby maximizing emission reductions.

As shown in Fig. 5, the reduced electricity demand in industries by 2040 can deactivate a total capacity of 103 GW coal, which enables the ambitious national plan aimed at a sustainable power fleet to go on wheels (i.e. annually cutting ~2 GW less efficient coal capacity) (NDRC et al., 2014). This drives all the commissioned small subcritical units (<100 MW), amounting to 11 GW (which far exceeds the total capacity (5 GW) of super-polluting units in China identified by Tong et al. (2018b)), into early retirement (lifetime <average operational lifetime of 40 years). Besides the

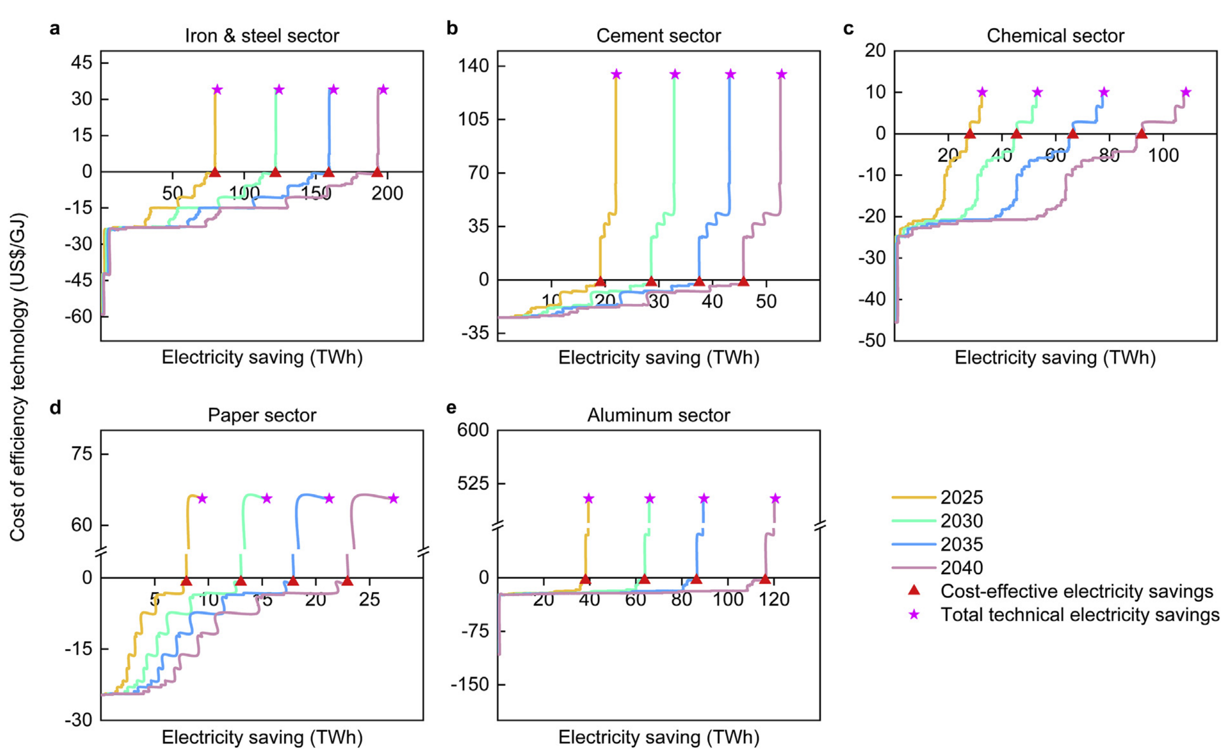

Fig. 4. Costs of high-efficiency technologies implemented in the energy-intensive industries and specific electricity savings at technology level. Panels a–e represent the iron & steel, cement, chemicals, paper, and aluminum sector, respectively. The bright colored curves represent the annual electricity savings cumulated by individual technologies. The red triangle is the demarcation point, which indicates the electricity savings generated by cost-effective technologies (those have negative or zero cost of conserved energy). The magenta five-pointed star represents the total electricity savings. Note: Section 2.2 describes the data collection and Appendix A provides the details of data sources.

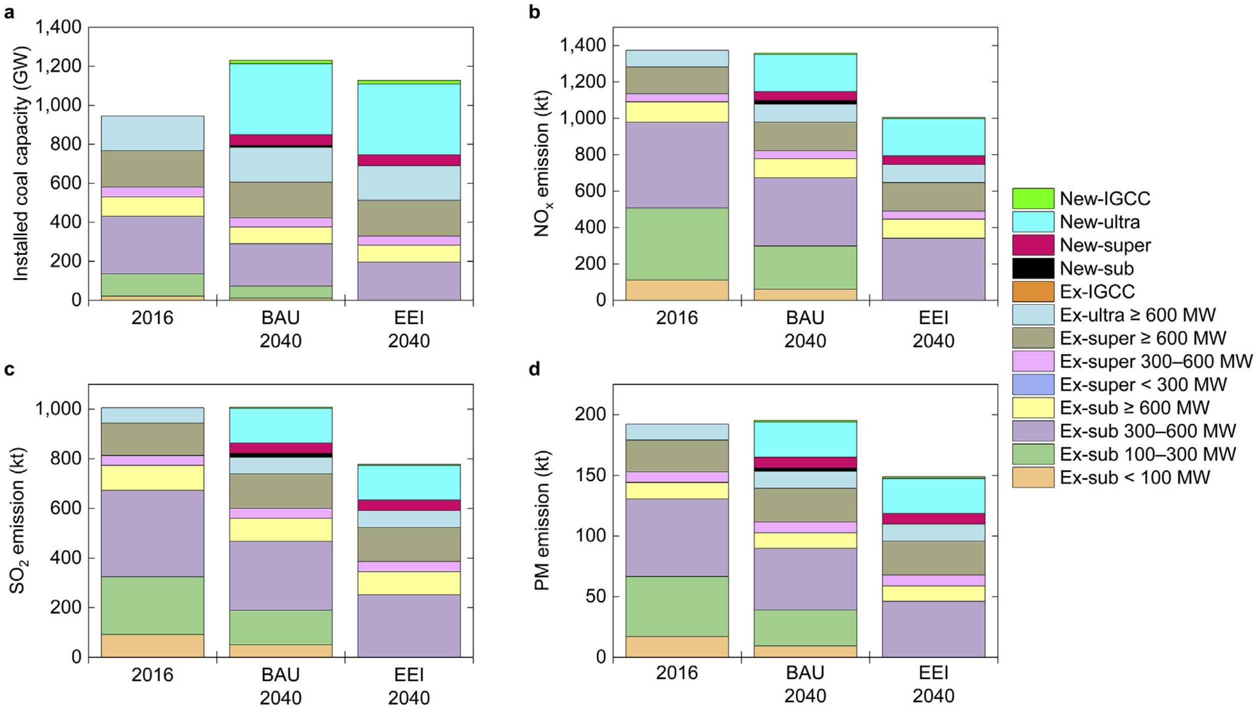

Fig. 5. Evolution of coal-fired power fleet and emission levels of air pollutants between 2016 and 2040 under different scenarios. Panel a shows the installed capacity by coal generation technology at unit-level. Panels b–d represent the unit-based emission levels of SO_2, NO_x, and PM by generation technology, respectively. In all panels, we use the light colours to mark existing coal units (ex-sub/super/ultra/IGCC) and bright colours to map newly proposed units (new-sub/super/ultra/IGCC). Abbreviation: ex, existing; sub, subcritical; super, supercritical; and ultra, ultra-supercritical. Note: Section 2.3 describes the data processing and Supplementary Information provides the details of data sources.

small units, we consider subcritical coal power units in the size range of 100–300 MW (63 GW in 2040) to be a priority in displacement, because of the poor environmental performance compared to the larger plants (unit $\geq$ 600 MW; see Appendix C). These two categories (subcritical units below 100 MW and between 100 and 300 MW) are typically the most polluting units (contributing 18.8%, 22.0%, and 20.0% of SO_2, NO_x, and PM emissions, respectively), but disproportionately account for a small share of capacity (representing 5.8% of total coal power capacity in 2040). Finally, the reduced electricity load can additionally curb all new to be constructed subcritical power plants (10 GW), and allow early retiring part of larger size (range of 300–600 MW) subcritical units (19 GW).

By eliminating these four categories of coal-fired power plants, we estimate that in total 230, 353, and 46 kt of SO_2, NO_x, and PM emissions can be abated by 2040, respectively (see Fig. 5). This contributes to 22.8%, 26.0%, and 23.8% emission reductions relative to BAU levels. When comparing 2040 to 2016, the contributions effectively diminish the emission levels by 22.7%, 26.9%, and 22.6% for SO_2, NO_x, and PM, respectively, in the EEI scenario. The reductions in air pollutants can conform with the tough emissions standards (ultra-low emissions requirements) that aim for cleaning the air in China (MEE et al., 2015; Tang et al., 2019). This clearly demonstrates that as more efficient technologies are promoted for electricity consumers, substantial improvements in air quality can be made. Critical here is that shutting down the most polluting units is prioritized.

3.3. Cost comparison of air pollution abatement portfolios

Here, we compare the costs of various portfolios to tackle air pollutants by industrial efficiency improvements and pollution control retrofits in coal power plants. Fig. 6 plots the net abatement costs of the different scenarios and the avoided new proposed investments of power capacity in the EEI scenario. Although promoting efficiency technologies in China's industries requires a much higher initial investment (total US$ 134 billion), the economic benefits, due to the cumulative energy savings and avoided new coal-fired power plants, significantly offset the capital costs with US$ 717 and US$ 6 billion by 2040, respectively (see Appendix B). These benefits are equivalent to 34% of the capital expenditures on all new proposed power projects by 2040 (see Fig. 6). Our results indicate that almost all investments in improving electricity use efficiency will have paid back before 2040. Conversely, when the same level of emission reduction is achieved by installing end-of-pipe treatment measures in the coal power fleet, it increases capital investments by US$ 3.8 billion by 2040 in comparison to the BAU scenario. Moreover, running the controls in the coal plants is more expensive (due to additional electricity consumption, sorbents, catalyst, and waste disposal), thus increasing additional economic burdens by US$ 4.0 billion by 2040. The economic results indicate that additional investments in installing flue gas controls, particularly for less efficient coal units, may generally be unnecessary and less cost-effective in comparison to demand-side efficiency improvements. Through a combined portfolio analysis, we further note that harmonizing the gains of efficiency improvements and the deployment of flue gas controls into a unified strategy would potentially achieve cost-effective deep emissions reductions (see Supplementary Discussion).

4. Discussion and conclusions

A scenario-based analysis approach is adopted in this study to arrive at the research outputs. This approach nowadays plays a key role in informing decision-makers about future trends in the energy system. However, different scenario storylines could impact

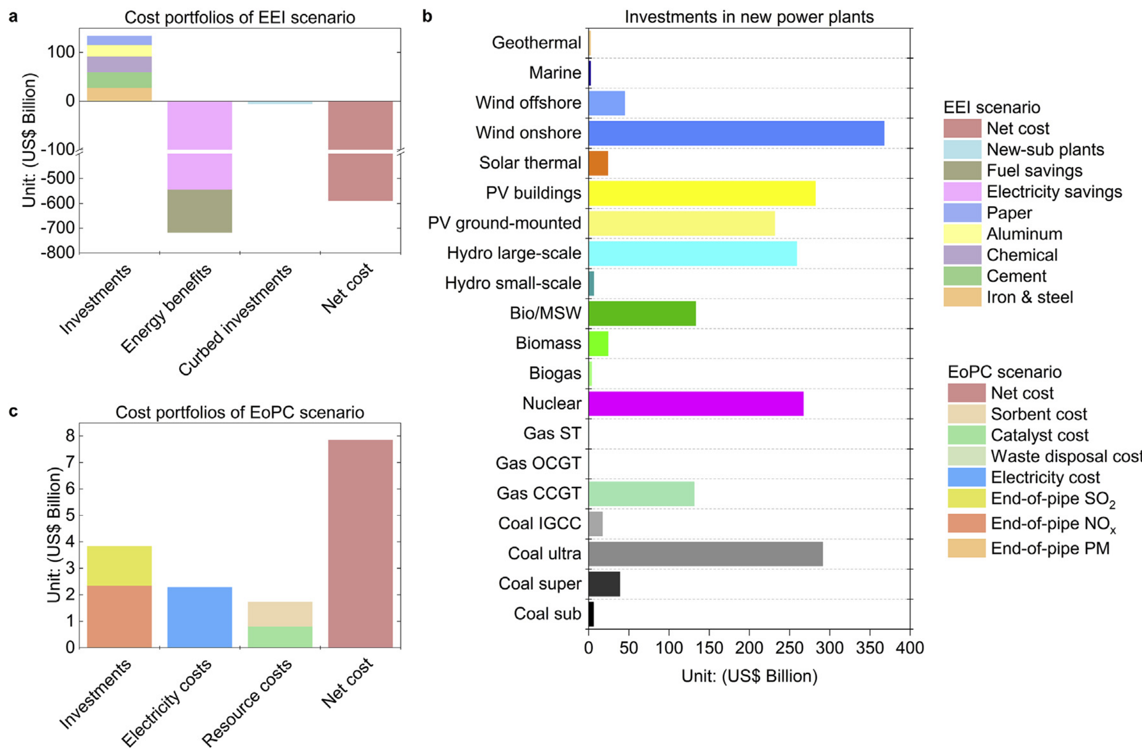

Fig. 6. Cost portfolios for tackling air pollutants from electricity generation by efficiency improvements (EEI scenario) and by end-of-pipe retrofits (EoPC scenario), and investments in newly proposed power plants in the BAU scenario up to 2040. a, Investments and benefits of energy efficiency measures. b, Capital budgets of newly constructed power plants by generation technology. c, Investments and operation costs (energy and resource bills) of air pollution control devices. Abbreviation: CCGT, combined cycle gas turbine; OCGT, open cycle gas turbine; ST, steam turbine; MSW, municipal solid waste; and PV, photovoltaic. Note: Section 2.3 describes the data processing and Supplementary Information provides the details of data sources.

the modeling results. Therefore, three sensitivity factors (including the industry-wide electricity saving potentials (Section 4.1.1), CO_2 emission changes (Section 4.1.2), and cancelation of newly proposed coal projects (Section 4.1.3)) are included in the uncertainty analysis. Subsequently, research limitations and directions are discussed in Section 4.1.4. Additional analysis is provided in the Supplementary Discussion to reveal the impacts of a joint scenario that combines demand-side efficiency improvements with pollution control retrofits. Section 4.2 concludes this paper.

4.1. Discussion

Our results show the potential for electricity savings in included industrial sectors and the impact of eliminating through these savings the most polluting power plants in the power generation fleet, including a financial assessment. We have validated the model outputs by comparing them to national statistics. Our modeled total electricity output from coal generation fleet in year 2016 is 4163 TWh, which is in line with the statistics of the World Energy Balances (IEA, 2018b), which indicates 4267 TWh. The small difference is due to the exclusions of some small power plants in our study. These excluded power plants lack key information, such as installed capacity, generation technology, and fuel type, which cannot be filled by cross-checking other open databases. The impact on results due to this exclusion is expected to be small, since it amounts to only 2% of total power generation. The future development of capacity is based on and in line with the data in the World Energy Oberschelp et al., 2019 edition (IEA, 2018c). This is widely accepted source for future developments in the energy sector.

4.1.1. Electricity savings from other industrial sectors

In the analysis, we looked specifically at savings in energy-intensive industrial sectors, together covering 46% of total electricity use in industries. However, we do not have such detailed technology profiles for the other industries that consume the remaining 54% due to the limited data availability and diverse industry structures (e.g. the manufacturing of textile consists of a large number of products per process and varying by plant (Hasanbeigi, 2010)). If we assume that the share of electricity savings in total consumption for the other industries is similar to the five studied industries (24% in 2040), this would lead to 600 TWh additional electricity savings in 2040. The total reduced electricity demand would then be able to avoid 226 GW (+123 GW) coal power capacity in China by 2040. This means that more coal-fired units characterized by high air pollutant emissions can be phased out at an accelerated pace by 2040. The reduced capacity could consist of early retirements of nearly 60% (+33%) of the subcritical generating capacity in operation in 2040, that was built before 2016. This additional coal phase-out would bring an additional 16%, 16%, and 15% of SO_2, NO_x, and PM reductions in 2040, respectively, compared to the BAU scenario. These results further highlight the importance of targeting efficiency improvements in demand-side as a strategy to address air quality concerns. Meanwhile, specific information and research on the other industries can provide a more comprehensive evaluation of the co-benefits based on detailed technological data.

4.1.2. CO_2 emission reductions

In addition to reducing air pollutants, the eliminated coal units can effectively mitigate climate change through reducing GHG emissions (Shindell and Smith, 2019; Zhai, 2019). China's CO_2

emissions from power generation are expected to increase substantially by 2040, as new projects with large-size (e.g. 1000 MW ultra-supercritical units) come online. The EEI scenario can deliver a total CO_2 emissions reduction of 275 and 462 Mt by 2030 and 2040, respectively, achieving 6.3% and 9.5% reductions relative to BAU emission levels, caused by coal-burning electricity. The emissions reduction shares are smaller than the reduction of air pollutants (e.g. 26.0% reductions of NO_x in 2040), because the eliminated power plants have a low level of implementation of air pollution controls, in comparison to the overall fleet. For CO_2 emissions though the share of reduction follows the reduction in coal-fired power generation in an approximate linear correlation. In this study, the implementation of carbon capture and storage (CCS) in coal-fired power plants is not considered. Coal plants retrofitted with CCS suffer about 20% parasitic loss of efficiency (Supekar and Skerlos, 2015), potentially indirectly increasing the emission intensity of air pollutants. Moreover, the retrofitting costs of CCS systems in China's existing coal fleet are likely to be expensive for power managers without any cost incentives (Fan et al., 2018), hindering the promotion of CCS in mid-term (ERI & NREC, 2018). Instead of installing CCS, China is aggressively promoting the deployment of renewable energy sources with policy incentives, aiming to increase installed renewable power capacity to 675 GW by 2020, to defend the environmental degradation (climate change, air pollution, and ecosystem damage). However, integrating high levels of intermittent renewable power (Rashid et al., 2020) will require increased demand-side flexibility to guarantee electricity grid stability, suggesting that the industrial sector, which is responsible for ~63% of China's electricity use (IEA, 2018b), has a critical role in enabling the expansion of the renewables fleet.

4.1.3. Prioritizing cancelation of new power plants

A total of nearly 450 GW of new coal capacity is expected to come online by 2040 to meet increased electricity requirements due to the fast penetration of electrification. The deployed coal-fired power plants can operate for several decades (~40 years in China), thereby have the potential to release emissions into the air throughout the century, with implications for local air quality. In this study, we present a scenario that includes early retirement. However, we can also assume that only new coal projects are avoided by the electricity savings (a total of 63 and 103 GW by 2030 and 2040, respectively). In that case, the estimated air pollution reductions would amount to 72, 90, and 15 kt of SO_2, NO_x, and PM in 2040, respectively, reducing emissions by 7.2%, 6.7%, and 7.5% compared to BAU levels. We find that the contributions of curbing new coal projects to reduce air pollutants are substantially less than prioritizing existing small and poor performing coal retirements (see Table 1). This is particularly the case because high efficiency generating technologies with low emission intensities are widely adopted in the newly proposed coal projects, of which ultra-supercritical and IGCC technologies together account for 85% of total new coal capacity in 2040 (see Appendix C).

4.1.4. Research limitations and directions

This study fully characterizes the multiple benefits of electricity savings on air emission reductions (SO_2, NO_x, PM, and CO_2) by connecting the Chinese industry and the power sector. Nevertheless, it fails to capture other derived benefits (e.g. air quality-related health benefits) and to consider the trade-offs between multiple environmental objectives. Quantifying the avoided premature deaths due to the reduced air pollutant concentration can provide a strong motivation for promoting the progress of energy efficiency. Scaling up demand-side energy efficiency to reduce the trade-offs between air quality, CO_2, and water is critical for planning electricity supply systems, such as deploying new power generation capacity. Additional work is needed to further understand the synergies and trade-offs, thus providing powerful evidence for design-makers to integrate energy efficiency into the policies of air quality or low-carbon electricity system design.

Despite the inclusion of five energy-intensive industries in this study, other end-use sectors with considerable electricity consumption, such as textile, building industries, as well as residential and commercial sectors, are not included. This is partly because of unavailable data (e.g. specific technology and unmeasured production) and unclear boundaries for these economic activities. Studies suggest that huge potentials for electricity savings would exist in these electricity consuming sectors. Challenges remain present to assess and understand the electricity saving potentials across multiple sectors in a whole country or region. The unidentified demand-side electricity savings would result in an underestimation of coal-fired power capacity phase-out in the current studies, thereby failing to understand the full potential to reduce emissions. Thus, further research is suggested to also study and include those electricity consumers in the analysis, and, furthermore, improve data quality and transparency for these sectors.

Although this research presents a cost-effective emission reduction pathway, most of its attention is focused on demand-side electricity savings. Accelerating electrification in demand-side and promoting renewable energy penetration in electricity supply systems are two recent strategies that are considered to deeply reduce global air emissions. Incorporated energy efficiency with renewables and electrification strategies would more effectively improve air quality and peak GHG emissions within the expected time or in the short term. Further research on the assessment of the impacts of these strategies is required to provide a more comprehensive understanding of the connections in terms of low-carbon measures, efficiency improvements, and air emissions.

The regional heterogeneity across a country needs to be investigated. Our study provides an understanding of the multiple benefits concentrating on a national level, but fails to characterize the energy systems on a regional level. It is more complicated to incorporate provincial characteristics into an internally-consistent

Table 1
Comparison of air quality impacts for different coal displacement options in the EEI scenario.

	Initial option (with early retirement)	Alternative option (without early retirement)
Avoided capacity (GW)		
Early retirement	93	0
New-built subcritical	10	10
New-built supercritical	0	55
New-built ultra-supercritical	0	38
Annually air pollutant reductions (kt)		
SO_2	230	72
NO_x	353	90
PM	46	15

analysis framework. The multi-regional perspective allows allocating the national climate or air quality targets to the regional level. This will help local governments formulate energy saving and emission reduction measures that suit their conditions. Thus, a multi-sectoral and multi-regional modeling framework is highly recommended in further research to provide greater technology and explore the spatial patterns of high-efficiency energy systems with low emissions of air pollutants and GHGs.

4.2. Conclusions

In this study, a technology-rich integrated framework is designed to capture the potentials of coal power capacity phase-out due to industrial electricity savings and quantify emission reductions at power plant unit-level in China. The costs between different abatement strategies are analyzed to identify a cost-effective air cleaning way. The main research outputs are concluded as follows.

Energy efficiency technologies can effectively curb the ever-increasing electricity demand in China's industry during the period of 2016–2040. The iron & steel, aluminum, and chemical sectors have the largest potential to improve electricity use efficiency, which together provides 84% of annual electricity savings in 2040. The remaining 16% of electricity savings can be accessed in the cement and paper sectors. A decomposition analysis by the production process shows the largest potentials per process and sector, thereby providing guidance for policy-makers to determine priority sectors in short-term. Considering the energy savings of energy efficiency measures, electricity conservation supply curves reveal that more than 90% of electricity savings can be achieved by cost-effective opportunities.

The reduced electricity load by industrial demand-side savings can displace a total of 103 GW coal generation capacity. In this study, the high-polluting generation units are identified, i.e. subcritical unit size below 300 MW, to be offset as a priority. As a result, all the high-polluting units together with part of the larger size (range of 300–600 MW) subcritical units (total 93 GW) can be shut down early. Meanwhile, all newly proposed subcritical power plants, around 10 GW, can be canceled. The displaced coal power units bring a significant decrease of air pollutant emissions from the electricity generation sector. Compared to 2016, the emission levels of SO_2, NO_x, and PM are reduced by 228, 369, and 43 kt in 2040 under energy-efficiency improvement scenario, respectively.

The costs of industrial efficiency improvements and retrofitting power plants with end-of-pipe treatment measures to tackle air pollutants are also assessed. The result shows that the initial investments in energy efficiency technologies are much higher than those of end-of-pipe measures. However, installing the end-of-pipe measures will induce additional bills on electricity and resource consumption. In contrast, the energy benefits generated by the efficiency improvements allow the initial investments to be recovered. Measures for saving electricity in industry are often cost-effective. However, getting measures implemented has proven to be a challenge. Effective policies that have been implemented in the past to achieve industrial energy savings include voluntary agreements, standards and fiscal incentives (Price et al., 2005).

This study suggests that integrating industrial efficiency improvements to accelerate existing high-polluting coal retirements along with appropriately curbing new coal deployment (particularly, subcritical units) across a country can optimize parallel initiatives to deploy renewable energy, GHG emission reduction, and tackle air pollution and human health concerns. The newly proposed framework in this paper can be applied to different efficiency improvement strategies by demand-side sector and various spatial scales (e.g. global, national, and regional levels), particularly the high-polluting countries dominated by coal-intensive electricity (such as Mongolia, India, Poland, and South Korea).

CRediT authorship contribution statement

Hui Yue: performed the model links between four modules (industrial demand, electricity supply, air emission, and GAINS), cross-checked the power plants data at unit-level and developed the energy efficiency technology dataset, contributed to the scenario analysis, Writing – original draft. **Ernst Worrell:** designed and performed the study, cross-checked the power plants data at unit-level and developed the energy efficiency technology dataset, contributed to the scenario analysis, Writing – original draft. **Wina Crijns-Graus:** designed and performed the study, cross-checked the power plants data at unit-level and developed the energy efficiency technology dataset, contributed to the scenario analysis, Writing – original draft. **Shaohui Zhang:** designed and performed the study, contributed the original power plants data and the scenario construction in GAINS model.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2021.126978.

Appendix B. Electricity saving potentials and associated capital expenditure for each industrial process

The annual electricity savings and required investments for individual production processes between 2030 and 2040 are shown in Table B.1.

Table B.1
Electricity savings and capital expenditure per industrial process.

Industrial sector	Production process	Number of available measures	Annual electricity savings (GWh)		Cumulative investment costs (Million $">$)	
			2030	2040	2030	2040
Iron & steel	Coke making	2	5580	8575	1784	2798
	Sintering	4	24153	38967	1509	2417
	Iron making - blast furnace	3	11673	15462	2641	4071

Table B.1 (*continued*)

Industrial sector	Production process	Number of available measures	Annual electricity savings (GWh)		Cumulative investment costs (Million $">$)	
			2030	2040	2030	2040
	Steelmaking - basic oxygen furnace	3	4042	6533	1977	3195
	Steelmaking - electric arc furnace	11	13111	21190	3180	5139
	Casting, rolling and finishing	6	63715	102978	6122	9894
	General measures	2	2091	3380	46	75
	Sum	31	124365	197084	17259	27590
Cement	Fuel preparation	3	2204	3527	4795	7675
	Raw material preparation	9	7575	12124	8368	13394
	Clinker making	10	7322	11720	4565	7307
	Finish grinding	6	8913	14266	1367	2188
	General measures	4	7010	11220	972	1555
	Sum	32	33024	52858	20067	32118
Ammonia	Gas generation	4	2821	4823	510	872
	Shift conversion	2	1308	2236	493	843
	Gas purification	7	4107	6786	1272	2019
	Ammonia synthesis	5	3522	6021	787	1345
	General measures	4	1302	2226	150	257
	Sum	22	13060	22092	3212	5336
Calcium carbide	Feedstock preparation	2	1318	2843	1685	3635
	Calcium carbide manufacturing	13	23574	50743	5265	11260
	General measures	2	181	390	48	103
	Sum	17	25073	53976	6998	14998
Caustic soda	Power rectification	1	851	1826	170	364
	Brine electrolysis	4	6319	13554	3810	8172
	Chlorine + hydrogen disposition	4	2332	5002	673	1445
	Caustic concentration	2	13	28	55	118
	General measures	2	1746	3745	314	674
	Sum	13	11261	24155	5022	10772

Table B.1. (*continued*)

Industrial sector	Production process	Number of available measures	Annual electricity savings (GWh)		Cumulative investment costs (Million $)	
			2030	2040	2030	2040
PVC	Acetylene production	1	541	1168	178	384
	Hydrochloride synthesis	1	110	237	116	251
	Vinyl chloride monomer synthesis	2	1493	3221	62	133
	PVC synthesis and dry process	4	1521	3280	195	421
	General measures	1	163	352	19	40
	Sum	9	3828	8258	570	1229
Aluminum	Alumina refining	8	5383	10444	3497	6786
	Aluminum smelting & anode making	22	58447	105775	9905	16668
	General measures	1	2246	4357	157	305
	Sum	31	66075	120577	13559	23759
Paper	Pulping making	5	3173	5656	954	1701
	Papermaking	10	8976	15999	8816	15713
	General measures	5	3288	5580	427	736
	Sum	20	15437	27235	10197	18150

Appendix C. Unit-based information on coal power plant fleet under BAU and EEI scenarios

Table C.1 covers the information of thermal efficiency and emission factors at unit-level, and describes the coal power capacity to be phased out unit-by-unit under EEI scenarios.

Table C.1
Unit-based coal capacity built-up and characteristics.

Technology	Service year	Size	Capacity in 2040 (GW)	Avoided capacity in 2040 (GW)	Thermal efficiency (%)	Air emission factors (g/kWh)			
						SO_2	NO_x	PM	CO_2
Subcritical	≤2016	<100 MW	11	11	34.6	0.96	1.16	0.18	980
		100–300 MW	63	63	36.9	0.45	0.77	0.10	920
		300–600 MW	216	19	39.3	0.26	0.35	0.05	870
		≥600 MW	86	0	40.7	0.22	0.25	0.03	840
	2016–2040	n.a.	10	10	39.1	0.31	0.42	0.06	870

(*continued on next page*)

Table C.1 (*continued*)

Technology	Service year	Size	Capacity in 2040 (GW)	Avoided capacity in 2040 (GW)	Thermal efficiency (%)	Air emission factors (g/kWh)			
						SO_2	NO_x	PM	CO_2
Supercritical	≤2016	<300 MW	0	0	35.6	0.30	0.23	0.04	960
		300–600 MW	47	0	39.9	0.18	0.20	0.04	850
		≥600 MW	183	0	41.9	0.15	0.17	0.03	810
	2016–2040	n.a.	55	0	41.5	0.16	0.18	0.03	820
Ultra-supercritical	≤2016	≥600 MW	177	0	44.6	0.08	0.12	0.02	760
	2016–2040	n.a.	364	0	44.6	0.08	0.12	0.02	760
IGCC[a]	≤2016	<300 MW	0	0	46.0	0.05	0.07	0.02	740
	2016–2040	n.a.	18	0	46.0	0.05	0.07	0.02	740

[a] Integrated gasification combined cycle. n.a., not applicable. Note: Supplementary Information details the data sources.

References

Abel, D.W., Holloway, T., Martínez-Santos, J., Harkey, M., Tao, M., Kubes, C., Hayes, S., 2019. Air quality-related health benefits of energy efficiency in the United States. Environ. Sci. Technol. 53 (7), 3987–3998. https://doi.org/10.1021/acs.est.8b06417.

Ackerman, F., Fisher, J., 2013. Is there a water–energy nexus in electricity generation? Long-term scenarios for the western United States. Energy Pol. 59, 235–241. https://doi.org/10.1016/j.enpol.2013.03.027.

Amann, M., Bertok, I., Borken-Kleefeld, J., Cofala, J., Heyes, C., Höglund-Isaksson, L., Klimont, Z., Nguyen, B., Posch, M., Rafaj, P., 2011. Cost-effective control of air quality and greenhouse gases in Europe: modeling and policy applications. Environ. Model. Software 26 (12), 1489–1501. https://doi.org/10.1016/j.envsoft.2011.07.012.

Byers, L., Friedrich, J., Hennig, R., Kressig, A., Li, X., McCormick, C., Malaguzzi Valeri, L., 2019. A Global Power Plant Database. World Resources Institute, Washington (USA. https://www.wri.org/publication/global-power-plant-database. (Accessed 20 July 2020).

CEC (China Electricity Council), 2018. Basic Information of Thermal Power Units (Size Larger than 100 MW) in China, vol. 2017.

China Electric Power Yearbook, 2018. China Electric Power Yearbook. China Electric Power Press, Beijing (China).

Chinese Research Academy of Environmental Sciences, 2010. First Chinese Pollution Source Census: Manual of Industrial Pollutants Production and Discharge Coefficients. Beijing (China).

Cofala, J., Syri, S., 1998a. Nitrogen Oxides Emissions, Abatement Technologies and Related Costs for Europe in the RAINS Model Database. International Institute for Applied Systems Analysis, Laxenburg (Austria). http://pure.iiasa.ac.at/id/eprint/5563/. (Accessed 20 July 2020).

Cofala, J., Syri, S., 1998b. Sulfur Emissions, Abatement Technologies and Related Costs for Europe in the RAINS Model Database. International Institute for Applied Systems Analysis, Laxenburg (Austria). http://pure.iiasa.ac.at/id/eprint/5613/. (Accessed 20 July 2020).

Cohen, A.J., Brauer, M., Burnett, R., Anderson, H.R., Frostad, J., Estep, K., Balakrishnan, K., Brunekreef, B., Dandona, L., Dandona, R., et al., 2017. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. Lancet 389 (10082), 1907–1918. https://doi.org/10.1016/S0140-6736(17)30505-6.

Cui, L., Li, Y., Tang, Y., Shi, Y., Wang, Q., Yuan, X., Kellett, J., 2018. Integrated assessment of the environmental and economic effects of an ultra-clean flue gas treatment process in coal-fired power plant. J. Clean. Prod. 199, 359–368. https://doi.org/10.1016/j.jclepro.2018.07.174.

Cui, R.Y., Hultman, N., Edwards, M.R., He, L., Sen, A., Surana, K., McJeon, H., Iyer, G., Patel, P., Yu, S., 2019. Quantifying operational lifetimes for coal power plants under the Paris goals. Nat. Commun. 10 (1), 1–9. https://doi.org/10.1038/s41467-019-12618-3.

Dai, Y., Xiong, H., Jiao, J., 2013. Roadmap Study on Achieving Technical Energy Conservation Potential in China's Industrial Sector by 2020. China Science and Technology Press, Beijing (China).

Davis, C.B., Chmieliauskas, A., Dijkema, G., Nikolic, I., 2015. Power Plants (Enipedia) Database. Energy & Industry group, TU Delft, Delft (The Netherlands). http://enipedia.tudelft.nl/wiki/Enipedia. (Accessed 20 July 2020).

Davis, S.J., Socolow, R.H., 2014. Commitment accounting of CO_2 emissions. Environ. Res. Lett. 9 (8), 084018 https://doi.org/10.1088/1748-9326/9/8/084018.

EIA (U.S. Energy Information Administration), 2018. Power Plant Operations Report (EIA-923), vol. 2016. https://www.eia.gov/electricity/data/eia923/. (Accessed 20 July 2020).

EPA (U.S. Environmental Protection Agency), 2015. Demand-side Energy Efficiency Technical Support Document. Washington (USA). https://19january2017snapshot.epa.gov/sites/production/files/2015-11/documents/tsd-cpp-demand-side-ee.pdf. (Accessed 10 December 2020).

EPA, 2018. Emissions & Generation Resource Integrated Database (eGrid) V. 2016. https://www.epa.gov/energy/emissions-generation-resource-integrated-database-egrid. (Accessed 20 July 2020).

ERI & NREC, 2018. China Renewable Energy Outlook 2018. Energy Research Institute of Academy of Macroeconomic Research & National Renewable Energy Centre of China, Beijing (China). http://boostre.cnrec.org.cn/wp-content/uploads/2018/11/CREO2018-EN-final-1.pdf. (Accessed 20 July 2020).

European Commission, 2019. Modelling tools for EU analysis. https://ec.europa.eu/clima/policies/strategies/analysis/models_en. (Accessed 20 July 2020).

Fan, J., Xu, M., Li, F., Yang, L., Zhang, X., 2018. Carbon capture and storage (CCS) retrofit potential of coal-fired power plants in China: the technology lock-in and cost optimization perspective. Appl. Energy 229, 326–334. https://doi.org/10.1016/j.apenergy.2018.07.117.

Farfan, J., Breyer, C., 2017. Structural changes of global power generation capacity towards sustainability and the risk of stranded investments supported by a sustainability indicator. J. Clean. Prod. 141, 370–384. https://doi.org/10.1016/j.jclepro.2016.09.068.

Fleischman, L., Cleetus, R., Deyette, J., Clemmer, S., Frenkel, S., 2013. Ripe for retirement: an economic analysis of the US coal fleet. Electr. J. 26 (10), 51–63. https://doi.org/10.1016/j.tej.2013.11.005.

Fleiter, T., Fehrenbach, D., Worrell, E., Eichhammer, W., 2012. Energy efficiency in the German pulp and paper industry–A model-based assessment of saving potentials. Energy 40 (1), 84–99. https://doi.org/10.1016/j.energy.2012.02.025.

Gao, M., Beig, G., Song, S., Zhang, H., Hu, J., Ying, Q., Liang, F., Liu, Y., Wang, H., Lu, X., Zhu, T., Carmichael, G.R., Nielsen, C.P., McElroy, M.B., 2018. The impact of power generation emissions on ambient $PM_{2.5}$ pollution and human health in China and India. Environ. Int. 121, 250–259. https://doi.org/10.1016/j.envint.2018.09.015.

GEM (Global Energy Monitor), 2019. Database of worldwide coal-fired power stations. https://globalenergymonitor.org/coal/. (Accessed 20 July 2020).

Graus, W., Worrell, E., 2007. Effects of SO_2 and NO_x control on energy-efficiency power generation. Energy Pol. 35 (7), 3898–3908. https://doi.org/10.1016/j.enpol.2007.01.011.

Graus, W., Worrell, E., 2011. Methods for calculating CO_2 intensity of power generation and consumption: a global perspective. Energy Pol. 39 (2), 613–627. https://doi.org/10.1016/j.enpol.2010.10.034.

Hasanbeigi, A., 2010. Energy-efficiency Improvement Opportunities for the Textile Industry. Lawrence Berkeley National Laboratory, Berkeley (USA). https://china.lbl.gov/sites/default/files/guidebooks/textile-guidebook-en.pdf.

IEA, 2018a. Energy Efficiency 2017. International Energy Agency, Paris (France).

IEA, 2018b. World Energy Balances, 2018 edition. International Energy Agency, Paris (France).

IEA, 2018c. World Energy Outlook 2018. International Energy Agency, Paris (France).

IIASA, 2018. Greenhouse Gas - Air Pollution Interactions and Synergies (GAINS) Model Description. International Institute for Applied Systems Analysis, Laxenburg (Austria). https://iiasa.ac.at/web/home/research/researchPrograms/air/GAINS.html. (Accessed 20 July 2020).

IIASA, 2015. ECLIPSE V5a Global Emission Fields. International Institute for Applied Systems Analysis, Laxenburg (Austria). https://iiasa.ac.at/web/home/research/researchPrograms/air/ECLIPSEv5a.html. (Accessed 20 July 2020).

IndustryAbout, 2019. Worldwide Industrial Information. https://www.industryabout.com/country-territories-3/1705-china/fossil-fuels-energy. (Accessed 20 July 2020).

Kanada, M., Dong, L., Fujita, T., Fujii, M., Inoue, T., Hirano, Y., Togawa, T., Geng, Y., 2013. Regional disparity and cost-effective SO_2 pollution control in China: a case study in 5 mega-cities. Energy Pol. 61, 1322–1331. https://doi.org/10.1016/j.enpol.2013.05.105.

Karplus, V.J., Zhang, S., Almond, D., 2018. Quantifying coal power plant responses to tighter SO_2 emissions standards in China. Proc. Natl. Acad. Sci. Unit. States Am. 115 (27), 7004–7009. https://doi.org/10.1073/pnas.1800605115.

Kermeli, K., ter Weer, P., Crijns-Graus, W., Worrell, E., 2015. Energy efficiency improvement and GHG abatement in the global production of primary aluminium. Energy Effic 8 (4), 629–666. https://doi.org/10.1007/s12053-014-9301-7.

Klimont, Z., Cofala, J., Bertok, I., Amann, M., Heyes, C., Gyarfas, F., 2002. Modeling Particulate Emissions in Europe: A Framework to Estimate Reduction Potential and Control Costs. International Institute for Applied Systems Analysis,

Laxenburg (Austria). http://pure.iiasa.ac.at/id/eprint/6712/. (Accessed 20 July 2020).
Langevin, J., Harris, C.B., Reyna, J.L., 2019. Assessing the potential to reduce US building CO_2 emissions 80% by 2050. Joule 3 (10), 2403–2424. https://doi.org/10.1016/j.joule.2019.07.013.
Lelieveld, J., Evans, J.S., Fnais, M., Giannadaki, D., Pozzer, A., 2015. The contribution of outdoor air pollution sources to premature mortality on a global scale. Nature 525 (7569), 367–371. https://doi.org/10.1038/nature15371.
Li, M., Patiño-Echeverri, D., 2017. Estimating benefits and costs of policies proposed in the 13th FYP to improve energy efficiency and reduce air emissions of China's electric power sector. Energy Pol. 111, 222–234. https://doi.org/10.1016/j.enpol.2017.09.011.
Lin, B., Xu, L., 2015. Energy conservation of electrolytic aluminum industry in China. Renew. Sustain. Energy Rev. 43, 676–686. https://doi.org/10.1016/j.rser.2014.11.021.
Lin, B., Zheng, Q., 2017. Energy efficiency evolution of China's paper industry. J. Clean. Prod. 140, 1105–1117. https://doi.org/10.1016/j.jclepro.2016.10.059.
Liu, F., Klimont, Z., Zhang, Q., Cofala, J., Zhao, L., Huo, H., Nguyen, B., Schöpp, W., Sander, R., Zheng, B., Hong, C., He, K., Amann, M., Heyes, C., 2013. Integrating mitigation of air pollutants and greenhouse gases in Chinese cities: development of GAINS-City model for Beijing. J. Clean. Prod. 58, 25–33. https://doi.org/10.1016/j.jclepro.2013.03.024.
Liu, J., Zhang, S., Wagner, F., 2018. Exploring the driving forces of energy consumption and environmental pollution in China's cement industry at the provincial level. J. Clean. Prod. 184, 274–285. https://doi.org/10.1016/j.jclepro.2018.02.277.
Ma, D., Chen, W., Yin, X., Wang, L., 2016. Quantifying the co-benefits of decarbonisation in China's steel sector: an integrated assessment approach. Appl. Energy 162, 1225–1237. https://doi.org/10.1016/j.apenergy.2015.08.005.
Ma, M., Yan, R., Du, Y., Ma, X., Cai, W., Xu, P., 2017. A methodology to assess China's building energy savings at the national level: an IPAT–LMDI model approach. J. Clean. Prod. 143, 784–793. https://doi.org/10.1016/j.jclepro.2016.12.046.
MEE (Ministry of Ecology and Environment of China), 2015. NDRC (national development and Reform commission of China), NEA (national energy administration). Full Implementation of the Ultra-low Emission and Energy-Saving Transformation for Coal-Fired Power Plants. http://www.mee.gov.cn/gkml/hbb/bwj/201512/W020151215366215476108.pdf. (Accessed 20 July 2020).
Meier, A.K., 1982. Supply Curves of Conserved Energy. PhD Thesis. University of California, Berkeley.
MIIT (Ministry of Industry and Information Technology of China), 2017. China's Industry Green Development Report 2017. Beijing Normal University Press, Beijing (China).
MIIT, 2014. Guideline of national industrial energy efficiency. http://www.miit.gov.cn/n1146285/n1146352/n3054355/n3057542/n3057546/c3634672/content.html. (Accessed 20 July 2020).
Morrow, W.R., Hasanbeigi, A., Sathaye, J., Xu, T., 2014. Assessment of energy efficiency improvement and CO_2 emission reduction potentials in India's cement and iron & steel industries. J. Clean. Prod. 65, 131–141. https://doi.org/10.1016/j.jclepro.2013.07.022.
NDRC, 2019. National Key Energy Conservation and Low Carbon Technologies Promotion Catalogue. http://www.mee.gov.cn/ywgz/ydqhbh/wsqtkz/201904/t20190419_700394.shtml. (Accessed 20 July 2020).
NDRC, 2016. Guidelines on Promoting the Use of Electricity to Replace Other Energy Sources. http://www.scio.gov.cn/xwfbh/xwbfbh/wqfbh/39595/41802/xgzc41808/Document/1664893/1664893.htm. (Accessed 20 July 2020).
NDRC, MEE, NEA, 2014. Action Plan 2014–2020 for Retrofitting and Upgrading the Coal-Fired Power Plants Aiming at Energy Conservation and Emissions Reduction. http://www.mee.gov.cn/gkml/hbb/gwy/201409/t20140925_289556.htm. (Accessed 20 July 2020).
Nerini, F.F., Tomei, J., To, L.S., Bisaga, I., Parikh, P., Black, M., Borrion, A., Spataru, C., Broto, V.C., Anandarajah, G., Milligan, B., Mulugetta, Y., 2018. Mapping synergies and trade-offs between energy and the sustainable development goals. Nat. Energy 3 (1), 10–15. https://doi.org/10.1038/s41560-017-0036-5.
Oberschelp, C., Pfister, S., Raptis, C.E., Hellweg, S., 2019. Global emission hotspots of coal power generation. Nat. Sustain. 2 (2), 113–121. https://doi.org/10.1038/s41893-019-0221-6.
Peng, W., Yang, J., Lu, X., Mauzerall, D.L., 2018. Potential co-benefits of electrification for air quality, health, and CO_2 mitigation in 2030 China. Appl. Energy 218, 511–519. https://doi.org/10.1016/j.apenergy.2018.02.048.
Price, L., Galitsky, C., Sinton, J., Worrell, E., Graus, W., 2005. Tax and Fiscal Policies for Promotion of Industrial Energy Efficiency: A Survey of International Experience. Lawrence Berkeley National Laboratory, Berkeley (USA). https://www.osti.gov/biblio/861361. (Accessed 10 January 2021).
Purohit, P., Amann, M., Kiesewetter, G., Rafaj, P., Chaturvedi, V., Dholakia, H.H., Koti, P.N., Klimont, Z., Borken-Kleefeld, J., Gomez-Sanabria, A., Schöpp, W., Sander, R., 2019. Mitigation pathways towards national ambient air quality standards in India. Environ. Int. 133, 105147. https://doi.org/10.1016/j.envint.2019.105147.
Qin, Y., Wagner, F., Scovronick, N., Peng, W., Yang, J., Zhu, T., Smith, K.R., Mauzerall, D.L., 2017. Air quality, health, and climate implications of China's synthetic natural gas development. Proc. Natl. Acad. Sci. Unit. States Am. 114 (19), 4887–4892. https://doi.org/10.1073/pnas.1703167114.
Rashid, K., 2019. Design, Economics, and Real-Time Optimization of a Solar/natural Gas Hybrid Power Plant. PhD thesis. The University of Utah.
Rashid, K., Mohammadi, K., Powell, K., 2020. Dynamic simulation and techno-economic analysis of a concentrated solar power (CSP) plant hybridized with both thermal energy storage and natural gas. J. Clean. Prod. 248, 119193. https://doi.org/10.1016/j.jclepro.2019.119193.
Reddington, C.L., Conibear, L., Knote, C., Silver, B.J., Li, Y.J., Chan, C.K., Arnold, S.R., Spracklen, D.V., 2019. Exploring the impacts of anthropogenic emission sectors on $PM_{2.5}$ and human health in South and East Asia. Atmos. Chem. Phys. 19 (18), 11887–11910. https://doi.org/10.5194/acp-19-11887-2019.
Reyna, J.L., Chester, M.V., 2017. Energy efficiency to reduce residential electricity and natural gas use under climate change. Nat. Commun. 8 (1), 1–12. https://doi.org/10.1038/ncomms14916.
S&P Global Platts, 2018. World Electric Power Plants (WEPP) Database V. September 2017. Washington (USA).
Shi, G., Bi, J., Wang, J., 2010. Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs. Energy Pol. 38 (10), 6172–6179. https://doi.org/10.1016/j.enpol.2010.06.003.
Shindell, D., Smith, C.J., 2019. Climate and air-quality benefits of a realistic phase-out of fossil fuels. Nature 573 (7774), 408–411. https://doi.org/10.1038/s41586-019-1554-z.
Stehfest, E., van Vuuren, D., Bouwman, L., Kram, T., 2014. Integrated Assessment of Global Environmental Change with IMAGE 3.0: Model Description and Policy Applications. PBL Netherlands Environmental Assessment Agency.
Supekar, S.D., Skerlos, S.J., 2015. Reassessing the efficiency penalty from carbon capture in coal-fired power plants. Environ. Sci. Technol. 49 (20), 12576–12584. https://doi.org/10.1021/acs.est.5b03052.
Talaei, A., Ahiduzzaman, M., Kumar, A., 2018. Assessment of long-term energy efficiency improvement and greenhouse gas emissions mitigation potentials in the chemical sector. Energy 153, 231–247. https://doi.org/10.1016/j.energy.2018.04.032.
Talaei, A., Pier, D., Iyer, A.V., Ahiduzzaman, M., Kumar, A., 2019. Assessment of long-term energy efficiency improvement and greenhouse gas emissions mitigation options for the cement industry. Energy 170, 1051–1066. https://doi.org/10.1016/j.energy.2018.12.088.
Tang, L., Qu, J., Mi, Z., Bo, X., Chang, X., Anadon, L.D., Wang, S., Xue, X., Li, S., Wang, X., 2019. Substantial emission reductions from Chinese power plants after the introduction of ultra-low emissions standards. Nat. Energy 4 (11), 929–938. https://doi.org/10.1038/s41560-019-0468-1.
Tian, X., Dai, H., Geng, Y., Wilson, J., Wu, R., Xie, Y., Hao, H., 2018. Economic impacts from $PM_{2.5}$ pollution-related health effects in China's road transport sector: a provincial-level analysis. Environ. Int. 115, 220–229. https://doi.org/10.1016/j.envint.2018.03.030.
Tong, D., Zhang, Q., Davis, S.J., Liu, F., Zheng, B., Geng, G., Xue, T., Li, M., Hong, C., Lu, Z., Streets, D.G., Guan, D., He, K., 2018a. Targeted emission reductions from global super-polluting power plant units. Nat. Sustain. 1 (1), 59–68. https://doi.org/10.1038/s41893-017-0003-y.
Tong, D., Zhang, Q., Liu, F., Geng, G., Zheng, Y., Xue, T., Hong, C., Wu, R., Qin, Y., Zhao, H., 2018b. Current emissions and future mitigation pathways of coal-fired power plants in China from 2010 to 2030. Environ. Sci. Technol. 52 (21), 12905–12914. https://doi.org/10.1021/acs.est.8b02919.
Ummel, K., 2012. CARMA revisited: an updated database of carbon dioxide emissions from power plants worldwide. Center for Global Development Working Paper (Personal contact 2019).
UNFCCC (United Nations Framework Convention on Climate Change), 2019. Clean Development Mechanism (CDM) Database. https://cdm.unfccc.int/about/index.html. (Accessed 20 July 2020).
Wang, Y., Byers, E., Parkinson, S., Wanders, N., Wada, Y., Mao, J., Bielicki, J.M., 2019a. Vulnerability of existing and planned coal-fired power plants in Developing Asia to changes in climate and water resources. Energy Environ. Sci. 12 (10), 3164–3181. https://doi.org/10.1039/C9EE02058F.
Wang, S., Li, C., Zhou, H., 2019b. Impact of China's economic growth and energy consumption structure on atmospheric pollutants: based on a panel threshold model. J. Clean. Prod. 236, 117694. https://doi.org/10.1016/j.jclepro.2019.117694.
Wen, Z., Meng, F., Chen, M., 2014. Estimates of the potential for energy conservation and CO_2 emissions mitigation based on Asian-Pacific Integrated Model (AIM): the case of the iron and steel industry in China. J. Clean. Prod. 65, 120–130. https://doi.org/10.1016/j.jclepro.2013.09.008.
Williams, J.H., DeBenedictis, A., Ghanadan, R., Mahone, A., Moore, J., Morrow, W.R., Price, S., Torn, M.S., 2012. The technology path to deep greenhouse gas emissions cuts by 2050: the pivotal role of electricity. Science 335 (6064), 53–59. https://doi.org/10.1126/science.1208365.
World Bank, 2016. The Cost of Air Pollution: Strengthening the Economic Case for Action. World Bank Group, Washington (USA). https://openknowledge.worldbank.org/handle/10986/25013. (Accessed 20 July 2020).
Worrell, E., Laitner, J.A., Ruth, M., Finman, H., 2003. Productivity benefits of industrial energy efficiency measures. Energy 28 (11), 1081–1098. https://doi.org/10.1016/S0360-5442(03)00091-4.
Worrell, E., Price, L., Neelis, M., Galitsky, C., Zhou, N., 2007. World best practice energy intensity values for selected industrial sectors. Lawrence Berkeley National Laboratory, Berkeley (USA).
Xiao, H., Li, S., Chevallier, J., Zhu, B., 2017. Electricity-savings pressure and electricity-savings potential among China's inter-provincial manufacturing sectors. Energy Syst 8 (3), 581–600. https://doi.org/10.1007/s12667-016-0214-8.
Xiao, K., Li, F., Dong, C., Cai, Y., Li, Y., Ye, P., Zhang, J., 2020. Unraveling effects of coal output cut policy on air pollution abatement in China using a CGE model. J. Clean. Prod. 269, 122369. https://doi.org/10.1016/j.jclepro.2020.122369.

Xu, J., Fleiter, T., Eichhammer, W., Fan, Y., 2012. Energy consumption and CO_2 emissions in China's cement industry: a perspective from LMDI decomposition analysis. Energy Pol. 50, 821–832. https://doi.org/10.1016/j.enpol.2012.08.038.

Yang, H., Zhang, Y., Zheng, C., Wu, X., Chen, L., Fu, J.S., Gao, X., 2018. Cost estimate of the multi-pollutant abatement in coal-fired power sector in China. Energy 161, 523–535. https://doi.org/10.1016/j.energy.2018.07.164.

Yue, H., Worrell, E., Crijns-Graus, W., 2018. Modeling the multiple benefits of electricity savings for emissions reduction on power grid level: a case study of China's chemical industry. Appl. Energy 230, 1603–1632. https://doi.org/10.1016/j.apenergy.2018.09.078.

Zhai, H., 2019. Deep reductions of committed emissions from existing power infrastructure: potential paths in the United States and China. Environ. Sci. Technol. 53, 14097–14098. https://doi.org/10.1021/acs.est.9b06858.

Zhang, Q., Xu, J., Wang, Y., Hasanbeigi, A., Zhang, W., Lu, H., Arens, M., 2018a. Comprehensive assessment of energy conservation and CO_2 emissions mitigation in China's iron and steel industry based on dynamic material flows. Appl. Energy 209, 251–265. https://doi.org/10.1016/j.apenergy.2017.10.084.

Zhang, S., Ren, H., Zhou, W., Yu, Y., Chen, C., 2018b. Assessing air pollution abatement co-benefits of energy efficiency improvement in cement industry: a city level analysis. J. Clean. Prod. 185, 761–771. https://doi.org/10.1016/j.jclepro.2018.02.293.

Zhang, S., Worrell, E., Crijns-Graus, W., 2015. Evaluating co-benefits of energy efficiency and air pollution abatement in China's cement industry. Appl. Energy 147, 192–213. https://doi.org/10.1016/j.apenergy.2015.02.081.

Zhang, S., Xie, Y., Sander, R., Yue, H., Shu, Y., 2021. Potentials of energy efficiency improvement and energy–emission–health nexus in Jing-Jin-Ji's cement industry. J. Clean. Prod. 278, 123335. https://doi.org/10.1016/j.jclepro.2020.123335.

Zhang, S., Yi, B., Worrell, E., Wagner, F., Crijns-Graus, W., Purohit, P., Wada, Y., Varis, O., 2019. Integrated assessment of resource-energy-environment nexus in China's iron and steel industry. J. Clean. Prod. 232, 235–249. https://doi.org/10.1016/j.jclepro.2019.05.392.

Zhou, N., Khanna, N., Feng, W., Ke, J., Levine, M., 2018. Scenarios of energy efficiency and CO_2 emissions reduction potential in the buildings sector in China to year 2050. Nat. Energy 3 (11), 978–984. https://doi.org/10.1038/s41560-018-0253-6.

Zuberi, M.J.S., Patel, M.K., 2017. Bottom-up analysis of energy efficiency improvement and CO_2 emission reduction potentials in the Swiss cement industry. J. Clean. Prod. 142, 4294–4309. https://doi.org/10.1016/j.jclepro.2016.11.178.