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Integrated assessment of resource-energy-environment nexus in China's iron and steel industry

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ABSTRACT

MESSAGEix model are widely used for forecasting long-term energy consumption and emissions, as well as modelling the possible GHGs mitigations. However, because of the complexity of manufacturing sectors, the MESSAGEix model aggregate detailed technology options and thereby miss linkages across sub-sectors, which leads to energy saving potentials are often not very realistic and cannot be used to design specific policies. Here, we integrate Material/Energy/water Flow Analysis (MEWFA) and nexus approach into the MESSAGEix to estimate resource-energy-environment nexus in China's iron and steel industry. Results show that between 2010 and 2050 energy efficiency measures and route shifting of China's steel industry will decrease raw material input by 14%, energy use by 7%, water consumption by 8%, CO_2 emissions by 7%, NOx emissions by 9%, and SO_2 emissions by 14%, respectively. However, water withdrawal and $PM_{2.5}$ emissions will increase by 14% and 20%, respectively. The main reason is that water withdrawal and $PM_{2.5}$ emissions in the process of BF-BOF are over 4 times lower than the process scrap-EAF. Therefore, policy makers should consider nexus effects when design integrated policy to achieve multiple targets. Finally, future directions on enhancing the representation of manufacturing sectors in IAMs are given.

1. Introduction

Energy system models are increasingly used to assess future climate change and its socio-economic impacts. Scenarios, such as Representative Concentration Pathways (RCPs) and Shared Socio-economic Pathways (SSPs), developed by several Integrated Assessment Models (IAMs) show a wide range of projections for assessing mitigation policies, depending on the actions modelled to response of the climate change and other relevant environmental issues, such as water scarcity and air pollution (Marangoni et al., 2017; Moss et al., 2010; Riahi et al., 2017; Rogelj et al., 2016; Wada et al., 2014; Walsh et al., 2017). Key feature of IAMs is that they integrated multiple knowledge into a single framework to explore human actions interact with natural world, especially help us understand how technologies, socioeconomic behaviour, and natural change can avoid greenhouse gas emissions (Bruckner, 2016).

Recently, nexus approach have been widely employed to identify trade-offs and synergies across space, and time (Albrecht et al., 2018; Kaddoura and El Khatib, 2017; Namany et al., 2019; Zhang et al., 2018a,b). Evaluating current literature, many studies simply distinguish three groups of nexus, namely system-wise approaches, holistic, and system think approaches (Harwood, 2018). Mannan et al. summarized the development of integrated Life Cycle Assessment (iLCA) and energy-water-food (EWF) nexus methodology and fund that iLCA and EWF nexus play a significant role in environmental burdens and would have large effects on EWF resource sectors (Mannan et al., 2018). There is growing recognition that integrating nexus approach into IAMs. For example, the

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Climate, Land, Energy and Water (CLEW), developed by International Atomic Energy Agency (IAEA), is an integrated tool that aims to assessing interactions between water, energy, climate, land, and material use at the global scale (International Atomic Energy Agency, 2017). Tokimatsu used a bottom-up energy model to assess potential for renewable energy technologies application and the associated metal demand, under different climate target scenarios, and found that energy-mineral nexus play an important role when underpin policy making (Tokimatsu et al., 2018, 2017). Fang et al. used a multiregional input-output model with an atmospheric chemical transport model to estimate clean air policy and the associated environmental impacts in China, and found that environmental policy not only can improve air quality in the target region, but also can lower CO_2 emissions and decrease water consumption (Fang et al., 2019).

To date, such model-based scenarios have not unambiguously examined the efficiency of various possible policies, and how they will be financed in major emitting sectors (e.g., building and industry) (Rogelj et al., 2016). For example, the specific industry characteristics and the complex interactions with and within sectors are not included in most of IAMs used to evaluate policy strategies (Kermeli et al., 2016; Worrell and Kermeli, 2017). Over time, narrowing scenario uncertainty is extremely difficult because it requires increased confidence in future technology and society conditions (Brown and Caldeira, 2017). Furthermore, it remains unclear how to best evaluate the synergies or co-benefits of resource/energy/water efficiency, climate, and air quality across sub-sectors and distinct features across regions (Pauliuk et al., 2017). Therefore, future IAMs need to provide more accuracy and transparent projections when designing specific policies to achieve future targets (e.g., Nationally Determined Contributions (NDCs), Sustainable Development Goals (SDGs)). New knowledge applied in state-of-the-art IAMs to further improve the representation of sub-sectors and the associated interactions is urgently required to support the design and evaluation of policies at national, regional, and global scales. The aim of this paper is to address this gap by integrate Material/Energy/water Flow Analysis (MEWFA) and nexus approach into the Model for Energy Supply Strategy Alternatives and their General Environmental Impacts (MESSAGEix) to estimate potential for energy and material efficiency improvement, emission reductions of GHG and air pollutants, and resource-energy-environment nexus. Specifically, resource-energy-environment nexus of China's iron and steel industry, in this study, aims estimate decline trade-offs, improve synergies of resource, energy, water, and emissions of GHGs and air pollutants, improve energy and resource or material efficiency, and guide development of new decision- and policy-making. To integrate industrial sub-sectors into system model (e.g., IAMs) and assess the associated potential solutions for climate mitigation, we firstly integrate iron and steel industry into the MESSAGEix model, because of its large contribution to CO_2 emissions (29% of industrial direct emissions) and pollution, and its high level of resource and energy demand (20% of industrial energy use) (Worrell and Carreon, 2017). This approach takes the advantages of the model's high level of detail technology to estimate the energy & resource saving potential, emission reductions, nexus with and within sectors, as well as the associated investment. Also, the future dynamic use of raw/process material, energy, water, and emissions of the system can be optimized in MESSAGEix. We first introduce the process technologies to quantify the future activity of energy and water consumption, emissions of greenhouse gases (GHGs) and air pollution and associated co-benefits and trade-offs in China's iron and steel industry during the period 2010–2050. Then, we investigate the potential resource requirements (including raw material and process material), energy and water use, and emissions of the selected energy efficiency measures within the alternative scenarios and compare these findings with those of the baseline scenario.

2. Overview of iron and steel industry in China

Iron and steel products, as key industrial materials, are widely used to meet requirements of economic development, especially for infrastructure and other construction projects (Cullen et al., 2012). Over the last 150 years, the world crude steel consumption increased to over 1.6 billion tons in 2016 and is expected to continue to rise also in the long-term future, partly because of the societal transition, via application of steel products in new technologies (Milford et al., 2013; Worrell and Carreon, 2017). China has been the world's largest steel consumer and producer since 1996. Crude steel production from China increased from 100 million tons (Mt) in 1996 to 808 Mt in 2016, nearly 50% of global total (World Steel Association, 2017). Studies in the Chinese iron and steel industry have demonstrated steel consumption will peak by around 2030 and then decline gradually (Yin and Chen, 2013; Zhang et al., 2014).

Steel can be produced via four main routes: blast furnace, basic oxygen furnace (BF-BOF), scrap- Electric arc furnace (EAF), direct reduction (DRI)-EAF (also named Direct Reduced Iron (DRI), and open-hearth furnace (OHFs). The process shares of steel production vary widely across countries. In 2016 BF-BOF dominated, accounting for 74.3% of world steel production, followed by scrap-EAF (25.2%) (World Steel Association, 2017). The other steel production routes, such as DRI-EAF and OHF contributed only a minor portion, with a share of around 5% of the total produced amount. However, China has the highest share of BF-BOF steel production, accounting for 94%, followed by scrap-EAF (6%) (World Steel Association, 2017). The BF-BOF route includes process technologies of coke making, sinter making, iron making and steel making, while the EAF route includes scrap melting or DRI and steel making. The key difference among the process technologies is the type/amount of raw material and energy they need. For example, iron ore and less scrap (range: 10–30%) are typically used in BF-BOF to produce steel. In contrast, almost 100% scrap is used in the scrap-EAF route (Yellishetty et al., 2010), where the scrap-EAF route consumes less energy than the BF-BOF route (Oda et al., 2013).

Regarding energy and environmental challenges, it is important to note that among industrial sectors, iron and steel industry is the globally largest one in energy needs, emissions of CO_2 and air pollution, and consumption of resource-based manufacturing sectors, accounting for 20% of world industrial energy use and 29% of industrial direct CO_2 emissions (Worrell and Carreon, 2017). The Chinese iron and steel industry is responsible for 24% of industrial energy and 22% of water use, and releases 21% of CO_2, 10% of SO_2, 15% NOx, and 10% of $PM_{2.5}$, respectively (Wang et al., 2017a,b; Zhang, 2016; Zhang et al., 2014). Specifically, the blast furnace is the most energy-intensive part of the steel making in the BF-BOF route, while sintering is the main source of air pollution in this route (Wu et al., 2015). Inversely, the EAF was the largest electricity consumer (CSDRI, 2016).

3. Methodology

3.1. MESSAGEix model

MESSAGE, developed by the International Institute for Applied Systems Analysis (IIASA), is a dynamic system optimization model that is widely used to investigate future development of medium-to long-term energy planning and policy analysis (Keppo and Strubegger, 2010; Sullivan et al., 2013). Further, MESSAGE links to the macro-economic model (MACRO) to consistently assess the interaction between macroeconomic production, natural resources, energy demand and supply, and emissions (Messner and Schrattenholzer, 2000). The advantage of the MESSAGE-MACRO combination is that its two components can run independently from each other.

Many different modelling frameworks and IAMs (including MESSAGE-V) have been developed and used to assess various purposes with specific constraints and diverse scales (Fattori et al., 2016). However, obstacles of interdisciplinary, transparency, scientific standards and uncertainty in most of energy systems modelling remain unaddressed (Hilpert et al., 2017). To closing the gaps, the MESSAGEix, based on MESSAGE-V, is developed and implemented under IIASA's ix modelling platform (ixmp). The new feature of MESSAGEix has allowed improved openness and transparency, compared to the existing MESSAGE-V model. In addition, the ixmp provides an efficient work-flow for data processing and implementation of models across disciplines and spatial scales. The key advantage of MESSAGEix is that it allows modellers to easily exchange data input, integrate external data source, and link with other models, such as the Greenhouse Gas - Air Pollution Interactions and Synergies (GAINS) model. More detailed modelling information of MESSAGEix as described by Huppmann et al. (Huppmann et al., 2019), and the tutorial of MESSAGEix (IIASA's Energy group, 2018).

3.2. MESSAGEix – iron and steel model

MESSAGEix – iron and steel model, developed in this study, is a technology-based model in the MESSAGEix family that depicts the system with a high level of details on natural resource, energy, water, emissions, and the associated technologies. We integrate material/energy/water Flow Analysis (MEWFA) and nexus approach into the MESSAGEix model to assess the impacts of raw/process materials on long-term scenario perspectives in the iron and steel industry. The work-flow of MESSAGEix – iron and steel model is given in Fig. 1, this efficient workflow can be summarized as: 1) forecast the future steel demand via sectorial intensity use curve (see section 3.2.1); 2) import database into IIASA's ix modelling platform (ixmp), MESSAGEix framework, run the model, and export/report the results, via Python standardized user interface; 3) assess the nexus of natural resources, energy, water and environment pollution. To increase the transparency and accessibility of the model the extensive information (e.g., database for iron and steel industry, specific technology parameters and related Python script) can be provide upon request, based on the discussion with the relevant policy makers and plant managers.

The core of MESSAGEix - iron and steel model is a Reference System for Material, Energy, and Water (RSMEW) flow that represents the most important carriers of energy, material and water and associated technologies. The detailed information of for the Reference System for Material, Energy, and Water (RSMEW) flow can be found in Appendix Table A. Technologies (including process technologies and related energy efficiency measures) characterized by capital and operating costs, installed capacity and related activities, different input/out efficiencies, and emission factors. For steel industry, iron ore is agglomerated in sinter plants to produce sinter, while pellets are formed from pellet plants at high process temperature. These products are converted to pig iron in a blast furnace. Then, the pig iron is supplied to the basic oxygen furnace (BOF) or electric arc furnace (EAF) to produce crude steel. The model in this study allows for a more complete description of the process (i.e. iron ore extraction, limestone extraction, coke making, sinter making, pellets making, pig iron making, steel making with BOF, steel making with EAF, direct reduced iron ore, and casting, rolling, and finishing (steel_crf)) involved in the iron and steel industry. Of overall 11 process technologies and 54 current best energy efficiency measures are considered in the current MESSAGEix - iron and steel model (see Appendix S1 and S2).

We modelled the period from 2010 to 2050 with a 5-year interval. The current best available energy efficiency measures are introduced to capture the changes in use energy, water, and subsequent emissions, based on scenario analysis. An important feature of this phase is the introduction of the functional parameters for process technology and energy efficiency measures (see

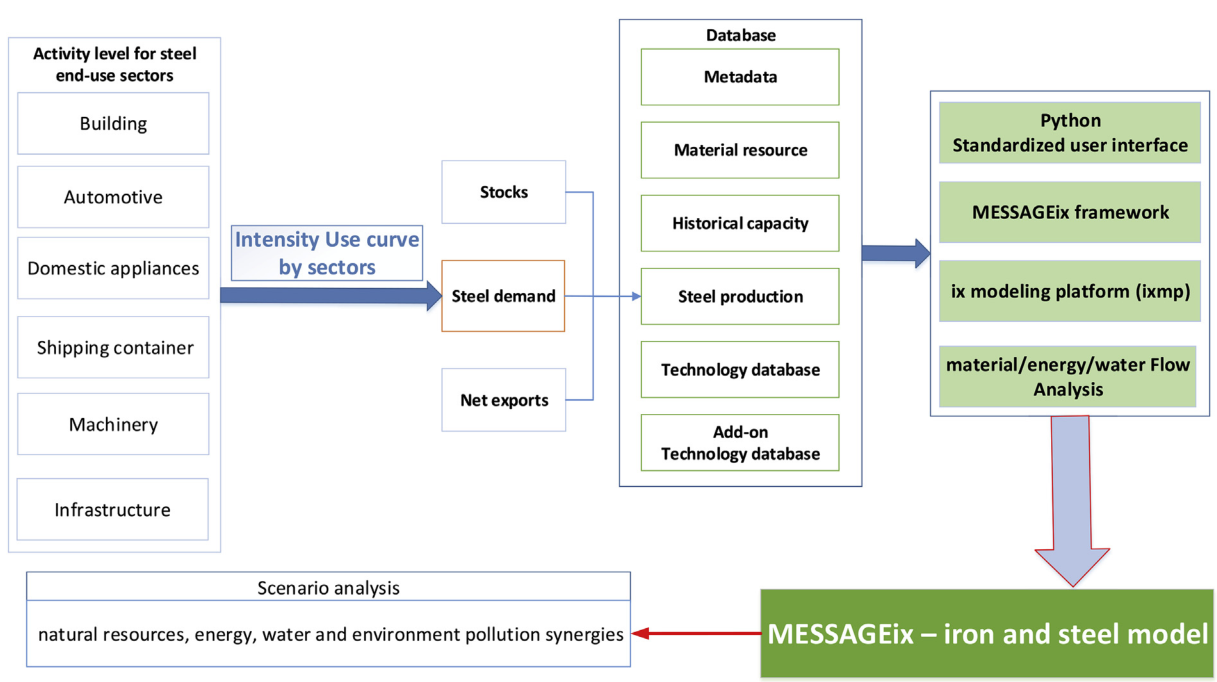

Fig. 1. Work-flow for MESSAGEix – iron and steel model.

3.2.2). Currently, the MESSAGEix – iron and steel model cannot automatically generate the dynamic feedback with the steel consumption sectors. Therefore, an exogenous assumption on the future activity of steel consumers is obtained from state-of-the-art models. Intensity use curves are developed and adopted to quantify the interactions between iron and steel industry and related key consumers of steel products (see 3.2.1).

3.2.1. Projection of future steel products/steel-cast

Currently, two approaches (e.g. demand curve, supply curve, and intensity use curve) are widely used to project future demands of industrial products, such as cement and steel. The first approach is based on the direct relationship with macro-economic variables (e.g. steel intensity to GDP per capita combined with investment share as a socio-economic variable) (M. Tanaka, 2010), which are often used in state-of-the-art energy models, like The Targets IMage Energy Regional (TIMER) model (Neelis and Patel, 2006). The second approach is the sector specific approach based on major steel consuming sectors, which depends heavily on the quality of information available for the economy (S. Zhang et al., 2018a,b).

In this study, the Intensity Use (IU)[1] Curve is developed to estimate interactions between steel industry and the associated end-use sectors. The historical steel consumption is shown in Appendix S3. Because of data constraints, the IU curves based on physical units are employed in the building, automotive, and domestic appliances, and shipping container sectors, while the IU curves, based on direct relationships with macro-economic variables, are developed and used in the machinery and infrastructure sectors (see Eq. (2)).

$$\begin{aligned} \textit{Steel demand} &= \sum_i \textit{steel demand} \\ &= \sum_i \frac{\textit{product}}{\textit{population}} * \frac{\textit{steel demand}}{\textit{product}} * \textit{Population} \\ &= \sum_i \textit{product intensity} * \textit{steel intensity} * \textit{population} \end{aligned} \tag{1}$$

$$\begin{aligned} \textit{Steel demand} &= \sum_i \textit{steel demand} \\ &= \sum_i \frac{\textit{value added}}{\textit{population}} * \frac{\textit{steel consumption}}{\textit{value added}} * \textit{Population} \\ &= \sum_i \textit{product intensity} * \textit{steel intensity} * \textit{population} \end{aligned} \tag{2}$$

3.2.2. Linkage between process technologies and energy efficiency measures

Energy efficiency is marked as the "first fuel" because it is considered to be more competitive than any other fuel, in terms of cost effectiveness and availability (IEA, 2016; Yang and Yu, 2015). Increasing energy efficiency and reducing GHG emissions, especially in the demand sectors, has been an integral part of the national climate strategy worldwide. However, the economic and technical emission mitigation potential of demand sectors (e.g., cement, steel, aluminium, chemical, and paper) based on specific retrofitting/new technology have not been systematically explored in state-of-the-art energy models, partly because there is limited data and few mature methodologies.

In this study, we developed a new feature that allows seamless interaction with process technologies and best energy efficiency measures in MESSAGEix – iron and steel industry model. Specifically, the parameter of addon_conversion (Eq. (4)), a conversion factor, was used to build linkages between add-on technologies and parent technology. Here, add-on technologies represent energy efficiency measures or retrofitting/mitigation technologies (e.g. coal moisture control, low temperature heat recovery, etc.), while parent technology represents the process technology (e.g. coke making, iron making). If the add-on technology is already implemented in the base year, the parameter of addon_minimum will be introduced to represent the minimum deployment fraction of add-on technology relative to parent technology. Further, the parameters of addon_activity_up and addon_activity_low will be used to model future diffusion of add-on technology. Note that these two parameters provide an upper/lower bound on the activity of an add-on technology that has to be operated jointly with a parent technology. The addon_activity_up is calculated by using Eq. (4), which provides an upper bound on the activity of an add-on technology. Similarly, the addon_activity_low is presented in Eq. (5), which provides a lower bound on the activity of an add-on technology.

$$\sum_{\substack{y^v \\ y^v \le y}} addon\_conversion_{n,t^a,y^v,y,m,h} * ACT_{n,t^a,y^v,y,m,h} \le \sum_{\substack{t,y^v \\ t\sim t^a \\ y^v \le y}} ACT_{n,t,y^v,y,m,h} \tag{3}$$

$$\sum_{\substack{y^v \\ y^v \le y}} addon\_minimum_{n,t^a,y^v,y,m,h} * addon\_conversion_{n,t^a,y^v,y,m,h} * ACT_{n,t^a,y^v,y,m,h} \ge \sum_{\substack{t,y^v \\ t\sim t^a \\ y^v \le y}} ACT_{n,t,y^v,y,m,h} \tag{4}$$

The net imports share of total steel product is assumed unchanged in the future, while transport losses and change of stocks of steel products are beyond the scope of this study.

Steel production = steel demand + net imports + change of stocks *Eq*. (3).

The advantage of this feature is that the MESSAGEix – iron and steel industry model not only can assess the accurate estimation of actual potential per technology and associated costs, but also allows to make accurate technology comparisons and figure out how to achieve single/multiple targets (e.g., by building new production line to change production structure or implementing retrofitting technology) and indicate what costs could be involved.

[1] The ratio between the material demand and these socio-economic variables are named as the intensity of use (IU).

3.4. Data sources and scenario assumptions

3.4.1. Data sources

The historical, annual outputs of floor space, passenger vehicles, trucks, washing machines, refrigerators, air conditioners, length of railways, highways, and petroleum and gas pipelines, as well as value added of the machinery sector are obtained from of the China Statistical Yearbook 2010–2016 (National Bureau of Statistics, 2016, pp. 2010–2016). The historic steel consumption by end-use sector (e.g. building, machinery, automotive, domestic appliances, shipping container, and infrastructure) is obtained from China Industrial Information Network (China Industry Information Network, 2015), China Metallurgical Mining Enterprises Association (China Metallurgical Mining Enterprises Association, 2014), and the report released by the company of Founderfu (Han, 2017). The intensity use curve by sector was developed on the basis of the above factors.

Exogenous scenario parameters of future activities of steel end-use sectors were taken from the baseline scenario of Integrated Policy Model for China (IPMC) and the Integrated Model of Economy, Energy and Environment for Sustainable Development/Computable General Equilibrium model (IMED/CGE) and combined with sectorial intensity use curve to forecast the steel demand by sectors until 2050 (Wang et al., 2017a,b). All data on domestic iron ore production, iron ore import and consumption of limestone were obtained from the China Steel Yearbook 2016 (CSDRI, 2016).

Developing technology database is a core part of MESSAGEix – iron and steel model. Parameters of energy use by fuel, material consumption, and water consumption, cost, by each process technology are taken from China Energy Statistical Yearbook, China Steel Yearbook, relevant literature surveys, and communication with Chinese experts (CSDRI, 2016; National Bureau of Statistics of China, 2013, 2011). Parameters of commodity prices are from the China Steel Yearbook (CSDRI, 2016), while variable cost by each process is taken from IEA-Clean Coal Centre and Metals Consulting International (MCI) (IEA, 2012; Metals Consulting International, 2018). Because we could not obtain sufficient information of China's Direct Reduced Iron (DRI) technology, the physical parameters related to DRI technology are based on German steel plants and Energiron DRI plant (Otto et al., 2017; Tenova, 2018). The cost of DRI technology is taken from the Energy Technology Systems Analysis Program (ETSAP) of the International Energy Agency (IEA) (IEA, 2010).

Several studies have demonstrated a substantial reduction of energy use and CO_2 emissions in the different processes of iron and steel industry by implementing energy efficient measures (Hasanbeigi et al., 2013; Hasanbeigi et al., 2013d; Zhou et al., 2011). However, most IAMs hardly consider the representation of energy efficiency measures in their industry modules (Kermeli et al., 2016). Therefore, it is important to integrate energy efficiency measures in IAMs to analyse what specific policies to be implemented and what are the cost-optimal strategies/measures for the mitigation of climate change.

In this study, we developed a mitigation technology database (including 54 energy efficiency measures by the process) in MESSAGEix – iron and steel model (see Appendix S2 and S3). In this database, the key parameters (e.g., fuel saving, electricity saving, water saving, cost, and application rate for base year) of selected energy efficiency measures were obtained from Energy Research Institute (ERI) of China, National Development and Reform Commission (NDRC) of China, The Institute for Industrial Productivity (IIP), Environmental Protection Agency (EPA) of USA, Lawrence Berkeley National Laboratory (LBNL), and related studies (IIP, 2013; Hasanbeigi et al., 2013a; Hasanbeigi et al., 2012; US EPA, 2010; Wang et al., 2017a,b; Xu, 2011; Zhang et al., 2014).

The CO_2 emission factor for coal is taken from LBNL (Hasanbeigi et al., 2013b; Ke et al., 2012). The CO_2 emission factor for electricity generation is taken from regional grid baseline emission factors of China (National Center for Climate Change Strategy and International Cooperation of China, 2010). The energy-related emission coefficients of SO_2, NOx, $PM_{2.5}$ are taken from the Ministry of Environmental Protection (MEP) of China (Ministry of Environmental Protection of China, 2013), and relevant literature (Hasanbeigi et al., 2017; Wu et al., 2015). The process emission factors for $PM_{2.5}$, SO_2, NOx, and CO_2 are taken from the GAINS model available at < http://gains.iiasa.ac.at/models/index.html> and other publicly available literature (Wu et al., 2015; Zhang et al., 2016, 2015a).

3.4.2. Scenario assumptions

The emphasis of this paper is not only on the introduction of the methodology, but also on modelling the synergies between raw/process material and energy use, water withdrawal and consumption, and emissions of GHG and air pollutants in Chinese iron and steel industry. Two scenarios are constructed: a baseline (BL) scenario and an energy efficiency (EE) scenario (see Table 1). The EE scenario is a mitigation scenario that requires stringent energy policies to accelerate the implementation of energy efficiency measures, whereas the BL scenario assume no additional policy adoptions. Specifically, we include 40 energy efficiency measures in EE scenario (see Appendix S4), which represents the cost-effective potential for energy efficiency improvement in China's iron and steel industry. The future technology diffusions of selected energy efficiency measures for energy efficiency scenario are projected through using linear deployment approach. The future steel production is assumed unchanged in both BL and EE scenarios during the study period. Note that the sulphur content of iron ore produced in China is higher than in other regions (e.g., Australia and Brazil) (China Pollution Source Census, 2011; MEP of China, 2017). To meet the demand for high-quality steel products, we therefore assumed that the imports share of total iron ore consumption remains unchanged in the future. One highlight of MESSAGEix is that it is easy to develop alternative scenarios. It means that the EE scenario can be simply constructed, via copying the BL scenario and introducing the function of add-on technology.

4. Results and discussion

4.1. Steel demand and production from 2010 to 2050

Fig. 2 presents the steel demand by end-use sectors and its

Table 1
Key features of different scenarios.

Scenarios	Scenario Description	
	Common features	Different features
Baseline (BL)	The future steel production is assumed unchanged Discount rate is 10%	The BOF share of total steel production will decrease by 2% per 5 year* No new policies are considered.
Energy efficiency (EE)	The imports share of total iron ore consumption remains unchanged in the future	40 cost effective energy efficiency measures (see appendix S4) will be introduced to MESSAGE-steel module

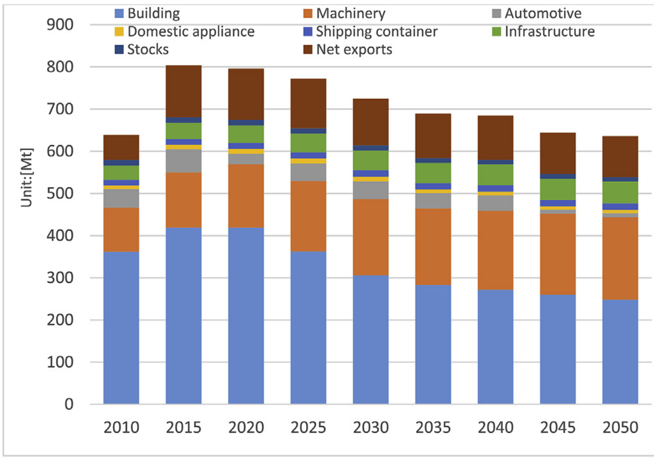

Fig. 2. Steel demand and production from 2010 to 2050.

production in China from 2010 to 2050. Between 2010 and 2015, steel production shows an annual increase of 5%, rising from 639 Mt to 804 Mt, and after that it decreases gradually to 636 Mt by 2050. These results are consistent with those of other studies, such as IEA (IEA, 2017) and Yin and Chen (2013). On the demand side, the building sector will retain a dominant role in total steel consumption, although with a declining overall share. Compared to 2010, the building share of total steel consumption is reduced by 18% by 2050 due to saturation of the market. In contrast, the machinery sector shows a minor increase of steel consumption over the forecast period. The main reason is that implementation of retrofitting/new technology to improve energy efficiency and emission mitigation leads to demand growth for steel products. Similarly, increasing personal income and population growth have a large contribution to the growth of steel consumption in the automotive sector. Domestic appliances and shipping containers are projected to decline at much lower annual rates of 0.3% and 0.4%, respectively.

4.2. Material consumption from 2010 to 2050

4.2.1. Raw material consumption

Fig. 3a (top panel) presents the total raw material consumption (i.e. iron ore, limestone and scrap) in China's iron and steel industry, under BL and EE scenarios. For both scenarios (BL and EE), raw material consumption peaks in 2015 at levels almost 20% higher than 2010. After 2015, the consumption in BL scenario reduces to 1138 Mt by 2050, due to decreased steel production. The EE scenario shows that the consumption will decrease by up to 20% compared with BL primarily due to the shift of steel production from BOF to EAF. Regarding the raw material demand by type (Fig. 3b (bottom panel)), in BL, Chinese steel production relies heavily on iron ore (amounting to 87% of the total), followed by scrap (10%). Compared to BL, the scrap share of total raw material consumption will increase by 13%, due to increased EAF production.

4.2.2. Process material consumption

Estimation of process material demand for steel industry is important because it does not only have large impact on energy/resource consumption and emissions, but also affects the accuracy of predictions for future economic growth. In the BL Scenario, the demand for process materials (i.e., sinter, pellets, flux, pig iron, and other pig iron) shows substantial increase before 2020, then gradually declines until by 2050 (Fig. 4 (upper left)). Specifically, the lowest demand of secondary materials (i.e., sinter, pellets, and flux) in EE is about 600 Mt in 2050, 26% lower than BL, due to reduction of pig iron demand. Compared to BL, the material efficiency (the ratio of useful product output to material input) has a large improvement, because crude steel production from the EAF route increases drastically. This projection is possible as EAF based steel production already accounts for 75% and 66% in USA and Europe, respectively (van Ruijven et al., 2016). Further, slag is a main waste material in the steel industry, which can occur at iron making and steel making processes. As shown in Fig. 4 (bottom right), slag production grows to 1800 Mt by 2020 in the BL scenario, then declines to 1400 Mt by 2050 and the share of iron making

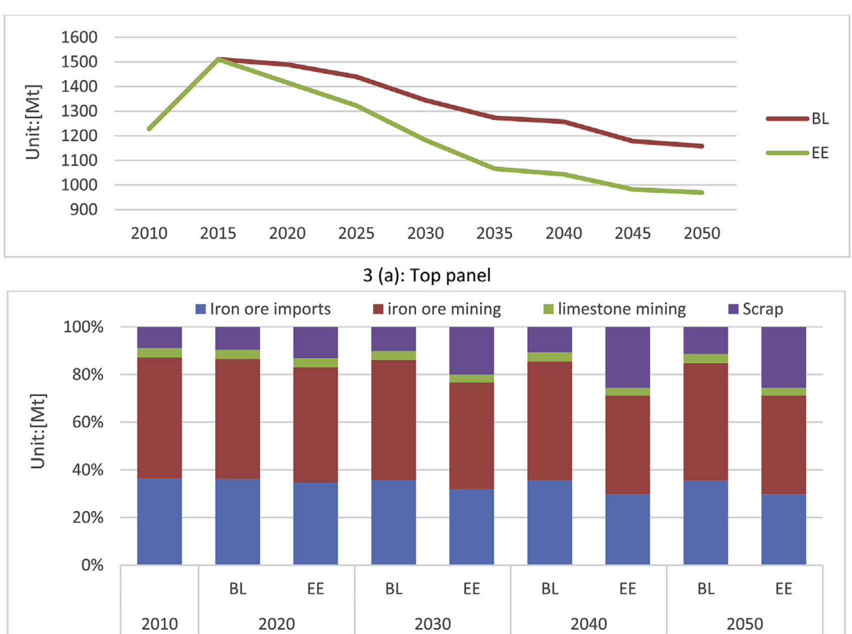

Fig. 3. Raw material consumptions in the baseline (BL) and energy efficiency (EE) scenarios.

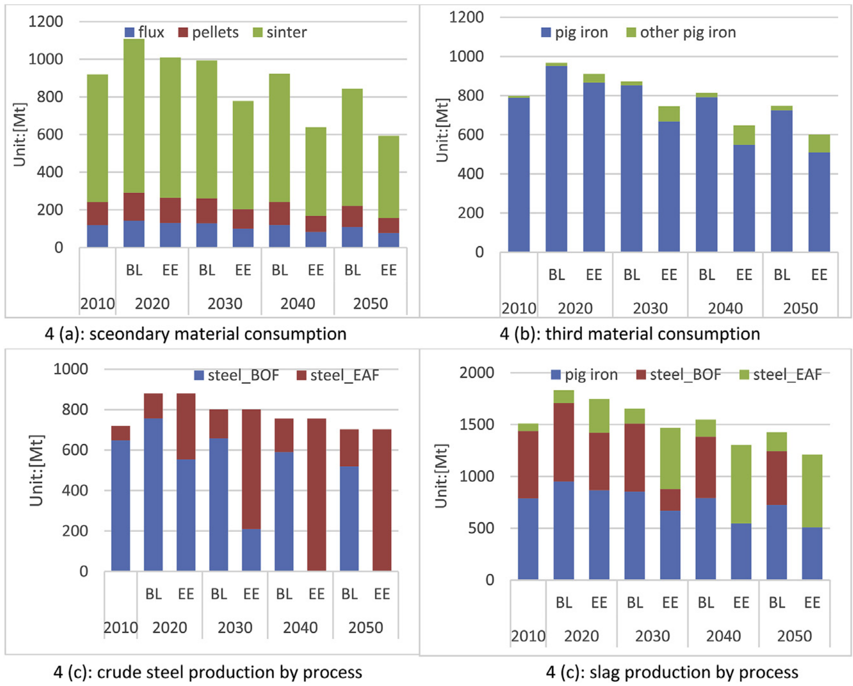

Fig. 4. Activities of process materials in baseline (BL) and energy efficiency (EE) scenarios.

process in total slag production declines slightly from 52% in 2010 to 43% by 2050. In the EE scenario, slag production is further reduced by 13% by 2050 compared with the BL. However, the share of EAF process is the largest contribution to slag production, 40% higher than in the BL scenario.

4.3. *Energy consumption from 2010 to 2050*

4.3.1. *Total final energy consumption*

Fig. 5 presents the historical and projected trends of total final energy consumption for the Chinese iron and steel industry. Energy consumption in 2010 of this study was 16% higher than our previous study (Zhang et al., 2014), due to different system boundaries used. Both scenarios show that energy consumption in the Chinese iron and steel industry reached a peak in 2015, at around 23 EJ, and then faces a decline as a result of a decrease in steel production. Further, 8% of energy consumption could be saved via implementation of energy efficiency measures. Regarding to energy mix in the Chinese iron and steel industry, coal and coke together account for 89% of total energy consumption, followed by electricity (10%) (See Figs. 5–6 and Fig. 8). In this study we assume that coal as raw materials and main energy will directly use to produce coke, via the coke making process.

4.3.2. *Coal consumption by process*

Fig. 6 shows coal consumption by process for the two scenarios. In the BL scenario, coal consumption is projected to increase to 20227 PJ by 2020 and then decrease to 15572 PJ by 2050, 23% higher and 13% lower than 2010, respectively. Implementing the selected energy efficiency measures in the EE scenario would further decrease the coal consumption by 5% in 2020 and 10% by 2050. The majority of coal consumption in the 2010–2050 period is for coke making, accounting for over 50%, followed by iron making (25%) and casting, rolling and finishing (7%). For coke making, adopting energy

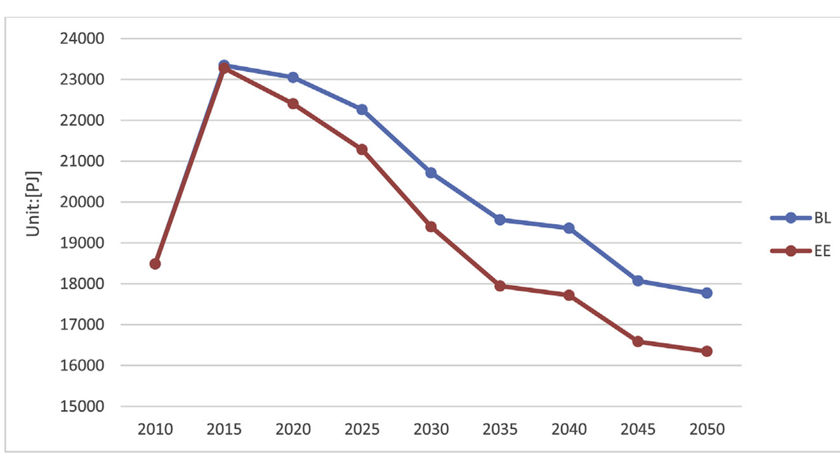

Fig. 5. Total final energy consumption in baseline (BL) and energy efficiency (EE) scenarios.

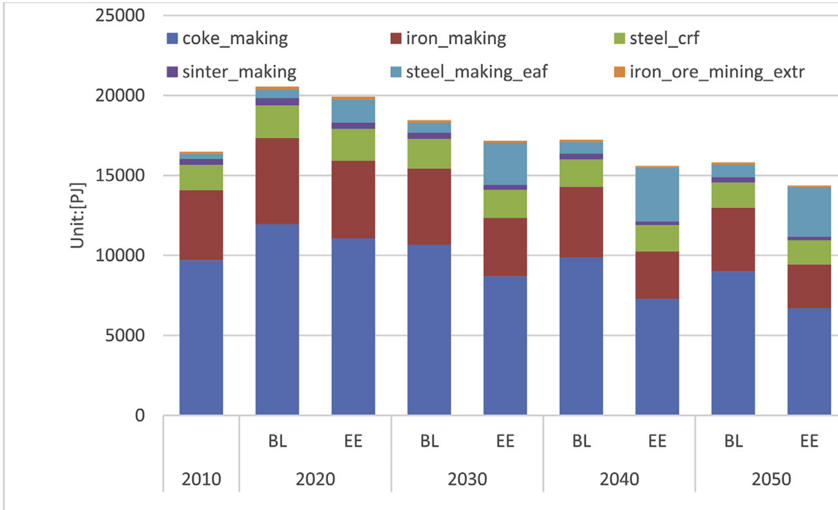

Fig. 6. Coal consumption by process in baseline (BL) and energy efficiency (EE) scenarios.

efficiency measures (i.e. coke dry quenching (CDQ), coal moisture control (CMC), variable speed drive on coke oven gas compressors, and programmed heating in coke oven) and reducing of coke demand would lead to 12–22% of coal saved, compared to BL.

4.3.3. *Coke consumption by process*

Coke consumption in steel industry is mainly due to the processes of iron making and casting, rolling, and finishing. Fig. 7 shows coke consumption by process from 2010 to 2050, under different scenarios. As shown in the figure, the coke consumption in BL scenario is projected to peak around 2020, and then decrease gradually, in line with declining pig iron demand. Coke consumption in BL scenario is forecast to decrease by 8% between 2010 and 2050, from 9020 PJ in 2010 and to 8281 PJ by 2050, while adopting energy efficiency measures in EE scenario will further decrease by 21% in 2050. Compared to BL, the EE scenario projects that the iron making process would decrease coke consumption from 7400 PJ in 2020–4200 PJ by 2050, while other processes (sinter making and pellets making) shares of coke consumption change slightly.

4.3.4. *Electricity consumption by process*

Fig. 8 presents process electricity consumption in the Chinese iron and steel industry from 2010 to 2050, under BL and EE scenarios. As compared to the consumption trends of coal and coke, the difference is that electricity consumption in both scenarios is projected to increase from 2000 PJ in 2010 to approximately 2500 PJ in 2020, and decline slightly thereafter. For the BL scenario, electricity consumption breakdown remains the same, with the majority of consumptions arising from the process of casting, rolling, and finishing (steel_crf), accounts for 37% of the total, followed by BF-BOF (20%) and iron making (16%). Electricity consumption of BF-BOF in the EE scenario will decrease drastically until 2040, while the EAF share of total electricity consumption will increase significantly (due to route switch from BF-BOF to EAF to produce steel). Energy efficiency measures would lead to a small decrease in electricity consumption for other processes (i.e., iron ore mining extraction, sinter making, pellets making, coke making, iron making, and casting, rolling, and finishing (steel_crf)) of Chinese iron and steel industry.

4.4. *Water withdrawal and consumption*

4.4.1. *Total water withdrawal and consumption*

Policy impacts on water resources management (e.g. water efficiency, and water scarcity) has become one of the most important parts of the Sustainable Development Goals (e.g., SDG-6 and SDG-

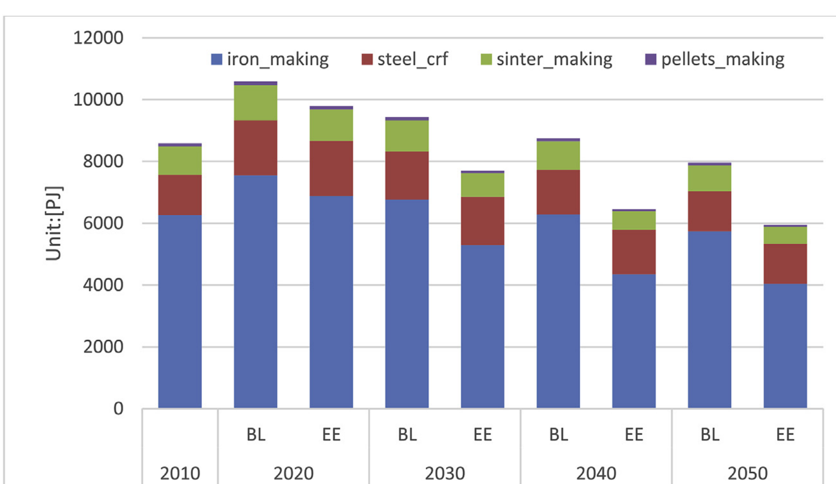

Fig. 7. Coke consumption by process in baseline (BL) and energy efficiency (EE) scenarios.

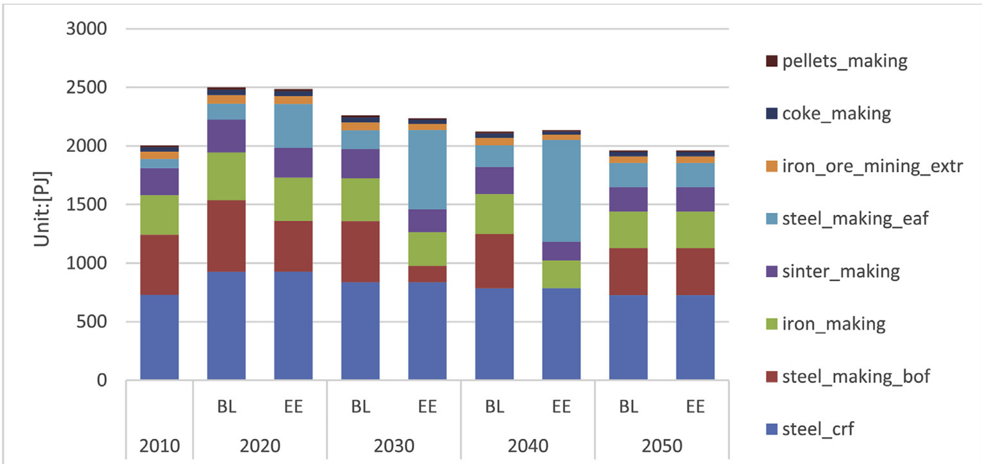

Fig. 8. Electricity consumption by process in baseline (BL) and energy efficiency (EE) scenarios.

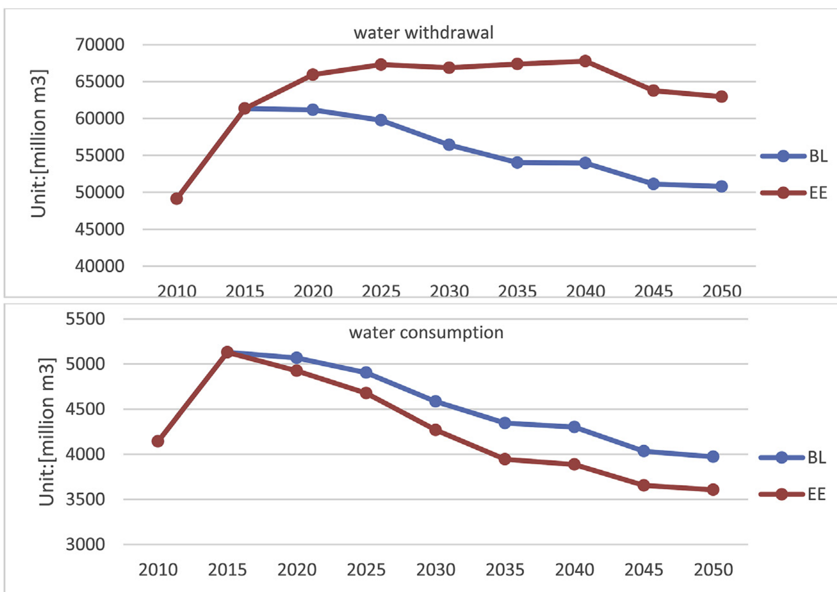

Fig. 9. Total water withdrawal and consumption in baseline (BL) and energy efficiency (EE) scenarios.

12). As mentioned before (see section 2), over 50% of the global steel production belongs to China, while only 7% of world freshwater reserves are in China (China Water Risk, 2017). In 2010, water withdrawal for the Chinese iron and steel industry was 48,900 million m^3 (representing 11% of all withdrawals in China), while 4,200 million m^3 water was consumed (China Water Risk, 2017; National Development and Reform Commission of China, 2013). Therefore, disruptions in water supply and competition for water use rights would have large impacts on steel production.

Fig. 9 shows the recent historic total water withdrawal and consumption[2] and the projection for these in steel industry between 2020 and 2050. Water withdrawal in the BL scenario peaks at 60,300 million m^3 by 2015, then decreases to 49,900 million m^3 by 2050 (Fig. 9 upper). However, the EE scenario projects an increase in water withdrawal an additional 40% by 2030 and 23% by 2050, respectively, compared to 2010. The main reason is that the technology shift from BF-BOF to scrap-EAF would cause an additional 40 m^3 of water withdrawal when producing 1 ton of crude steel (CSDRI, 2016). For BL scenario, route shift from BF-BOF to scrap-EAF and demand reduction leads to a larger drop in water consumption (the reduction potentials are 1% higher than water withdrawal). The trend of water consumption in the EE scenario differs greatly when compared to the trajectory of water withdrawal (Fig. 9 bottom panel). In the medium term, that is, up to 2035, the water consumption decreases from 5,100 million m^3 in 2015 to 3,960 million m^3 in 2035, at an annual average of 1.2%.

[2] In this study, water withdrawal is defined as the total volume removed from a water source such as a lake or river. Often, a portion of this water is returned to the source and is available to be used again, while water consumption is defined as water removed for use and not returned to its source (Duke Energy, 2018).

4.4.2. Water withdrawal and consumption by process

A detailed breakdown of the water withdrawal and consumption projected for 2010–2050 is presented in Fig. 10. As shown in Fig. 10 upper, in 2010 water withdrawal of the Chinese iron and steel industry was around 50000 million m^3, 27% of which was

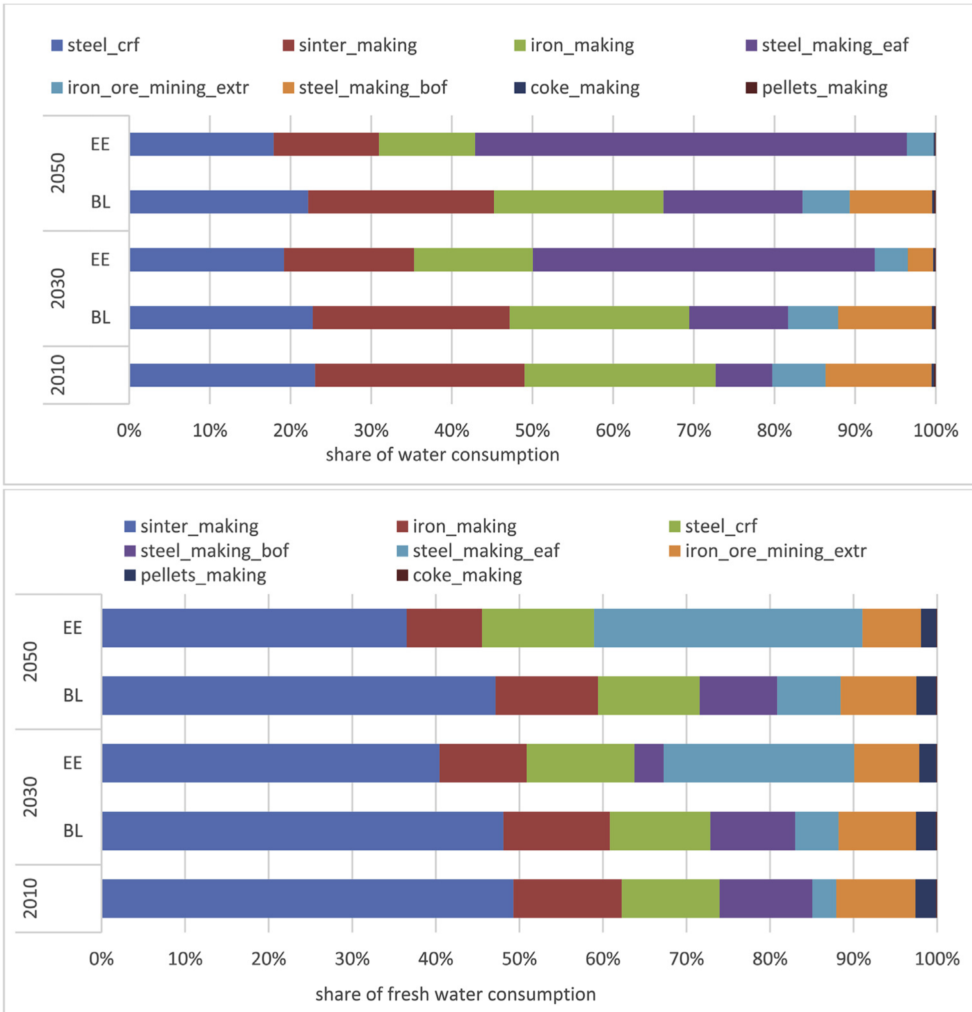

Fig. 10. Share of water withdrawal and consumptions in baseline (BL) and energy efficiency (EE) scenarios.

consumed by sinter making, followed by iron making, and steel_crf, which accounted for 27%, 24%, and 23% respectively. For the BL scenario, the water withdrawal and consumption by the process will change slightly over the study period. For example, EAF's share of total water withdrawal in the BL scenario increases only by 10% from 2010 to 2050, while it is expected to further grow to 40% by 2050, under EE scenario assumptions.

In terms of water consumption by process, as illustrated in Fig. 10 (bottom panel), in 2010 48% of freshwater was consumed for sinter making, followed by processes of iron making, steel_crf, and BOF, which respective shares of 14%, 11%, and 11%, respectively. For the EE scenario, the top largest share of fresh water withdrawal is projected in sinter making, which accounts for 37%, followed by EAF (28%), due to route shift from BF-BOF to scrap-EAF. Combined, coke making, BOF, and pellets making account for only 3%, partly caused by the implementation of energy efficiency measures such as Top-pressure recovery turbines (TRT) in iron making, and Coal moisture control (CMC) and Coke Dry Quenching (CDQ) in coke making.

4.5. *Projected emissions of CO_2 and air pollutants*

4.5.1. *CO_2 emissions by types*

We estimate the CO_2 emissions of China's iron and steel industry by 2050 under BL and EE scenarios. Note that the total CO_2 emissions in this study is higher than previous studies (Hasanbeigi et al., 2017; Zhang et al., 2014), due to different system boundaries used. For example, most of previous studies have only calculated the direct energy related CO_2 emissions (Hasanbeigi et al., 2013c; Zhang et al., 2014), while we consider both the direct and indirect emissions - the process emissions from limestone and energy related emissions from the processes of coke making, and iron ore mining. As shown in Fig. 11, in 2010 the largest source for Chinese iron and steel industry is coke that accounts for 44%, followed by coal (31%) and electricity (23%). We show that fossil fuel related CO_2 emissions in both scenarios are expected to remain at the present level. The total CO_2 emissions in BL scenario are projected to peak at around 2500 Mt in 2020, and then decrease to 1957 Mt by 2050. Adopting energy efficiency measures and shifting from BF-BOF to scrap-EAF in EE scenario leads to 5–8% of emissions avoided during the study period.

4.5.2. *p.m.$_{2.5}$ emissions by process*

Major sources of $PM_{2.5}$ emissions in steel production are from fuel combustion, process emissions (e.g., sinter making, iron making, steel making, and raw material extraction), and indirect emissions of electricity consumption. We present the levels of total $PM_{2.5}$ emissions and its contributors in Chinese iron and steel industry (see Fig. 12). In future projections, the total $PM_{2.5}$ emissions

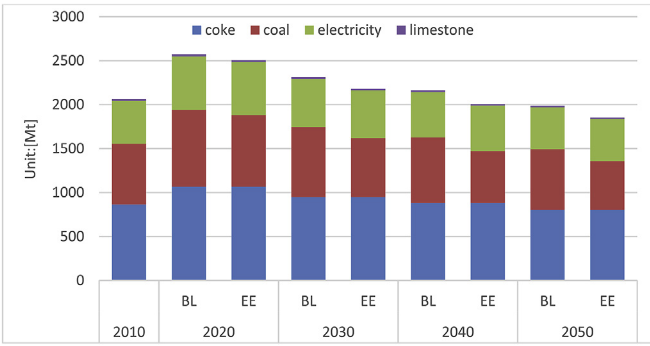

Fig. 11. CO_2 emissions by fuel types in baseline (BL) and energy efficiency (EE) scenarios.

in the BL scenario increase drastically until they peak at around 1200 kt in 2015 and decrease thereafter, due to the changes of outputs of steel products (see Fig. 12 – top panel). However, the emissions in the EE scenario will increase until around 2025, and then start to go down slowly, due to the increasing share of EAF technology, which has the process emission factor of EAF 3 times higher than BOF in China (Wang et al., 2016; Wu et al., 2015).

Regarding $PM_{2.5}$ emissions by types for the China's iron and steel industry (see Fig. 12 – bottom panel), in 2010 around 50% of emissions come from coal combustion in Chinese iron and steel industry, followed by the process emissions of sinter making and BOF, which together account for 30%. The shares evolve along the same patterns as the year 2010 in BL scenario. For the EE scenario, with increasing application of EAF technology, EAF's share of total $PM_{2.5}$ emissions will increase by 35% in 2050, compared to 2010 (see Fig. 12 - bottom panel). If we only consider the emissions from fuel combustion and electricity consumption for steel production, the energy related $PM_{2.5}$ emissions in the EE scenario will decrease by 20% as compared to the BL scenario, as result of the implementation of energy efficiency measures.

4.5.3. NOx emissions by process

NOx emissions of China's iron and steel industry for the period 2010–2050 are shown in Fig. 13. Overall, the emissions in BL scenario will increase up to 5900 kt by 2020 and 4500 kt by 2050 - approximately 20% higher and 6% lower respectively, than the year 2010. For the EE scenario, the total NOx emissions are expected to further decline by 5–10% through the implementation of energy efficiency measures. In comparison to the contributors of $PM_{2.5}$ emissions, coal's share of total NOx emissions in Chinese iron and steel industry is significantly higher, as the emissions are mostly formed under the high temperature conditions – meaning that the combustion of fossil fuels is usually involved. Both scenarios show that the energy related NOx emissions (including coal and electricity) is projected to remain steady, over 90%, from 2010 through 2050.

4.5.4. SO_2 emissions by process

The iron and steel sector is China's largest industrial SO_2 source, and originates mostly direct emissions of coal combustion and sinter making, as well as indirect emissions of electricity consumption (Ma et al., 2012). Fig. 14 gives an overview of SO_2 emissions for the period 2010–2050, which after a rapid increase until 2015, shows a gradual decline up to 2050. In the BL scenario, SO_2 emissions peak at around 3000 kt in 2020 and fall to 2300 kt in 2050, due to reductions in steel products. With the implementation of energy efficiency measures and adoptions of EAF in EE scenario, the SO_2 emissions peak at 2770 kt in 2020 and fall to 2000 kt in

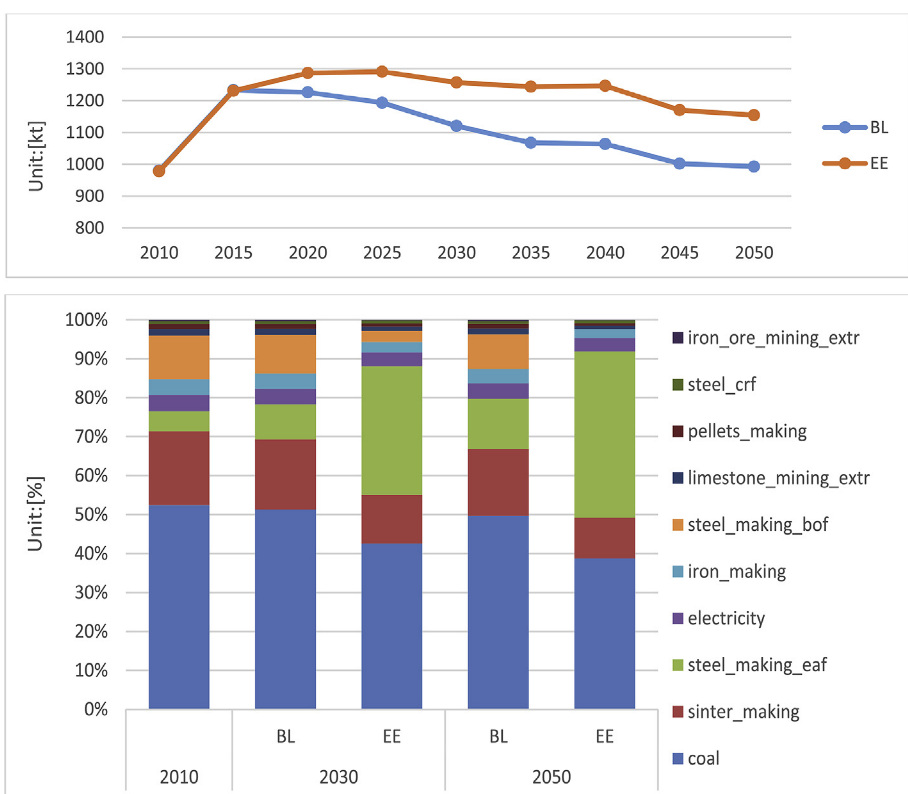

Fig. 12. $PM_{2.5}$ emissions by fuel types and process in baseline (BL) and energy efficiency (EE) scenarios.

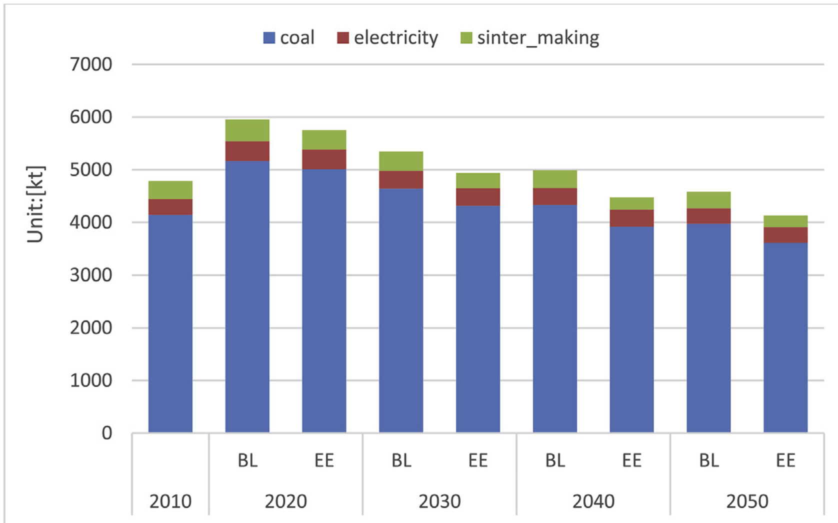

Fig. 13. NOx emissions by fuel types and process in baseline (BL) and energy efficiency (EE) scenarios.

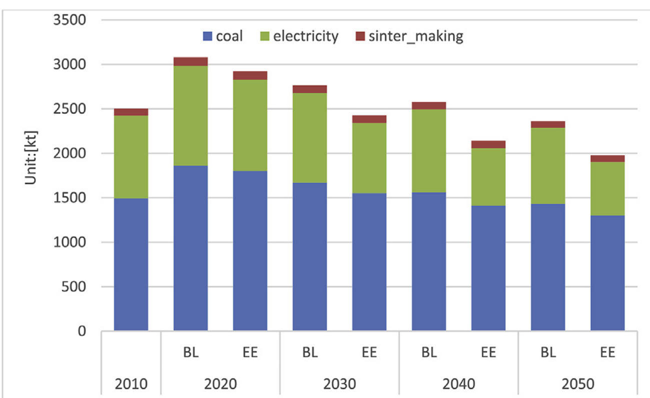

Fig. 14. SO_2 emissions by fuel types and process in baseline (BL) and energy efficiency (EE) scenarios.

2050, at average 8–13% lower than BL level. Both scenarios also demonstrate that coal is expected to account for the major share (60%) of total the emissions, whereas coal's share remains consistent in BL and EE scenarios over the study period.

This study demonstrates that adopting energy efficiency measures combined with shifting route from BF-BOF to scrap-EAF have large potentials to reduce raw material consumption, improve energy and water use efficiencies, and decrease emissions of SO_2 and NOx. At the same time, these efforts lead to higher scrap consumption and water withdrawal, and increased $PM_{2.5}$ emissions. Further, air pollution control technologies (e.g. electrostatic precipitator, Selective Non Catalytic Reduction or Selective Catalytic Reduction, and Flue Gas Desulfurization) and Carbon Capture and Storage can further decrease emissions of GHG and air pollutants, but will need extra investment and consume additional energy.

5. Discussion for model uncertainty

Model uncertainty (i.e. model structure uncertainty, parameter uncertainty, and the uncertainty related to assumptions such as boundary conditions) is very important in the decision-support processes, because models cannot predict the future with precision (Nilsen and Aven, 2003; Zhang et al., 2015b). Development of the demand sector in integrated assessment models, like MESSAGEix – iron and steel model, is a key issue to provide a holistic understanding of the dynamics energy and resources systems. Like all integrated assessment models, there are several considerable uncertainties in certain parts of the MESSAGEix – iron and steel model, e.g. natural resource availability, material/energy substitution and its trade off across regions, development of the markets of iron and steel both nationally and internationally, as well as in robust technology strategies and related investment portfolios. Several studies indicate that policy makers are more interested in robust strategies rather than uncertainties, due to the robustness of policy actions have lesser impacts via changes in the uncertain model elements (Amann et al., 2011). Therefore, a MESSAGE robust decision-making framework with an endogenous representation of uncertainties (e.g. errors of input parameters) has been developed (Krey and Riahi, 2009) and used to quantify the uncertainties inherent in socioeconomic and technological response strategies to energy and climate challenges. Specifically, stochastic optimization with a fully endogenous representation of uncertain parameters (e.g., technology parameters, and intensity use of materials) and policy robustness (e.g., changes in carbon price) can be used to tackle multiple challenges with minimization cost or maximization resource utilization. Note that the objective of this study is to introduce that how to develop sub-sectors in the IAM MESSAGEix. Therefore, the model uncertainty of the case study was intentionally left beyond the scope of this paper.

6. Conclusion and implications for further research

Improvement in the representation of the industry in MESSAGEix is necessary to reconcile how behaviour and policy interacts with strategies to tackle multiple challenges, e.g. climate targets and SDGs. To depict the individual characteristics and complex interactions within and with industries, this paper describes how the iron and steel industry is modelled in MESSAGEix. Specifically, we integrate Material/Energy/Water Flow Analysis (represents carriers of energy, material and water and the associated technologies) and nexus approach into the MESSAGEix framework to develop the MESSAGEix – iron and steel industry model. This model can not only quantify synergies between raw material uses, consumptions of scrap, energy and water, emissions of CO_2 and air pollution, and the potential costs and benefits of different efforts, but can also yield valuable insights into the interactions across sectors. For example, adopting energy efficiency measures and switching BF-BOF to scrap-EAF in the EE scenario is projected to decrease raw material by 14%, energy by 7%, water by 8%, CO_2 by 7%, NOx by 9%, and SO_2 by 14% respectively, compared to BL scenario. At the same time, water withdrawal and $PM_{2.5}$ emissions in the EE scenario will increase by 14% and 20%, compared to the BL scenario. However, additional air pollution control technologies can efficiently decrease $PM_{2.5}$ (Zhang et al., 2014). It means that the energy efficiency measures of Chinese iron and steel industry would leads to huge resource-energy-environment nexus and have large impacts on economic saving potential. Therefore, policy makers should consider nexus effects to overcome the barriers (e.g., capital constraint, imperfect information, institution governance et al.) of energy efficiency measures when designing integrated policies to achieve multiple targets.

Moreover, for future works within the MESSAGEix - iron and steel model, we need to consider what innovation technology/measures will be used to improve the efficiency of steel production, e.g., how to introduce the hydrogen and renewables in the steel industry in a cost-effective manner. We also need to evaluate that new steel products will be required by the demand sectors (e.g., building and transportation industries). We recommend that introducing manufacturing sub-sectors to IAMs would allow to study new specific energy/water saving and emission mitigation options and develop more efficient policies, including co-benefits of improvement options for IAMs to be modelled more accurately. Therefore, future works that employ and expand the presented approach to develop the manufacturing sectors (e.g., steel, cement, pulp and paper, chemical, aluminium, etc.) in MESSAGEix at global and regional/country scales would be valuable, so these efforts can accurately quantify the impacts of various strategies and response to future challenges. For the purpose, the MESSAGEix model is already distributed on Github with an open-source license (Huppmann et al., 2019).

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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.2019.05.392.

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