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Modeling technological change and its impact on energy savings in the U.S. iron and steel sector

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HIGHLIGHTS

- Provides a framework for dynamic modeling of cost for new and emerging technologies.
- Demonstrates impact of learning on technology penetrations and corresponding cost savings.
- Demonstrates impact of learning on energy savings and CO_2 emissions reduction.

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ABSTRACT

Market penetration of energy-efficient technologies can be estimated using energy optimization models that minimize cost; however, such models typically estimate the minimum cost of optimal pathways under a certain set of non-dynamic assumptions, so technology penetrations determined for the long-term do not fully respond to changing circumstances or costs. In this study, investment costs of energy-efficient technologies are modeled dynamically in the Industrial Sector Energy-Efficiency Model (ISEEM) using a technological learning formula. Results from 24 energy-efficient technologies – 14 existing, 10 emerging – selected from the United States (U.S.) iron and steel sector show that when technological learning is incorporated into the model, total energy consumption of this sector is expected to decrease by 13% (180 PJ) in 2050 compared to energy consumption in a non-learning scenario. Average energy intensity of the steel production improves from 12.3 GJ/t in the non-learning scenario to 10.7 GJ/t in the learning scenario in 2050. This decrease represents a cost savings of US$1.6 billion and a carbon dioxide emissions reduction potential of 14.9 billion tonnes. Results discussed in this paper focus on the U.S. iron and steel sector, but the proposed framework can be applied to study new technology development in any other industrial processes and regions.

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1. Introduction

Energy models have been used for decades to support understanding of current and future energy-related issues such as demand and supply, environmental impacts, economic performance, and policies. Energy models also assist those responsible for policy and technology investment decisions for future energy systems.

Energy models with the objective of minimizing cost typically allocate weights to technologies using assumptions and parameters from a given point in time. This static approach prevents optimization from responding to evolving circumstances, such as decreasing technology costs [1]. Although new and emerging energy-efficient technologies have significant potential to save energy and reduce carbon dioxide (CO_2) emissions, most are, in their early stages, not cost-competitive against conventional practices. As a result, they are unlikely to be included in the optimal mix determined by a model minimizing cost, or their adoption is not anticipated to be rapid enough to reach a specified level of energy savings unless the cost reduction resulting from these technologies is modeled properly. Similarly, technology adoption rates determined by the model are also unlikely to be realistic if the cost decrease associated with the technology is optimistic.

Studies have shown a strong correlation between technology investment cost and market adoption. The learning curve can capture this relationship by considering the cost of a given technology as a function of cumulative installed capacity or cumulative production. The curve approximates the "experience or knowledge" accumulated when the technology is deployed. The cost of a technology might decline as a result of increasing market adoption because of the accumulation of knowledge through

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Nomenclature

b	learning parameter
BF_AUCOG	additional use of coke oven gas
BF_HR	blast furnace heat recuperation
BF_ING140	injection of natural gas to 140 kg/thm
BF_IO130	injection of oil up to 130 kg/thm
BF_PCI130	pulverized coal injection to 130 kg/thm
BF_PCI225	pulverized coal injection to 225 kg/thm
BOF	basic oxygen furnace
BOF_ABA	aluminum bronze alloy to improve hood, roof, & side-wall life
BOF_CR_HC	hot charging
BOF_CR_ISRT	in-situ real-time measurement of melt constituents
BOF_CR_RB	recuperative burners
BOF_CR_TSC	thin slab casting
BOF_SHR	blast furnace slag heat recovery
C_t	unit cost of production at time t
C_1	first unit's production cost
CdTe	cadmium telluride
CO_2	carbon dioxide
COK_NRCO	non-Recovery Coke Ovens
COK_SCCR	single-chamber-system coking reactors
COK_SCOPE21	advanced coke oven (SCOPE21)
EAF	electric-arc furnace
EAF_ABA	aluminum bronze alloy to improve hood, roof, & side-wall life
EAF_BS	Bottom Stirring/Stirring gas injection
EAF_CR_ISRT	in-situ real-time measurement of melt constituents
EAF_DF	DC-arc furnace
EAF_EBT	eccentric bottom tapping on existing furnace
EAF_FS	foamy slag
EAF_TS	twin shell w/scrap preheating
EPA	Energy Protection Agency
ETL	endogenous technological learning
GENIE	energy system model with uncertain learning
GHG	greenhouse gas
GJ	gigajoule
ISEEM	industry sector energy-efficiency model
LR	learning rate
MESSAGE	model for energy supply strategy alternatives and their general environmental impact
MIP	mixed-integer programming
NHTSA	National Highway Traffic Safety Administration
PR	progress ratio
PJ	petajoule
PV	photovoltaics
SIN_SWGR	selective waste gas recycling - EPOSINT Process
SIN_UWFSP	use of waste fuels in the sinter plant
t	time period
U.S.	United States
X_t	cumulative production at time t

learning-by-doing and learning-by-using [2–4]. Although a number of factors, including technical, economic, environmental, social, and policy, can influence cost reductions, the learning curve approach can still be a useful tool to project cost reductions and has been widely used to describe cost change during the period when a technology is deployed. In their wind turbine price analysis, Yu et al. [5] showed that learning is the most important factor associated with the larger turbine price reductions in China.

Integration of endogenous technological learning (ETL) in energy models allows the models to dynamically decrease the cost with increasing market adoption rates [6]. Faster adoption of the technology may simulate further decrease in costs [6–9]. Learning curve approach has been incorporated into many energy models to project cost reductions from investment in new energy generation or conversion [10]. Yao et al. [11] used a learning curve approach while investigating financing options to support grid parity for wind electricity in China. Their results showed that a learning rate of 8.9% would be necessary to make wind electricity competitive. Bergesen and Suh [12] investigated the impact of technological learning with cadmium telluride (CdTe) photovoltaics (PV) on greenhouse gas (GHG) emissions and costs. According to the results, learning could further reduce emissions and costs by up to 1–2%, compared to a non-learning case. Wu et al. [13] explored long-term cost of carbon capture and storage in China when learning was included. Wand and Leuthold [14] examined the potential effects of Germany's feed-in tariff policy for roof-top solar PV systems for 2009 and 2030 by using a dynamic optimization model including learning-by-doing. Nakata et al. [15] integrated ETL into a bottom-up energy-economic model to examine clean coal technologies in Japan. Their results illustrated that technological progress by learning has a positive impact on the penetration of clean coal technologies in the electricity market, and the learning model has a potential for assessing upcoming technologies in future.

To the authors' knowledge, no study has investigated the impacts of learning on energy-efficient technologies in industrial processes. Evaluating the energy and environmental impacts of emerging energy-efficient technologies in industrial processes requires a prospective modeling of how total costs and inputs change with scale and experience. In this paper, energy savings and CO_2 emission reduction potentials in the United States (U.S.) iron and steel sector are assessed by incorporating learning curves for energy-efficient technologies into a bottom-up linear optimization model, the Industry Sector Energy Efficiency Model (ISEEM), so that investment costs of selected technologies decrease as a function of their cumulative activity. Iron and steel sector is one of the highest energy and emission intensive industrial sectors, accounting for about 22% of world total industrial energy use and 31% of industrial direct CO_2 emissions in 2012 [16]. The U.S. is the fourth largest steelmaking country in the world with a production of 78.8 Million tonnes (Mtonnes) in 2015 [17]. Our analysis focuses on a selection of energy-efficiency measures: 14 existing and 10 emerging technologies. The examination of the existing and future energy efficiency potential in this sector with presence of learning will help us better understand long-term energy needs and improvement opportunities.

The remainder of the paper is organized as follows: Section 2 presents an overview of learning curve studies. Section 3 presents our methodology, assumptions, and energy model. Section 4 discusses analysis results. Section 5 reports our conclusions.

2. Literature review

Technological learning, often termed leaning-by-doing, was proposed as a way to represent technical change in Wright [18] and Arrow [19]. The traditional learning curve considers the specific cost of a given technology as a function of cumulative capacity or cumulative production. Specifically, for each doubling of cumulative production, the unit production cost decreases by a certain value known as the learning rate [10]. The typical learning curve function (as in Wright's model) takes the form of:

$$C_t = C_1 X_t^{-b} \quad (1)$$

$$\log C_t = logC_1 - b * logX_t \quad (2)$$

$$PR = 2^{-b} \quad (3)$$

$$LR = 1 - PR \quad (4)$$

where C_t is the unit cost of production at time t, C_1 is the first unit's production cost, X_t is the cumulative production at time t, b is the learning parameter (i.e., experience index), PR is the progress ratio, and LR is the learning rate. The progress ratio expresses the rate at which unit production cost declines for every doubling of cumulative production. Nagy et al. [20] tested the effectiveness of several models for predicting technological progress and showed that Wright's model produces the best forecast.

The Boston Consulting Group applied learning phenomena to analyze the relationship between the average unit price and cumulative output of 24 industrial products in 1968. Since then, this approach has been used in empirical studies in a wide range of sectors, including manufacturing [3,21], consumer products [22,23], energy supply technologies [24–41], energy demand technologies [42–44] and environmental control technologies [45–47].

Learning curves have also been widely used to model the future costs of energy technologies in energy models (see Table 1 for examples), and to forecast future energy mixes based on the projected costs of technologies [12,48]. Junginger et al. [10] provides a review of energy models incorporating technological learning, and discusses how learning has been captured. Energy models are generally divided into two categories: bottom-up models and top-down models. Grubler et al. [49] describes the bottom-up models as the models that typically seek to minimize the costs of serving an exogenous energy demand subject to technological and environmental constraints, by choosing which technology to install. Top-down models typically evaluate the system from aggregate economic variables and apply macroeconomic theory and econometric techniques. Technology is commonly described through the relationship of inputs and outputs of the general equilibrium in top-down models [10]. Even though there happened several attempts to include learning in top-down models as a consequence of consumption and capacity expansion and R&D expenditures, top-down models are mostly combined with bottom-up sub-models to include learning [10]. Most applications of the learning-by-doing concept are found in bottom-up energy models. Junginger et al. [10] claims that bottom-up models are more suitable for learning curve integration, since the technologies and specific investment costs are explicitly represented.

Incorporating learning in an endogenous manner into bottom-up linear optimization models often causes computational problems because the learning curve is non-convex and non-linear [50]. The most common way of solving this problem in linear programming models is mixed-integer programming (MIP), as reported in the literature for MARKAL [51], MESSAGE [52] and GENIE energy models [53]. However, this approach is very computer intensive and more computationally complex than conventional linear programming models. The solution time and degree of success in finding optimal solutions depend on specific solver options.

Capros et al. [54] discusses that full endogenisation of learning even with simplistic assumptions is not viable yet for some large-scale energy models. Thus, a number of results are based on a highly aggregated versions of the models or clustering of technologies. For example, Anandarajah et al. [55] used a multi-cluster global technology learning approach in the TIAM-UCL global energy system model to analyze the role of hydrogen and electricity in decarbonizing the transport sector. Rafaj and Kypreos [56] used the Global MARKAL-Model (GMM) with ETL to address impacts of internalization of external costs from power production. They do not involve in clustering of technologies or aggregation of the sectors. However, in this analysis, learning is limited only for some specific technologies for the simplicity of the calculation. Riahi et al. [57] incorporated the learning curve into the energy-modeling framework MESSAGE-MACRO to analyze market potentials of carbon capture and sequestration technologies. They concluded that endogenized technological learning is computationally infeasible for their model, which included over 400 energy technologies and operate on 11 world regions. They used an iterative approach between MESSAGE and the learning curve to adjust technology cost and cumulative installed capacities. Balash et al. [58] also used the MARKAL model to analyze the influence of regulations and market-based environmental policy approaches on the mix of fuels used for electricity generation and the cost of electricity in different parts of the U.S. Similarly, they indicated that they were not able to run the MARKAL model with ETL since it presented a challenge in terms of solution time. Instead, they derived normalization parameter and cumulative capacity installation from the results of the ETL – MARKAL runs under different scenario assumptions and estimated cost of reduction outside of the model using a learning rate parameter. This approach is capable of capturing the reduction of cost due to installed capacity investment in the modeling period. However, the relation is only one way and does not consider the possibility of further investment due to low prices.

Table 1
Technological learning in selected energy models.

Approach	Model	Parameter affected by learning	References
Bottom-up	MESSAGE	Energy investment cost	[52]
	GENIE	Energy investment cost	[53,68]
	MESSAGE	Energy investment cost	[4]
	MESSAGE	Energy investment cost	[69]
	MARKAL	Energy investment cost	[70]
	POLES	Energy investment cost	[71,72]
	MERGE	Energy investment cost	[73]
	DNE21 +	Energy investment cost	[74]
	MESSAGE-MACRO	Energy investment cost	[75]
	GET-LFL	Energy capital cost and energy conversion activities.	[76]
Top-down	DEMETER	Energy production cost	[40,77]
	ETC-RICE	Abatement activities and knowledge stock.	[78]
	RICE	Energy investment cost and knowledge stock.	[79]
	E3 MG	Energy investment cost (electricity generation technologies).	[80]
	IMACLIM-R	Energy investment cost (electricity generation technologies).	[81]

3. Methodology

To overcome the computational difficulties discussed, we followed a similar approach to Riahi et al. [57] and applied an iterative solution algorithm between ISEEM and the learning curve formula. As mentioned earlier in Section 1, to author's knowledge, there is no literature that has investigated the impacts of learning on energy-efficient technologies in industrial processes. Cumulative output, or cumulative installed capacity of energy-generation or energy-conversion technology is often the variable that interacts with cost in learning curve analyses. However, energy-efficient technologies do not provide a direct output (i.e., energy) but rather conserve output (i.e., save energy) [59]. In this study, we define energy-efficient technologies as alternatives that decrease the energy requirements of production processes, at additional cost. Cumulative activity, which represents the operation of the energy-efficient technologies, is the variable that interacts with cost in the learning curve.

3.1. Industry sector energy efficiency model (ISEEM)

ISEEM is a bottom-up linear energy model with a cost minimization objective, designed to represent energy consumption and emissions of industrial processes and sectors on periodic basis [60]. In the standard form, ISEEM assumes exogenous technological change, i.e., unit costs of technologies can improve by flat rates over time, independent of technology penetration. The iterative solution approach integrates the ISEEM and learning curve outside of the optimization (Fig. 1), which avoids the mathematical difficulties mentioned in the previous section. This iteration continues until the end of the modeling period.

The iterative solution algorithm requires the following input parameters for each energy-efficient technology:

- Cost at the start period, i.e., the initial year of the modeling horizon.
- Penetration rate at the start period.
- Learning rate.

The penetration rate enables ISEEM to calculate initial (i.e., start period) cumulative activity of the energy-efficient technology. ISEEM begins accumulating activity of the technology from the model's start period; cumulative activity of the existing energy-efficient technologies before the beginning of the modeling horizon is not taken into account. Because the cost at the start period of the modeling horizon is the initial cost of the learning curve formula,

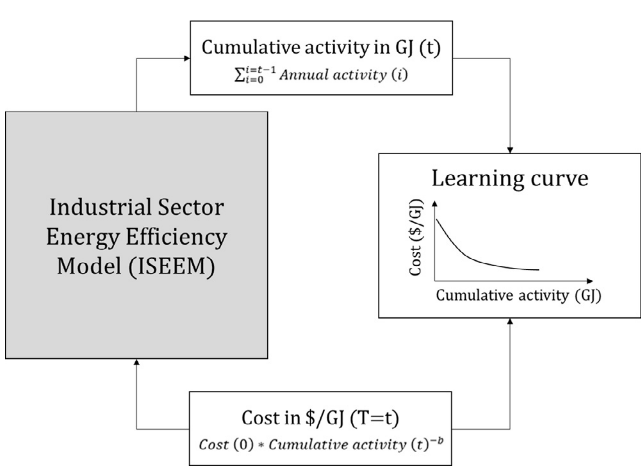

Fig. 1. The iterative solution algorithm between ISEEM and learning curve formula.

this approach would not affect the accuracy of the calculations. The learning curve formula is used as follows:

$$Cumulative\ activity(t) = \sum_{i=0}^{i=t-1} Annual\ activity(i) \tag{5}$$

$$Cost(t) = Cost(0) * Cumulative\ activity\ (t)^{-b} \tag{6}$$

$$PR = 2^{-b} \tag{7}$$

where the cumulative activity of an energy-efficient technology at period t (Cumulative activity (t) in gigajoules [GJ]) is the sum of annual activity of the technology until the period t (i.e., between the start period ($t = 0$) and the period $t - 1$ [excluding period t]). Cost (t) is the unit retrofit cost (in US$/GJ) of the technology at period t, Cost (0) is the unit retrofit cost (in US$/GJ) of the technology in the first period that it is available, b is the learning parameter, and PR is the progress ratio.

3.2. Assumptions and scenarios

In this study, we analyze the U.S. iron and steel sector. The U.S. iron and steel sector model is based on our earlier studies [61,62] and contains 18 production technologies, including basic oxygen furnace (BOF) and electric-arc furnace (EAF). Because sintering, blast furnaces, BOFs, EAFs, and casting are mature technologies, no technological learning is considered for them. More than 70 energy-efficiency measures are currently applied at different scales (e.g., low penetration or mature) in the U.S. iron and steel industry. About 60% of these technologies are used at their maximum potential or close to maximum [63]. The model calibration includes all the energy-efficient technologies. Our analysis focuses on existing energy-efficiency technologies with low penetration levels, i.e., whose penetration could be significantly expanded, and emerging technologies.

3.2.1. Selection of energy-efficient technologies

Our study includes 24 energy-efficient technologies, listed in Table 2. Fourteen are existing; of these, 13 have low market penetration while foamy slag currently has 60% penetration. Ten are emerging technologies with no current penetration. All energy-efficient technologies, except three coke-making technologies, are retrofits of existing infrastructure. With the exception of injection of hydrocarbon sources into blast furnaces, the other retrofit measures do not compete with each other and could be used together to reduce the overall cost. Coal, natural gas, and oil are the main substances injected in U.S. blast furnaces to replace coke. Each requires a different technological structure, so they are alternatives to each other. Similarly, each of the efficient coke-making technologies is an alternative to the traditional system and to the other efficient coke-making technologies.

Basic parameters and assumptions for the U.S. iron and steel production processes can be found in Karali et al. [61,62] and for 14 energy-efficient technologies in Table A1 in Appendix A. Technology-specific learning rates and maximum penetration levels used in this study for existing energy-efficient technologies come from an earlier study by the authors, which calculates the learning rates of energy-efficient technologies used in the U.S. iron and steel sector [63]. For emerging technologies, we use the average learning rate from the same study for energy-efficient technologies that have penetration levels of 20% or below (i.e., learning rate of 10%). Emerging technologies are assumed to be available starting from the year 2020, and have maximum penetration limits of 2%; 25%; and 80% in 2020, 2035, and 2050, respectively. Existing technologies are included in the model from the start period onward. Definitions of existing and emerging

Table 2
Energy-efficiency measures and technologies included in the analysis.

Route	Process	Measure/technology	Code	Existing status (2015)	Learning rate
BOF*	Sintering	Use of waste fuels in the sinter plant	SIN_UWFSP	10% penetration	2%
		Selective waste gas recycling - EPOSINT Process	SIN_SWGR	0% (emerging)	10%
	Coke making	Non-recovery coke ovens	COK_NRCO	18% penetration	10%
		Single-chamber-system coking reactors	COK_SCCR	0% (emerging)	10%
		Advanced coke oven (SCOPE21)	COK_SCOPE21	0% (emerging)	10%
	Blast furnace	Pulverized coal injection to 130 kg/thm*	BF_PCI130	21% penetration	6%
		Pulverized coal injection to 225 kg/thm	BF_PCI225	26% penetration	6%
		Injection of natural gas to 140 kg/thm	BF_ING140	21% penetration	6%
		Injection of oil up to 130 kg/thm	BF_IO130	21% penetration	6%
		Additional use of coke oven gas	BF_AUCOG	0% (emerging)	10%
		Blast furnace heat recuperation	BF_HR	0% (emerging)	10%
	BOF	Aluminum bronze alloy to improve hood, roof and sidewall life	BOF_ABA	0% (emerging)	10%
		Blast furnace slag heat recovery	BOF_SHR	0% (emerging)	10%
		In-situ real-time measurement of melt constituents	BOF_CR_ISRT	0% (emerging)	10%
	Casting	Thin slab casting	BOF_CR_TSC	18% penetration	6%
	Rolling	Hot charging	BOF_CR_HC	21% penetration	7%
		Recuperative burners	BOF_CR_RB	21% penetration	7%
EAF*	EAF	Bottom stirring/Stirring gas injection	EAF_BS	11% penetration	4%
		Foamy slag	EAF_FS	60% penetration	2%
		Eccentric bottom tapping on existing furnace	EAF_EBT	5% penetration	6%
		DC-arc furnace	EAF_DF	20% penetration	6%
		Aluminum bronze alloy to improve hood, roof and sidewall life	EAF_ABA	0% (emerging)	10%
		In-situ real-time measurement of melt constituents	EAF_CR_ISRT	0% (emerging)	10%
	Casting	Twin shell w/scrap preheating	EAF_TS	10% penetration	4%

See Karali et al. [64] for details of the learning rates.
* BOF - basic oxygen furnace, EAF - electric-arc furnace, kg/thm- kilograms per therm.

energy-efficient technologies used in this study can be found in U.S. EPA [64], Hasanbeigi et al. [65], and Worrell et al. [66].

3.2.2. Modeling scenarios

Energy consumption and CO_2 emissions are forecasted for the U. S. iron and steel sector between the 2010 and 2050 at five-year time intervals. We calibrated the model in 2010 based on realized steel production, energy consumption, CO_2 emissions, and production cost.

We assess energy consumption and CO_2 emissions using three scenarios, described below:

Static (Frozen) Case:
In this scenario, we assume that the following are unchanged from 2010 levels: production shares of EAF and BOF processes, market penetration of energy-efficient technologies, and energy intensities and material requirements for all processes within the system boundary. This limitation does not apply to the other scenarios.
Non-learning Case:
This is a business-as-usual scenario without any technological learning, i.e., with constant technology cost.
Learning Case:
In this scenario, we apply learning parameters to energy-efficient technologies starting from 2015. Each technology's investment cost reduces as the technology activates in this scenario.

We run the static scenario first to investigate how energy consumption and emission levels would evolve in the long term (i.e., between 2010 and 2050) without any change in the existing structure. Then, we analyze how those variables would change with and without technological learning for energy-efficiency measures.

3.2.3. Other inputs

Steel demand is an exogenous input to the model. The U.S. steel industry is mature with a slow growth rate. Production was around 100 Mt per year during the 2000s, except during the recession years of 2001 and 2009. In particular, production dropped by half in 2009, and has not fully recovered from that drop. For future projections, we use 1.5% annual growth between 2015 and 2025 with production reaching pre-crisis levels around 2025. After that, we use a growth rate of 0.5% per year thorough the planning horizon. Details of exogenous steel production projection can be found in Fig. A1 in Appendix A.

4. Results

This section discusses our analysis results regarding how the penetration of energy-efficient technologies changes as a consequence of the changes in cost that result when learning is applied. Then, we discuss energy consumption, CO_2 emissions, and costs under all scenarios.

4.1. Market penetration under learning scenarios

The influence of the learning scenario on investment in energy-efficient technologies varies (see Fig. 2). Some technologies, such as hot charging in BOF rolling (code: BOF_CR_HC) show a slowly increasing penetration through the years with learning, and some technologies such as DC-Arc furnace on existing furnace for EAFs (code: EAF_DF) reach maximum potential immediately after the learning becomes active (i.e., starting from 2015), which shows that even a small decrease in specific investment cost would make a difference in investment decisions for those technologies.

Some technologies such as bottom stirring/stirring gas injection in EAFs (code: EAF_BS) do not add new capacity, and their current market penetration levels remain constant throughout the study period, even though there is cost reduction. Other technologies such as pulverized coal injection to 225 kg/thm in blast furnaces (code: BF_PCI225) and non-recovery coke ovens (code: COK_NRCO) lose their market penetration levels to competitive technologies.

As seen in Fig. 2, most of the existing efficient technologies eventually approach their maximum penetration potential in the learning scenario. Seven out of 10 emerging technologies are not adopted.

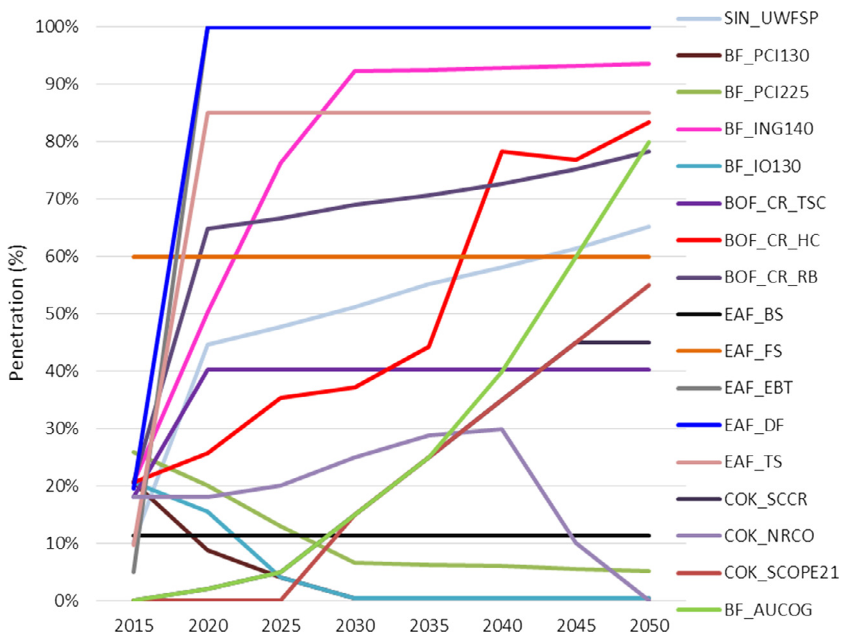

Fig. 2. Market penetration of selected technologies under the learning scenario. Note: Maximum penetration potential of technologies varies and is an input parameter for ISEEM. See Tables A1 and A2 in Appendix A for details.

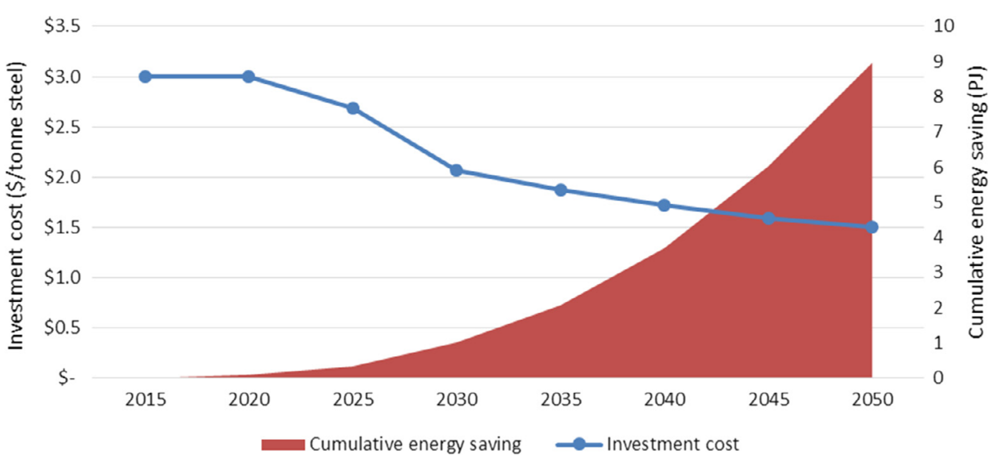

Fig. 3. Projected investment cost and cumulative energy saving of *additional use of coke oven gas in blast furnaces* (code: BF_AUCOG) in the learning scenario (LR = 10%).

Fig. 3 shows an example of dynamic cost modeling, i.e., the decrease in investment costs, of the emerging technology "additional use of coke oven gas in blast furnaces" (code: BF_AUCOG). As a consequence of the increasing penetration of the technology, boosted by the cumulative activity, cost reduces by 50%, reaching about US$1.5/tonne steel in 2050 compared to 2020 levels. Fig. 3 also illustrates the cumulative energy savings associated with this technology in the learning scenario.

4.2. Energy savings and CO2 emissions reductions

The impact of decreasing prices via learning is clearly observed in the learning scenario. The U.S. iron and steel sector becomes more energy efficient as investment in energy-efficient technologies increases through the years.

Fig. 4 shows projected primary energy consumption in the U.S. iron and steel sector for three scenarios: static, non-learning, and learning. Compared to the static scenario, energy consumption is substantially lower in both the non-learning and learning scenarios. The difference grows over time: 7% (non-learning) and 15% (learning) in 2030, and 14% (non-learning) and 25% (learning) in 2050. In addition, even though steel production increases by 13% between 2025 and 2050, the analysis shows that the total energy consumption increase in the sector is expected to be very small (2.6% between 2025 and 2050) in the non-learning scenario and that total energy consumption will decrease in the learning scenario. Compared to the non-learning scenario, the learning scenario consumes 7% and 13% less primary energy in 2030 and 2050, respectively.

Reduction in energy consumption in the non-learning scenario is mainly the result of changing production structure. BOF production is replaced by EAF production based on the cost minimization objective. This result is similar in the learning scenario. The BOF share decreases from 39% in 2010 to 27% in 2030, and 18% in 2050. The EAF process requires about 2.2 times less primary energy than the BOF process (BOF production involves the most energy-intensive steps in the sector). In addition, an abundance of scrap, which is the main raw material for the EAF production route in the U.S., makes EAF production less expensive in the U.S. than countries such as China and India. Fig. 5 illustrates primary energy consumption in the U.S. iron and steel sector by process. As seen in the figure, together with the shift from BOF to EAF production,

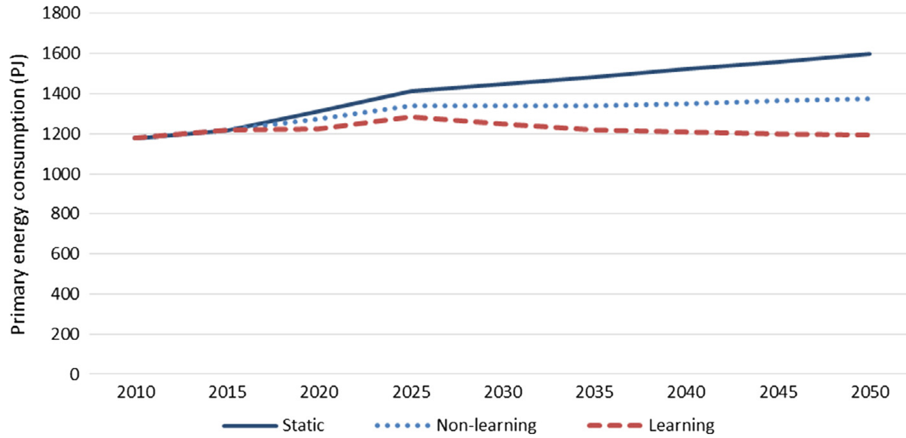

Fig. 4. Projection of total primary energy consumption in the U.S. Iron and Steel Sector in three scenarios. Note: PJ: petajoule.

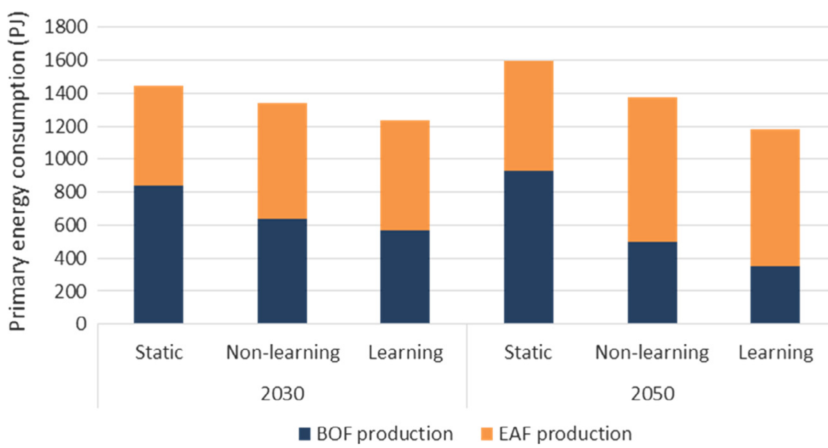

Fig. 5. Projection of primary energy consumption in the U.S. Iron and Steel Sector by production process in 2030 and 2050.

energy-efficient technologies reduce overall energy consumption in both the non-learning and learning scenarios, even though the energy consumed by EAF production increases with increasing production volumes.

Coking coal and natural gas are the main fuels used in U.S. BOF production. Fig. 6 shows savings in coking coal and natural gas consumption in the non-learning and learning scenarios. There is less demand for both fuels as market penetration of energy-efficient technologies increases. In particular, high penetration of efficient coke-making technologies and natural gas injection in blast furnaces in place of coke enable the savings. Coking coal is the highest-carbon-intensive fuel in BOF production. Results show that 55% of coke comes from new and efficient coke-making technologies in 2030. In 2050, old coke-making technologies are entirely replaced by new technologies. Thus, the coking coal intensity of the BOF route improves over time. For example, coking coal intensity in the learning scenario is 7.7 GJ/t of steel in 2050, compared to 12.8 GJ/t of steel in the non-learning scenario. Similarly, high penetration of energy-efficient technologies reduces natural gas demand in BOF production. Natural gas consumption in the learning scenario is 15% and 33% lower in 2030 and 2050, respectively, compared to the levels in the non-learning scenario.

Increased penetration of energy-efficient technologies as a result of technological learning also lowers the electricity intensity

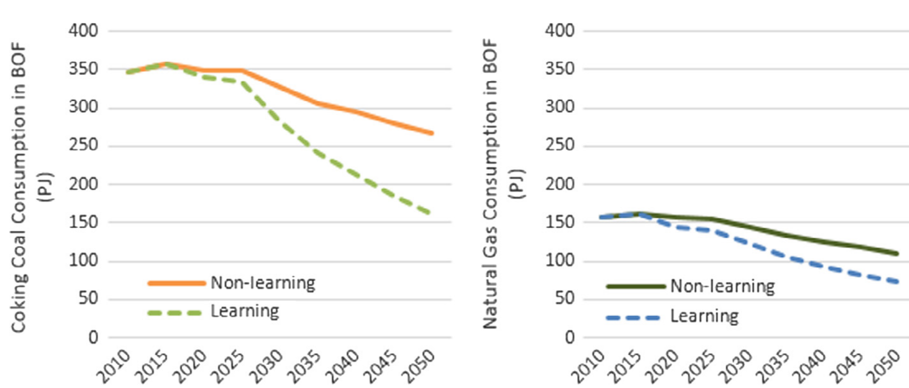

Fig. 6. Coking coal and natural gas consumption in U.S. BOF steel production.

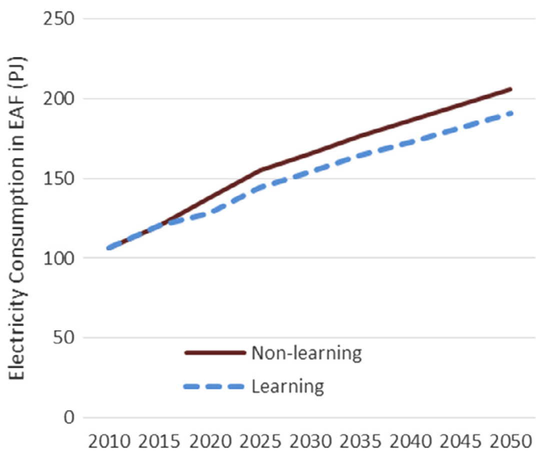

Fig. 7. Electricity consumption in the U.S. EAF steel production.

of EAF production. Electricity consumption drops by 7% on average in the learning scenario throughout the analysis period, compared to electricity consumption in the non-learning scenario (see Fig. 7). As shown in Fig. 2, three energy-efficient technologies (code: EAF_EBT, EAF_DF, EAF_TS) used in EAF production in this study reach their maximum potentials in 2020, and the penetrations of the other two remain constant at base-year levels.

When CO_2 emissions are compared among the scenarios, the impact of shifting production from BOF to EAF process is also obvious. CO_2 emissions in the non-learning scenario are 17% and 31% lower in 2030 and 2050, respectively, compared to emissions in the static scenario. As shown in Fig. 8, increasing energy efficiency in production, with learning, leads to additional reductions (e.g., 10% and 16% in 2030 and 2050, respectively). These results show that technologies that might be assessed as "too expensive" at the moment of their deployment can become economically attractive in a cost-optimal solution over time, as well as saving energy and reducing emissions. Inclusion of learning in energy modeling enables us to see potentials for technology adoption that we would not otherwise see.

4.3. Cost

Fig. 9 shows the total cost of steel production in the scenarios. The total cost of steel production in the learning scenario is always less than that in the non-learning scenario. In absolute terms, total cost savings in the learning scenario are US$0.5 billion in 2030 and US$1.6 billion in 2050 compared to costs in the non-learning scenario.

Fig. 10 shows the cost and energy intensities of U.S. steel production in the scenarios (non-learning and learning) in 2020 and 2050. In all scenarios, cost and energy intensities decrease in 2050 compared to 2020 levels. When these scenarios are compared to each other, the average cost of per tonne of steel in 2020 is about US$1 less in the learning scenario than that in the non-learning scenario. The difference increases to US$14/t of steel in 2050. At the same time, overall energy intensity improves in 2050 in the learning scenario. The average energy intensity of steel production in 2050 decreases from 12.3 GJ/t of steel in the non-learning scenario to 10.7 GJ/t of steel in the learning scenario (13% improvement).

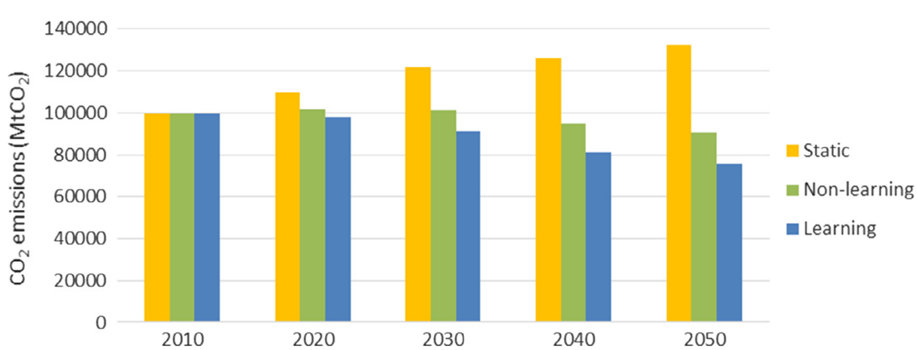

Fig. 8. Total CO_2 emissions in the U.S. Iron and Steel sector.

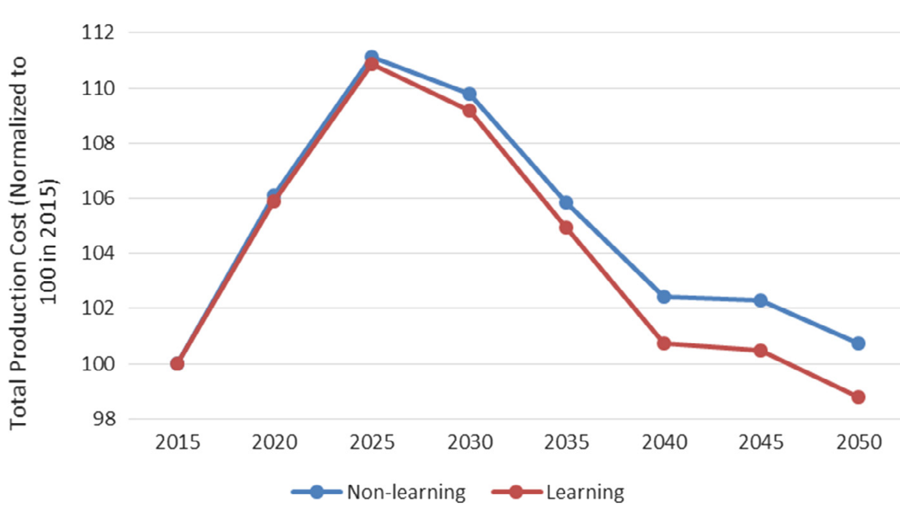

Fig. 9. Projection of total annual steel production cost.

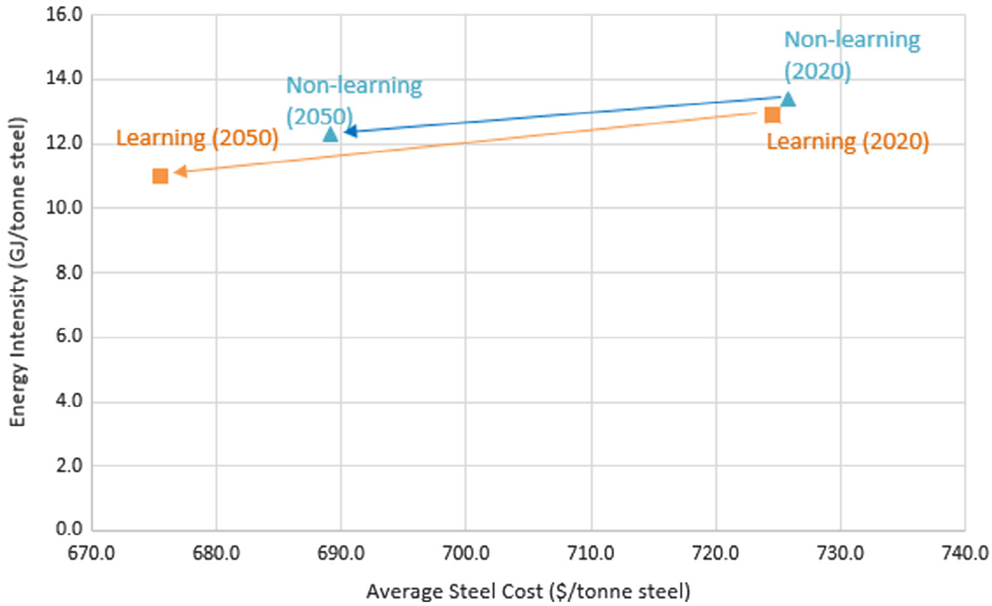

Fig. 10. Steel production cost and energy intensity tradeoff in 2020 and 2050.

5. Discussion and conclusions

This study models penetration of 24 energy-efficient technologies with and without technological learning in the U.S. iron and steel sector using an iterative-solution approach between the ISEEM model and a learning curve formula. In the learning scenario, most of the existing efficient technologies eventually approach their maximum penetration potential, while seven out of 10 emerging technologies are not adopted. Total energy consumption of the sector decreases 7% in 2030 and 13% in 2050 in the learning scenario compared to consumption in the non-learning scenario. This corresponds to 1.6 GJ/t (from 12.3 GJ/t in the non-learning scenario to 10.7 GJ/t in the learning scenario) improvement at the average energy intensity of steel production in 2050. The reductions shown in our results might be even more dramatic if we considered a larger set of efficient technologies.

The results show that technology investment costs drop as a function of their cumulative activity with the learning. Average cost of per tonne of steel decreases US$14/t of steel by 2050 in the learning scenario. This decrease represents a total cost saving of US$1.6 billion and also a CO_2 emissions reduction potential of 14.9 billion tonnes by 2050.

The results discussed in this paper highlight the importance of including technological learning in optimization-based energy models when evaluating production systems, energy-savings, and emissions-reduction potentials. As a consequence of their structure, models with cost minimization objectives favor low-cost production processes. Thus, in these models, technologies that are assessed as expensive investments at a given time would probably never be adopted in an optimal technology mix unless cost-reduction over time is taken into account. Because energy-efficient technology costs are expected to decrease as these technologies penetrate the market, model results can be misleading if cost reduction over time is not considered, particularly for new energy-efficient technologies that have significant potential for energy-savings and emissions reduction but seem initially to be expensive compared to current practices.

Our investigation is designed to improve upon the simplistic picture of optimization-based energy models, in order to better understand impact of learning in penetration of energy-efficient technologies. Results discussed in this paper focus on the U.S. iron and steel sector, but the proposed framework can be applied to study new technology development in any other industrial processes and regions.

The approach used in this study can be also used to support policies to facilitate the adoption of energy efficiency improvement opportunities that are necessary to correct market failures such as uncaptured economic and environmental benefits from energy-efficient technologies in the industry. For example, learning curves using price data were incorporated into recent energy conservation standards analyses of key appliances such as room air conditioners, clothes dryers, and refrigerators and freezers [42]. The joint approach of the Energy Protection Agency (EPA) and the National Highway Traffic Safety Administration (NHTSA) to apply learning curves in vehicle regulator impact assessments assumes different rates of learning to reflect likely substantial learning impact of newer technologies in the near future and limited learning opportunities for mature technologies [67]. Future work focusing on the effect of policy measures, such as financial incentives or carbon taxes, to boost early penetration of emerging energy-efficient technologies by reducing their initial costs, would be beneficial. Technologies that initially do not appear economically competitive can become cost competitive in the future as a result of these types of policy measures. The authors plan to address this topic in future research.

Learning rates that we used in this study might vary according to the type of industrial processes and also regions. While the variations of the learning rates is beyond the scope of this paper, we nonetheless suggest a number of areas for a robust analyses. They include: extensive decomposition of learning rates into process and geography based components such as labor and materials; and, better data and better econometric models to explain the underlying factors that govern or influence technological innovation and penetration.

Acknowledgements

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Appendix A

See Fig. A1 and Tables A1 and A2.

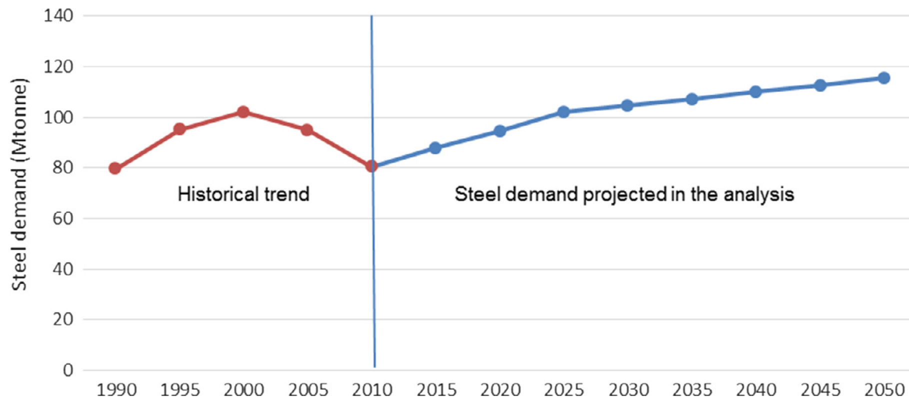

Fig. A1. Historical (1990–2010) and projected (2011–2050) U.S. steel production. Note: see Karali et al. [61] for the details of the demand projection.

Table A1
Details of energy-efficient technologies analyzed in the study - *14 existing technologies*.

Measure/technology	Specific investment cost US$/tonne steel	O&M cost* US$/tonne steel	Energy saving potential %	Lifetime Years	Max penetration %	Additional notes
BF_ING140	US$14.25	−US$2	6.2%**	20	100%	Natural gas/coke replacement rate: 1
BF_IO130	US$13.75	−US$2	5.7%**	20	100%	Fuel oil/coke replacement rate: 1
BF_PCI130	US$13.75	−US$2	5.3%**	20	100%	Coal/coke replacement rate: 1.08
BF_PCI225	US$17.75	−US$1	9.1%**	20	75%	Coal/coke replacement rate: 1.08. Penetration is assumed for large volume blast furnaces only.
BOF_CR_HC	US$15	−US$1.15	19%	20	100%	
BOF_CR_RB	US$2.5		23%	10	100%	
BOF_CR_TSC	US$134	−US$31	32%	20	40%	Estimation based on integrated hot strip and sheet production capacity in 2010
COK_NRCO	US$13.90*		0%	30	85%	On-site electricity generation 0.023 kWh/tonne steel, no process-based CO_2 emission
EAF_BS	US$0.94		4%	0.5	100%	4% of electricity is replaced with inert gas. Cost of inert gas assumed US$2/tonne inert gas.
EAF_DF	US$6.1		4%	30	100%	Applicable to new capacity investments
EAF_EBT	US$5		3%	20	100%	
EAF_FS	US$12.7		1.5%	10	100%	
EAF_TS	US$9.4	−US$31	4%	30	85%	Estimation based on in mini mills not currently continuously cast
SIN_UWFSP	US$0.05		11.5%	10	100%	Sludge/natural gas replacement rate: 1. Sludge comes from cold rolling process. Cold rolling process produce 0.0001 tonne sludge (i.e., 0.0045 GJ waste fuel) per tonne steel produced.

Note: O&M cost includes maintenance and other operational costs, does not include energy cost.
* Per GJ coke.
** on coke consumption.

Table A2
Details of energy-efficient technologies considered in the study - *Emerging Technologies*.

Measure/ technology	Specific investmen cost US$/tonne steel	O&M Cost* US$/tonne steel	Energy saving potential %	Lifetime Years	Max Penetration %	Additional notes
BF_AUCOG	US$3.00		35%**	10	2% at 2020; 25% at	Coking gas/Coal replacement rate: 1
BF_HR	US$20.00		100%**	15	2035; 80% at 2050	Blast furnace gas/coal replacement rate:1
BOF_ABA	US$0.64		0.4%	5		
BOF_CR_ISRT	US$45.40		1.3%	15		
BOF_SHR	US$20.00		68.5% saving on natural gas; 16% saving on electricity consumption	15		Slag/natural gas replacement rate: 1. Blast furnaces produce 0.35 tonne slag per tonne big iron.
COK_SCCR	US$45*		30.0%	30		10% productivity increased assumed
COK_SCOPE21	US$45*		21.0%	30		86% increase in electricity consumption per GJ coke is assumed.
EAF_ABA	US$0.64		1.0%	5		
EAF_CR_ISRT	US$45.40		1.3%	15		
SIN_SWGR	US$35.00		7.0%	10		5% increase in electricity consumption per GJ coke is assumed.

Note: O&M cost includes maintenance and other operational costs, does not include energy cost.
* Per GJ coke.
** on coal consumption.

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