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Using learning curves on energy-efficient technologies to estimate future energy savings and emission reduction potentials in the U.S. iron and steel industry

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Abbreviations and Acronyms

ABA	Aluminum Bronze Alloy to Improve Hood, Roof and Sidewall Life
AUCOG	Additional Use of Coke Oven Gas
BLS	U.S. Bureau of Labor Statistics
BOF	Basic Oxygen Furnace
CES	Cumulative Energy Saving
CO_2	Carbon Dioxide
COK-APCS	Automation and Process Control System
COK-NRCO	Non-Recovery Coke Ovens
DEMETER	Dynamic Top-Down Economy–Energy–Environment (EEE) Model
DNE21	Dynamic New Earth 21 Model
EAF	Electric Arc Furnace
EE	Energy Efficient (used for energy efficient technologies)
EIA	Energy Information Administration
EPA	Environmental Protection Agency
EPPA	Economic Prediction and Policy Analysis
ETC	Environmental Technical Change
E3MG	Global Energy Environment Economy Model
GENIE	Global Energy System with Internalized Experience Curves
GET-LFL	Global Energy Transition – Limited Foresight with Learning
GIR	Greenhouse Gas Inventory and Research Center of Korea
GJ	Gigajoule
HR	Blast Furnace Heat Recuperation
NEMS	U.S. National Energy Modeling System
NHTSA	The U.S. Department of Transportation's National Highway Safety Administration
IEA	International Energy Agency
IMACLIM-R	Multi-Sector Multi-Region Dynamic Recursive Growth Model
ISEEM	Industrial Sector Energy Efficiency Model
ISEEM-USIS	Industrial Sector Energy Efficiency Model for the U.S. Iron and Steel Industry
ISRT	In-Situ Real-Time Measurement of Melt Constituents –BOF
I/O	Input/Output
LBNL	Lawrence Berkeley National Laboratory
LR	Learning Rate
MARKAL	Market Allocation Model
MEPS	Minimum Energy Performance Standard
MERGE	Integrated Assessment Model for Global Climate Change
MESSAGE	Model for Energy Supply Systems and their General Environment
MIP	Mixed Integer Programming
Mtonnes	Million metric tonnes
NEMS	National Energy Modeling System
PCI225	225kg Pulverized Coal Injection
PJ	Petajoule

POLES	Prospective Outlook on Long-Term Energy Systems Model
PPI	Producer Price Index
PR	Progress Ratio
PV	Photovoltaics
R&D	Research and Development
RICE	Regional Integrated Model of Climate and the Economy
SCOPE21	Advanced coke oven
SHR	Slag Heat Recovery
SWGR	Selective Waste Gas Recycling - EPOSINT Process
U.S.	The United States
US DOE	U.S. Department of Energy
US EIA	U.S. Energy Information Administration
US EPA	U.S. Environmental Protection Agency
WSA	World Steel Association

Abstract

Increasing concerns on non-sustainable energy use and climate change spur a growing research interest in energy efficiency potentials in various critical areas such as industrial production. This paper focuses on learning curve aspects of energy efficiency measures in the U.S iron and steel sector. A number of early-stage efficient technologies (i.e., emerging or demonstration technologies) are technically feasible and have the potential to make a significant contribution to energy saving and CO2 emissions reduction, but fall short economically to be included. However, they may also have the cost effective potential for significant cost reduction and/or performance improvement in the future under learning effects such as 'learning-by-doing'.

The investigation is carried out using ISEEM, a technology oriented, linear optimization model. We investigated how steel demand is balanced with/without the availability learning curve, compared to a Reference scenario. The retrofit (or investment in some cases) costs of energy efficient technologies decline in the scenario where learning curve is applied. The analysis also addresses market penetration of energy efficient technologies, energy saving, and CO2 emissions in the U.S. iron and steel sector with/without learning impact. Accordingly, the study helps those who use energy models better manage the price barriers preventing unrealistic diffusion of energy-efficiency technologies, better understand the market and learning system involved, predict future achievable learning rates more accurately, and project future savings via energy-efficiency technologies with presence of learning.

We conclude from our analysis that, most of the existing energy efficiency technologies that are currently used in the U.S. iron and steel sector are cost effective. Penetration levels increases through the years, even though there is no price reduction. However, demonstration technologies are not economically feasible in the U.S. iron and steel sector with the current cost structure. In contrast, some of the demonstration technologies are adapted in the mid-term and their penetration levels increase as the prices go down with learning curve. We also observe large penetration of 225kg pulverized coal injection with the presence of learning.

Chapter 1 Introduction

The Inha-Industry Partnership of Inha University, sponsored by the Greenhouse Gas Inventory and Research Center of Korea (GIR), commissioned with the International Energy Studies group at Lawrence Berkeley National Laboratory (LBNL) to conduct a study that analyzes energy and emissions reduction arising from energy efficient technologies applied with technological learning factors in the United States (U.S.) iron and steel sector by using LBNL's Industrial Sector Energy Efficiency Model (ISEEM)[1].

This study

- derives experience curves or learning factors from the U.S. iron and steel industry,
- incorporates applicable learning parameters into ISEEM,
- uses the model to create multiple production/efficiency scenarios including the application of learning curves,
- forecasts potential energy savings, impacts on carbon dioxide (CO_2) emissions, and overall cost savings,
- and provides insight for improvement modeling for industrial sector.

An analysis of learning curves for energy efficient technologies in the U.S. iron and steel industry is needed for three reasons.

First, policies to facilitate the adoption of energy efficiency improvement opportunities are necessary to correct market failures such as uncaptured economic and environmental benefits from energy efficient technologies in the industry. Technological change, also referred to as technological progress, plays a fundamental role in the achievement of affordable, efficient and clean production systems. Technological change can be seen as a continuous process of replacement and improvement of new and existing technologies in the market (Gomez, 2001). New technologies, particularly, have the potential to make a significant contribution to reduction in energy consumption, CO_2 emissions, and overall cost savings in the future. However, even though they are technically feasible, their adoption is currently not cost effective relative to current practices. At the same time, they may have significant potential for cost reduction and/or performance improvement as experience gained. Thus, rather than taking current characteristics of existing and emerging technologies as a given while evaluating technologies, technological change should be considered and incorporated into the analysis. Better modeling of the introduction and diffusion of new technologies into the market and improvement of existing ones are particularly important while doing future projections. Learning was proposed as a distinct presentation of technical change in Wright (1936) and Arrow (1962) and is often termed as

[1] ISEEM is a bottom-up, dynamic linear programming model of industrial systems developed by Karali et al. (2012) in LBNL.

learning by doing. The learning effect is measured in terms of reduction in the unit cost (or price) of a product as a function of experience gained from an increase in its cumulative capacity or output (Jamasb and Kohler, 2007). The typical representation is through learning, or experience, curves. The standard learning curve considers the specific cost of a given technology as a function of cumulative capacity or cumulative production, which is used as an approximation for the experience accumulated when the technology is deployed. The formulation reflects the fact that some technologies experience declining costs as a result of their increasing adoption (Argote and Epple, 1990).

Second, iron and steel is one of the highest energy and emission intensive industrial sectors, accounting for about 5% of total world CO_2 emissions (IEA, 2007). The U.S. is the third largest steelmaking country in the world with a production of 86.9 Million tonnes (Mtonnes) in 2013 (WSA, 2014a). The examination of the existing and future energy efficiency potential in this sector helps us better understand long-term energy needs and improvement opportunities.

Third, the literature focused on the role of learning curves for estimating future energy and cost savings in the iron and steel sector is limited. Understanding how to better represent existing technologies and emerging technologies that are not yet commercialized, in the long-term energy mixes/forecasts through the use of learning curves, requires improved methods of modelling. Energy optimization models are often applied for comprehensive analysis of sectoral and national energy and emission reduction potentials, outlining the likely future structure of the system under particular conditions and, thus providing insights into the technological paths and structural evolution (Mattson and Wene, 1997). The manner in which technological dynamics is considered in these models has a significant influence on the results. In linear programming models, extensively used for energy modelling purposes, technological change is generally introduced as an exogenous factor. The cost and efficiency of a given technology are considered either constant or as an exogenous function of time. This structure makes analysis of learning effects on technology costs and consequent penetrations levels almost impossible. Our investigation is designed to improve upon this simplistic picture, in order to better understand impact of learning in penetration of energy efficient technologies to the US iron and steel sector in the long term (e.g., from 2010 to 2050 defined in this analysis). The investigation is carried out using ISEEM, a technology oriented, linear optimization model for the U.S. iron and steel sector (ISEEM-USIS). In this study, the model is run in an iterative fashion in combination with a classical learning curve function (i.e., one factor learning curve). Accordingly, the study helps those who use energy models better manage the price barriers preventing unrealistic diffusion of energy-efficiency technologies, better understand the market and learning system involved, predict future achievable learning rates more accurately, and project future savings via energy-efficiency technologies with presence of learning.

Chapter 2 Learning Curve Approach

Technological learning is a phenomenon by which production costs decrease in a specific relation to increased cumulative production. It assumes that a technology's performance improves as experience with the technology accumulates. Specifically, for each doubling of cumulative production, the unit production costs decrease by a certain value known as the *learning rate* (Junginger et al., 2010).

2.1. Learning curve literature

The learning curve concept was first developed by Wright (1936), who reported that unit assembly costs of airplanes declined significantly with accumulated experience of the workers (i.e., repetitions), and that this cost reduction was a constant percentage with every doubling of cumulative output.

After being applied to analyze the relationship between the average unit price and cumulative output of 24 selected industrial products by Boston Consulting Group in 1968, learning phenomena has been adopted in empirical studies in a wide range of sectors (Arrow, 1962; Dutton and Thomas, 1984; and Yelle, 1979), including the following:

- manufacturing (Argote and Epple, 1990; Nadeau, 2010),
- consumer products (Bass, 1980; Teng and Thompson, 1996),
- energy supply technologies (Criqui et al., 2015; Goldemberg et al., 2004; Hettinga et al., 2009; Hong et al., 2015; OECD/IEA, 2000; Junginger et al., 2006; Li et al., 2012; McDonald and Schrattenholzer, 2001; Neij, 1997; Neij, 1999a&b; Neij et al., 2004; Nemet, 2006; Rose and Joskow, 1990; Rubin et al., 2006; Schoots et al., 2008; van der Zwaan and Rabl, 2003; Wene et al., 2005; and Yeh and Rubin, 2007),
- energy demand technologies (Desroches et al., 2013; Weiss et al., 2010) and
- environmental control technologies (Rubin et al., 2004; Taylor et al., 2013; and Yeh et al., 2007).

2.2. The learning curve formula

The learning curve is a well-known analytical concept that describes the cost reduction potential of a technology as a function of experience quantified in terms of cumulative production. A typical one-factor learning curve has the form of

$$C_t = C_1 X_t^{-b} \tag{2.1}$$

$$\log C_t = logC_1 - b * logX_t \tag{2.2}$$

$$PR = 2^{-b} \tag{2.3}$$

$$LR = 1 - PR \tag{2.4}$$

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*, and *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. For example, a progress ratio of 90% equals a learning rate of 10% and thus means that unit production cost would decline 10% and reach 90% value whenever the production doubles. When learning takes place, the values of the progress ratios are expected to be between 0 and 1 (or 0% to 100%). As the ratio gets closer to zero, the learning becomes more rapid while getting close to one indicates lower rates of learning. On the other hand, *PR = 1* means there is no change at unit production cost. *PR > 1* indicates a cost increase and a loss in efficiency as the total production increases (instead of cost reduction and efficiency improvement).

The learning curve in principle defines short-run (over which a firm's size is fixed and the only variable resources are labor and raw materials) average variable cost (C_t in Eq. 2.1) as a function of the short-run average cost of the first unit of a commodity or service that was produced (C_1 in Eq. 2.1), the cumulative total number of units produced (X_t in Eq. 2.1), and a parameter that measures the rate at which average cost declines as the total production increases (-*b*, Eq. 2.1). As the cumulative production used in the learning curve approach represents the total production up to a point in time, not total units per time period, the effect of learning curves are different from the result of economies of scale (Salvatore, 2014).

Graphically, the learning curve is conventionally represented in a logarithmic scale Figure 1 shows an example for a linear scale and a log linear scale learning curve.

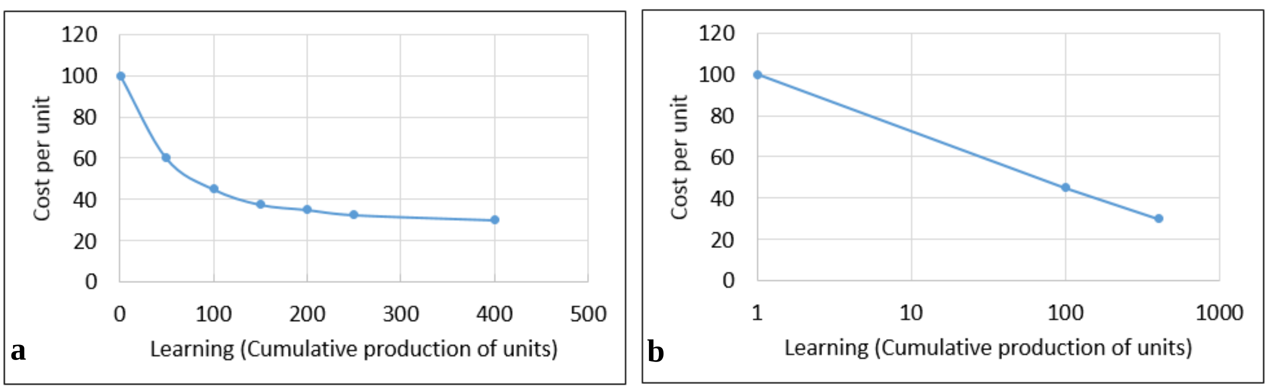
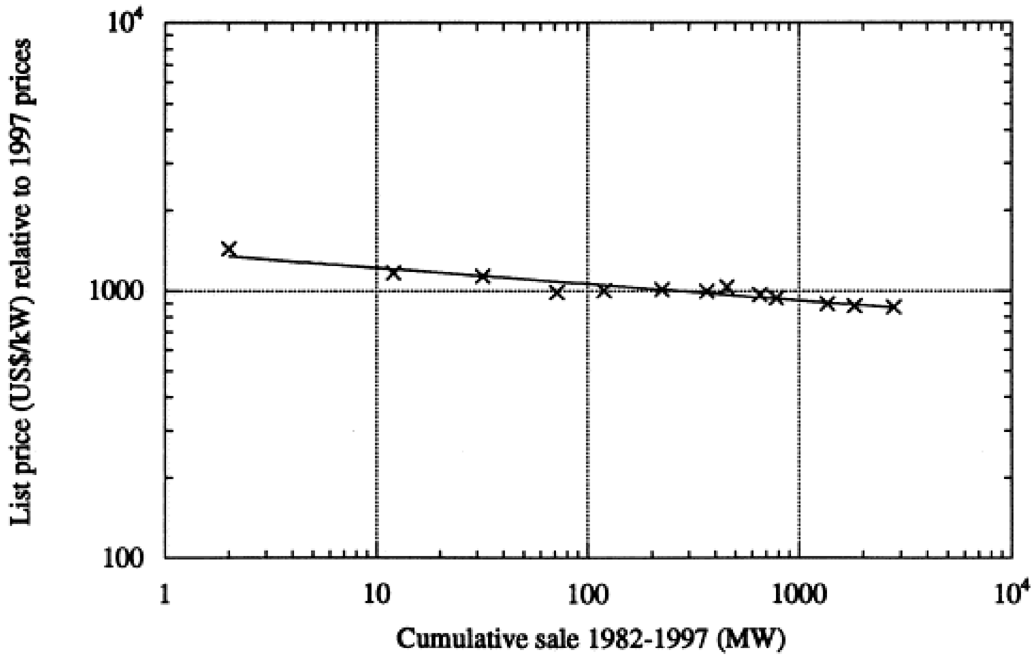


Figure 1 Learning curve in linear scale (a) and log linear scale (b)

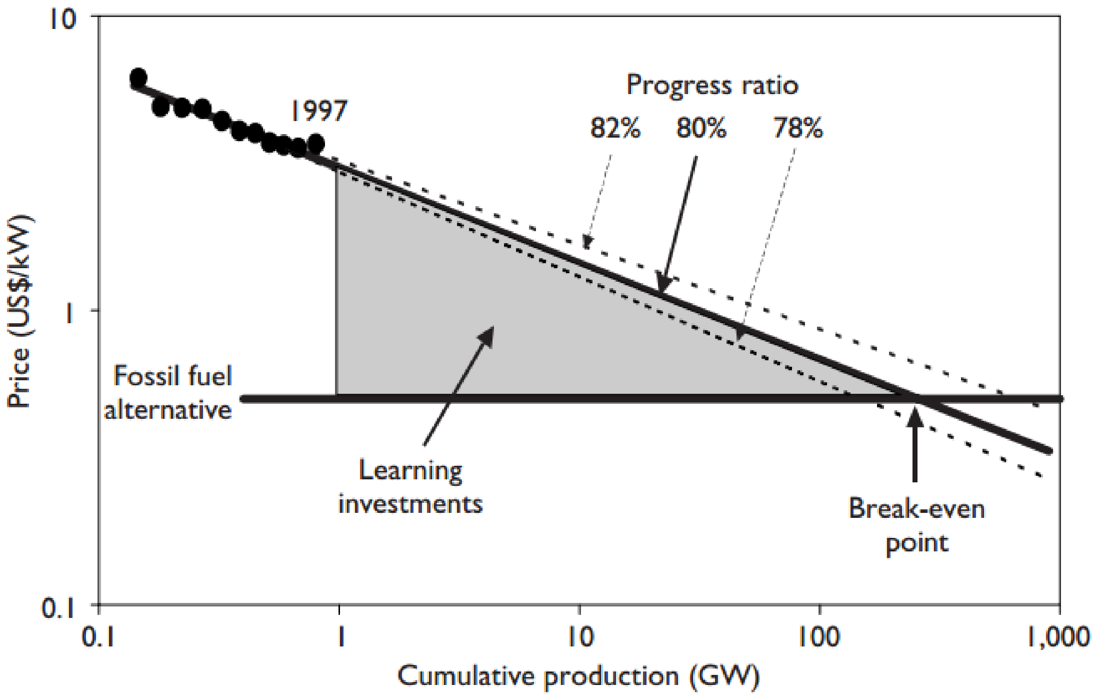
Figure 2 depicts a learning curve for wind turbines in which the unit price decreases as a function of cumulative sales.



Source: Neij, 1999a

Figure 2 Learning curve for Danish-produced wind turbines (The PR is 96%)

Learning curves are used to project the future cost reduction of a technology. Assessment of future costs are particularly important for emerging technologies that are new to the market. The cost of a new technology must decrease to a level that can be competitive against conventional technologies to be involved in the market. Figure 3 shows the decrease in cost of photovoltaic modules via learning curve. The difference between actual price and break-even price, that is, the additional costs for technology compared with the same service from technologies that are already in the market, is called the learning investment.



Source: OECD/IEA, 2000

Figure 3 Learning curve for photovoltaic modules

The conventional one-factor learning curve considers the specific investment cost of a given technology only as a function of cumulative capacity or cumulative production. This representation takes into account the effects of experience due to actual deployment of technologies, but is often criticized for not providing a mechanism to capture explicitly the effects of public and private research and development (R&D) efforts, which may also constitute another component of cost reductions, particularly in the early stages of development of a technology (Barreto and Kypres, 2004). Kouvariatakis et al. (2000a) extended the conventional learning curve formula to the so-called two-factor learning curve to include the impact of R&D expenditures on cost reductions.

While the concept of two-factor learning curve is theoretically appealing, significant problems were noted for this approach (Holmes, 2011). For example, reliable data on R&D spending is hard to collect and the quality of available data is often an issue. In addition, high degree of co-linearity between two variables, R&D investments and cumulative capacity or production, (e.g., they may influence one another), can lead to misleading conclusions. For this reason, one-factor learning curve formula is still widely used for predicting production rate and cost in repetitive operations in the vast majority of studies. We are also using one-factor learning curve in this study.

2.3. Learning curve criticisms

While the basic learning curve approach itself stands out due to its simplicity, using the learning curve is in practice often not as straightforward as it may be seen (Junginger et al, 2010). A number of uncertainties in the use of learning curves for forecasting or modeling future cost trends has been identified and their impacts in the analysis of cost developments has been criticized in the literature (Neij et al., 2004; Nemet, 2006; Alberth, 2008). Since the uncertainties can significantly influence the results, it is important to acknowledge these critiques.

Choice of performance and learning indicators

Production cost is the ideal performance indicator in the learning curve due to its direct relation to technical improvement. However, usually only price data is available for analysis. Using price instead of cost may be useful when price-cost margins are constant over time. This, unfortunately, requires a number of unlikely things to stay constant in an industry (Taylor and Fujita, 2013). Whereas cost changes occur over time due to changes in input prices and production efficiency, price changes can occur from several other factors (such as government subsidization, various marketing decisions, funding allocated to R&D, and commercialization initiatives). Learning analysis based on prices may be uninformative if price changes occur not based on production costs but based on other reasons unrelated to cost changes Papineau (2006). However, as Junginger et al. (2010) mentioned, even though cost data are a better measure of technical improvement, technology adaptation decisions are based on prices that consumers face, not the costs that producers face.

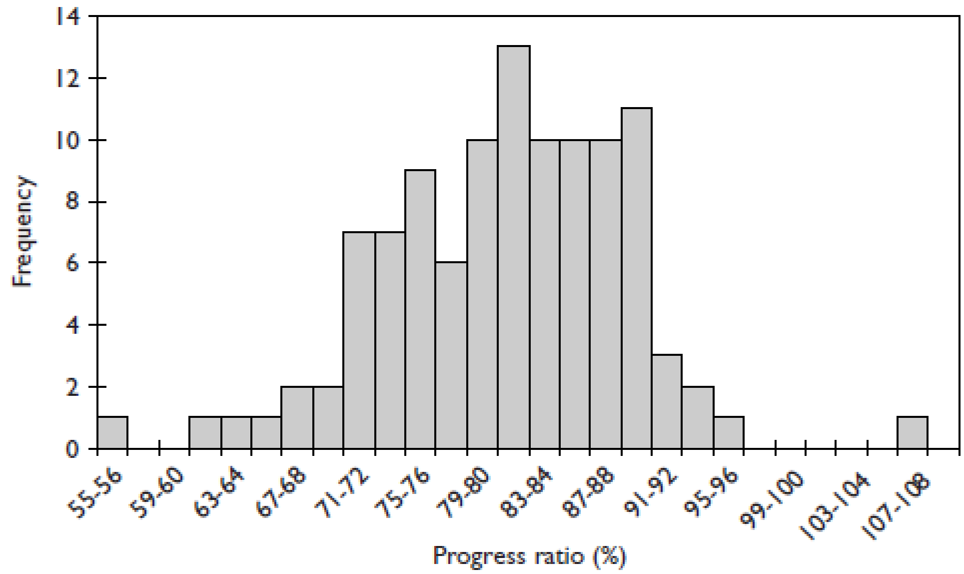
Likewise, cumulative production (or cumulative output of the generating or converting technologies in the energy context) or cumulative installed capacity is often used in learning curve analysis as a substitute for accumulated learning. However, this assumption ignores the effect of knowledge acquired from other sources, such as from R&D or from other industries. In addition, for some specific cases, cumulative production or capacity is not well suited. For example, energy efficiency technologies and measures do not provide a direct output (i.e., energy), but rather conserving it (i.e. energy saving), which requires a clear definition of the energy saved, or alternatively, of energy efficiency gained (Jakob and Madlener, 2004). Thus, in the case of energy efficient technologies, learning curve reduces the cost for every doubling of cumulative energy savings.

Using a constant progress ratio (learning rate)

Whether the learning curves flatten out with increasing penetration or not, that is whether *PR* is constant or not is another issue often debated in the literature. Does the progress ratio (and therefore learning rate) remain constant over time, or does it change over the modeling period? Grubler (1998) argues that costs are reduced relatively rapidly during the innovation and R&D phase, but that the *PR* may change to a higher level (i.e., lower cost reductions) when a technology enters to the commercial market. Nemet (2009) has looked at the stability of learning rates for photovoltaic (PV) and wind technologies between 1975 and 2005, and also found evidence supporting the arguments of some slowing in learning. Also, the joint approach of EPA and NHTSA to applying learning curves in vehicle regulatory impact assessments assumes a “steep” learning rate of 20% to reflect likely substantial learning in the near future for newer technologies, and a “flat” learning rate (1-3%) or no learning rate (0%) to reflect more limited learning opportunities, primarily associated with autonomous learning, for mature technologies Others, such as McDonald and Schrattenholzer (2002) argue that a constant *PR* may depend on exponential market growth. As soon as the turning point in the S-shaped penetration curve is reached, and annual production volumes become linear or even decrease, the learning curve will eventually flatten out and *PR* may reach unity (or *LR* may reach to zero). On the other hand, Junginger et al. (2010) argues that cumulative doublings of unit production are achieved with relative ease during the innovation and niche market phase of a technology, but as the market reaches saturation, it may take much time to get another doubling of cumulative production. Thus, the cost reduction possibilities are also limited by the market volume. Cost reduction may then slow in time, and come to a halt when the market is saturated, which does not necessarily require *PR* to change. However, Junginger et al. (2010) also mentions that products may change over time, as will input prices, and so on. Thus, the timeframe used in the learning curve analysis is also essential while estimating *PR*.

Uncertainty of progress ratio (learning rate)

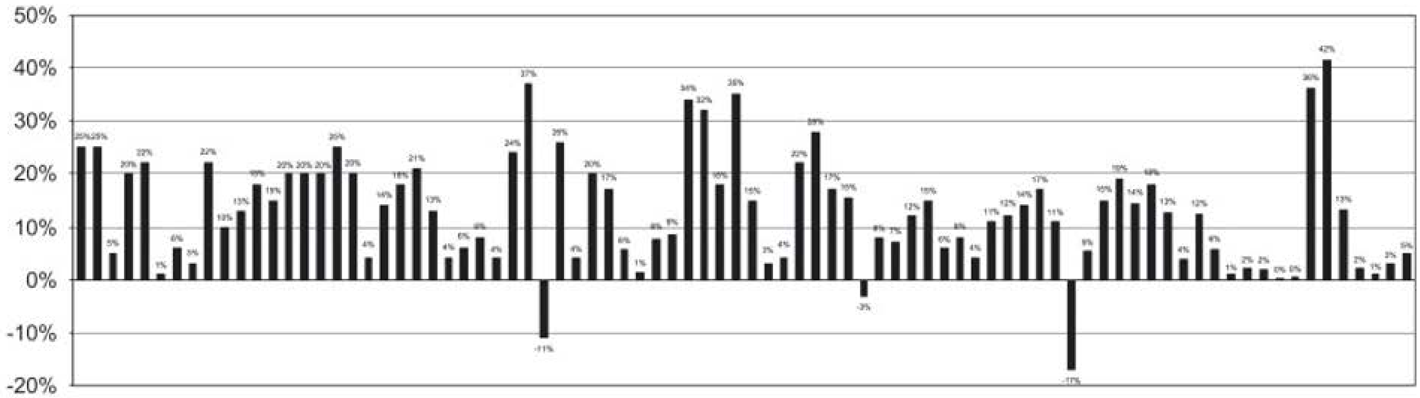
Variation in progress rates, can have significant consequences, especially for exercises examining long-term perspectives. The literature provides some evidence of *PR* variability among different data sets, and sometimes within the same data set analyzing different time intervals or technology clusters. Dutton and Thomas (1984) compiled cost based learning curves from a wide spectrum of industries and found a peak of a distribution of *PR* values at 80% (see Figure 4), but with a wide distribution (and the second largest one indicates 89%-90%). McDonald and Schrattenholzer (2001) looked at the distribution of price-based *PR* values for energy technologies and reproduced Dutton and Thomas’s peak around 80%, but observed another peak around 95%. They concluded that 80-81% median value of progress ratios from general manufacturing firms could be a useful starting point until more detailed studies of energy technologies become available. However, as *PR* estimates directly affects cost forecasts, detailed sensitivity analysis of results to *PR* variability is necessary. This variability may be driven by several factors such as technology life cycle, market pricing strategies, assumptions about initial cumulative production and the associated start-off costs, definition of variables (cost or price data, cumulative capacity, production, or energy savings) (Junginger et al. 2010).



Source: Dutton and Thomas, 1984

Figure 4 Progress ratios for industrial production

In addition, variability in progress ratios may depend on how system boundaries are defined and differ depending on the properties of the technology. In particular, using the progress ratios based on national learning curves in global energy models or in modeling of another country, may provide misleading results. For different technology categories, Neij (1997) defines three different progress ratios. He indicates that the *PR* for modular technologies (such as solar panels) ranges from 75-90% (average 80%), for plant technologies (such as power plants) from 82-100% (average 90%), and for continuous processes (such as bulk production of chemical compounds) from 64-90% (average 78%). However, one can also argue that plant technologies are all technologies that combine several learning components. Such uncertainties should be taken into account while evaluating model outcomes. Figure 5 illustrates the range of learning rates (1% to 41.5%) from literature for various energy technologies (see Appendix A for the full list of 77 technologies) and shows a wide range of learning rates (varying - by source, country, and time period).



Source: Kahouli-Brahmi, 2008 (See Appendix A for details)

Figure 5 Learning-by doing rates for selected energy technologies

Detailed reviews on the histories, applications, and uncertainties of the experience curve can be found in the literature Yeh et al, 2007; OECD/IEA, 2000; Mattsson and Wene, 1997; Neij, 1997.

2.4. Using learning curves in energy models

Learning curves show the investment necessary to make an emerging technology competitive, but it does not forecast when the technology will reach a break-even point. Incorporation of learning in energy models helps identify the optimal timing for integrating the emerging technologies in the market. The learning curve is widely incorporated in energy models. Table 1 provides some examples of bottom-up, top-down, and hybrid energy models incorporating learning curves[2].

[2] Bottom-up models represent the energy system with a technology rich description and put the emphasis on the correct description of energy sources and technologies at the disaggregated microeconomic level Fishbone et al., 1983, Junginger et al., 2010, Loulou et al., 2004, Schrattenholzer, 1981). Top-down models evaluate the system from aggregate economic variables and apply macroeconomic theory and econometric techniques to historical data on consumption, income, investments, GDP, imports, prices and factor costs to model the final demand for goods and services (Junginger et al., 2010, Karali, 2012). Hybrid models combine technological explicitness of bottom-up models with the economic comprehensiveness of top-down models (Hourcade et al., 2006).

Table 1 Technological learning in bottom-up and top-down models

Approach	**Model**	**Parameter affected by learning**	**Baseline**
Bottom-up	MESSAGE	Energy investment cost	Messner (1997)
	GENIE	Energy investment cost	Mattsson (1997) and Mattsson; Wene (1997)
	MESSAGE	Energy investment cost	Grübler and Messner (1998)
	MESSAGE	Energy investment cost	Gritsevskyi and Nakicenovic (2000)
	MARKAL	Energy investment cost	Seebregts et al. (2000)
	POLES	Energy investment cost	Kouvaritakis et al., 2000a and Kouvaritakis et al., 2000b
	MERGE	Energy investment cost	Manne and Richels (2004)
	DNE21+	Energy investment cost	Sano et al. (2006)
	MESSAGE-MACRO	Energy investment cost	Rao et al. (2006)
	GET-LFL	Energy capital cost and energy conversion activities.	Hedenus et al. (2006)
Top-down	DEMETER	Energy production cost	Van der Zwaan et al. (2002) and Gerlagh and van der Zwaan (2003)
	ETC-RICE	Abatement activities and knowledge stock.	Buonanno et al. (2003)
	RICE	Energy investment cost and knowledge stock.	Castelnuovo et al. (2005)
	E3MG	Energy investment cost (electricity generation technologies).	Barker et al. (2006)
	IMACLIM-R	Energy investment cost (electricity generation technologies).	Crassous et al. (2006)
Hybrid	NEMS	Energy investment cost (electricity generation technologies)	US EIA 2014 (2014)

Source: Junginger et al. 2010, US EIA 2014

In addition, Table 2 shows examples of learning parameters for new generating technology components reflected in the NEMS Electricity Market Module.

Table 2 Learning parameters for new generating technology components

Technology Component	Period 1 (LR 1)	Period 2 (LR 2)	Period 3 (LR 3)	Period 1 (Doublings)	Period 2 (Doublings)	Minimum Total Learning by 2035
Pulverized Coal	-	-	1%	-	-	5%
Combustion Turbine - conventional	-	-	1%	-	-	5%
Combustion Turbine -	-	10%	1%	-	5	10%
Heat Recovery Steam	-	-	1%	-	-	5%
Gasifier	-	10%	1%	-	5	10%
Carbon Capture/Sequestration	20%	10%	1%	3	5	20%
Balance of Plant - IGCC	-	-	1%	-	-	5%
Balance of Plant - Turbine	-	-	1%	-	-	5%
Balance of Plant - Combined	-	-	1%	-	-	5%
Fuel Cell	20%	10%	1%	3	5	20%
Advanced Nuclear	5%	3%	1%	3	5	10%
Fuel prep - Biomass	-	10%	1%	-	5	10%
Distributed Generation - Base	-	5%	1%	-	5	10%
Distributed Generation - Peak	-	5%	1%	-	5	10%
Geothermal	-	8%	1%	-	5	10%
Municipal Solid Waste	-	-	1%	-	-	5%
Hydropower	-	-	1%	-	-	5%
Wind	-	-	1%	-	-	5%
Wind Offshore	20%	10%	1%	3	5	20%
Solar Thermal	20%	10%	1%	3	5	10%
Solar PV - Module	-	10%	1%	-	5	10%
Balance of Plant - Solar PV	-	10%	1%	-	5	10%

Source: US EIA 2014 (U.S. Energy Information Administration, Office of Electricity, Coal, Nuclear and Renewables Analysis)

Since bottom-up models can capture technologies with a very detailed level of technical and economic characteristics, they are more suitable to implementing learning curves for specific technologies, compared to top-down models. In top-down models, technological learning is generally incorporated to analyze the impact of learning on abatement costs. Bottom-up models, on the other hand generally model investment costs of a technology as a function of cumulative installed capacity or production (Junginger et al. 2010). Introduction of learning curves in bottom-up energy system models as endogenous variable, however, results in non-convex and non-linear mathematical problems. This topic is discussed more detailed in Chapter 3.

2.5. Using learning Curves for the U.S. Iron and Steel Sector

Existing literature shows that learning curves provide a rational and systematic approach to estimate future cost trends based on historical observations and performance of technologies.

Data and Methodology

In this study, we analyze the learning effect on cost developments and technological progress of energy efficient (EE) technologies in the U.S. iron and steel sector. We first develop a set of learning curves characterizing historical cost trends for 75 EE technologies (43 in the Basic Oxygen Furnace (BOF) production route and 32 in the Electric Arc Furnace (EAF) production route) currently in use in the U.S. iron and steel sector (Karali et al., 2013; Worrell et al., 1999; See Table B1 in Appendix B for the entire list). The cost associated with EE technologies represents the expense of retrofitting the existing production structure with an EE technology.

For those 75 technologies, we have obtained cost and energy savings data from the literature for two specific years; 1994 and 2002. In an energy context, learning curves typically describe the relation between specific costs of energy generated (or converted) and the cumulative output of the generating or converting technologies studied (measured in capacity units such as kW, or number of units produced such as kWh, and the like) (Jakob and Madlener, 2004). In contrast, energy efficiency technologies and measures do not provide energy, but rather help to conserve it (i.e. to bring energy saving), which calls for the definition of a Baseline (or baseline) for the measurement of the amount of energy conserved (i.e., energy saving), or energy efficiency gained, respectively (Jakob and Madlener, 2004; see Section 2.3.). In addition, our historical data only provides energy saving associated with each energy efficient technology.

Accordingly, our independent variable in the one-factor learning curve formula is cumulative energy saving, while retrofit cost of an EE technology is the dependent variable. We assume the cost of a unit energy saving (1 GJ in this specific case) in 1994 as our initial cost (i.e., start-off cost). The cost in 2002, then, is the product of the cumulative energy saving (in GJ) between 1994 and 2002.Accordingly, the learning curve formula that we use to derive learning rates is in the following form:

$$C_{2002} = C_{1994}(X_{2002} - X_{1994} + 1)^{-b} \quad (2.5)$$

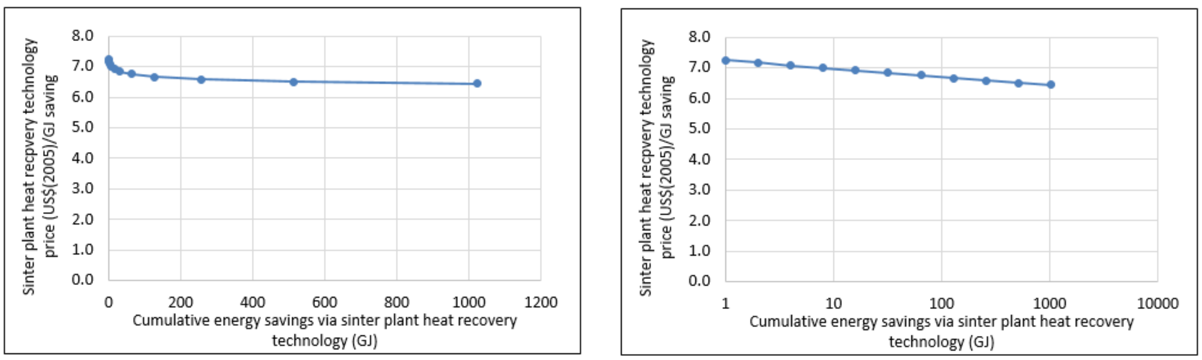
$$PR = 1 - LR \quad (2.6)$$

$$LR = 1 - 2^{-b} \quad (2.7)$$

where C_{2002} is the unit retrofit cost at 2002, C_{1994} is the unit retrofit cost at 1994 (i.e., our start-off cost), $X_{2002} - X_{1994}$ is the cumulative energy saving between 1994 and 2002 (‘1’ in the formula,

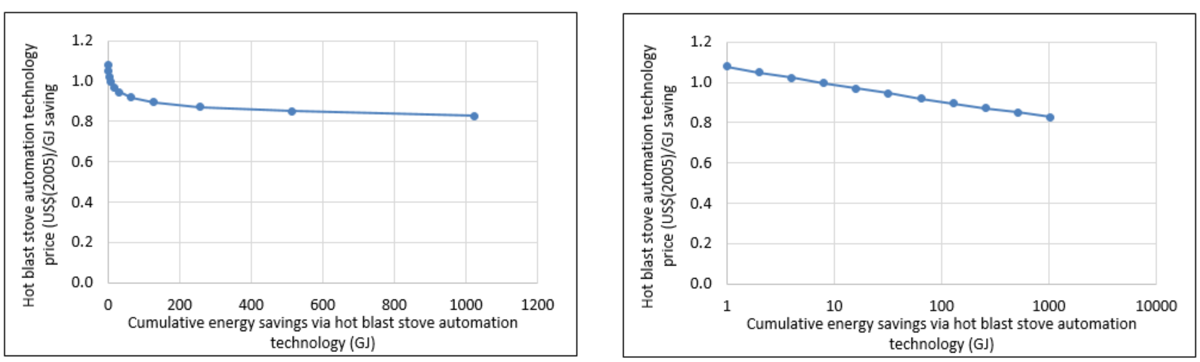
$X_{2002} - X_{1994} + 1$, represents the initial unit energy saving), b is the learning parameter, PR is the progress ratio, and LR is the learning rate. Retrofit cost decreases according to PR in each doubling of energy savings (in GJ).

The investment cost learning curves for four sample technologies are shown graphically in both linear and log-linear (on X-axis) scales in Figure 6 - 9. These sample technologies have different penetration levels in 2002, representing the variety of penetrations in existing EE technologies in the U.S. iron and steel sector. Figure 6-9 illustrates how learning acquired through cumulative energy saving reduces the costs between 1994 and 2002. Table B 2 in Appendix B summarizes the learning rates for retrofit cost for the 75 technologies examined in this study. All learning rates derived in this study fall within the range of 1%-41.5% reported in the literature for an array of energy-related technologies studied by Kahouli-Brahmi (2008).



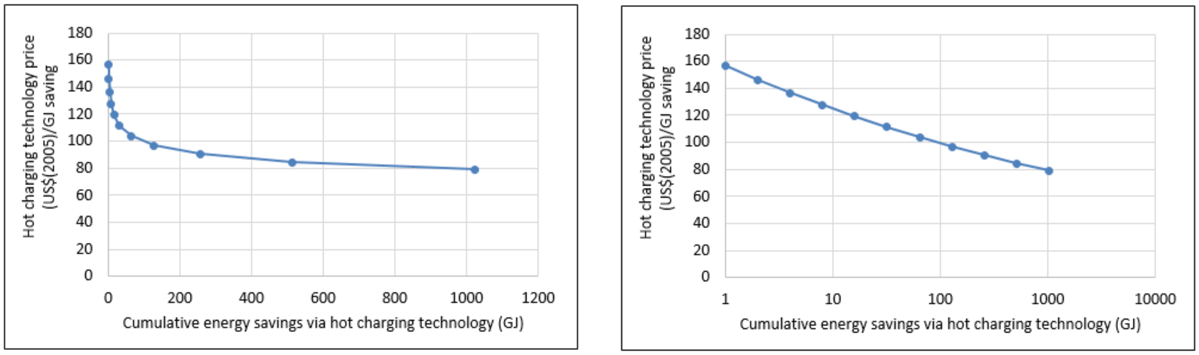
(a) (b)

Figure 6 (a) Linear scale learning curve for Sinter Plant Heat Recovery, (b) Log-linear scale learning curve for Sinter Plant Heat Recovery (Cumulative energy saving (CES) between 1994 and 2002 = 48.1 PJ, Penetration in 2002 = 100%, LR = 0.012)



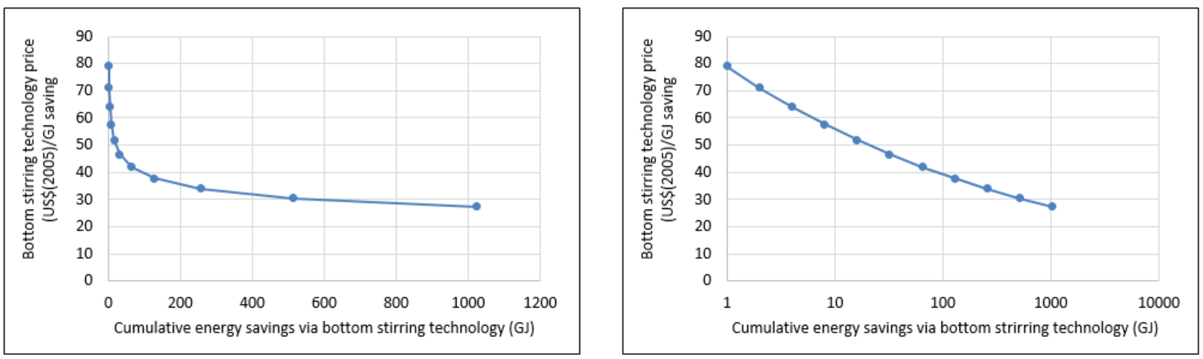
(a) (b)

Figure 7 (a) Linear scale learning curve for Hot Blast Stove Automation, (b) Log-linear scale learning curve for Hot Blast Stove Automation (CES between 1994 and 2002 = 131.8 PJ, Penetration in 2002 = 60%, LR = 0.026)



(a) (b)

Figure 8 Linear scale learning curve for Hot Charging, (b) Log-linear scale learning curve for Hot Charging (CES between 1994 and 2002 = 44.5 PJ, Penetration in 2002 = 21%, LR = 0.067)



(a) (b)

Figure 9 Linear scale learning curve for Bottom Stirring, (b) Log-linear scale learning curve for Bottom Stirring (CES between 1994 and 2002 = 4.2 PJ, Penetration in 2002 = 11%, LR = 0.101)

Figure 6 shows the learning curve for sinter plant heat recovery technology, which has penetration level of 100% in 2002 on the U.S. market. This is an example of a technology which has reached maturity. The learning curve for sinter plant heat recovery shows a modest progress ratio of 98.8%, corresponding to a learning rate of 1.2%. Hot blast stove automation, which has penetration level of 60% in 2002, is similar to sinter plant heat recovery. This technology in Figure 7 shows progress ratio of 97.4%, corresponding to a learning rate of 2.6%.

On the other hand, learning curves for hot charging technology in Figure 8 and bottom stirring technology in Figure 9 indicate a decrease in prices through cumulative energy saving. They have 6.7% and 10.1% learning rates, respectively. Both of those technologies have relatively low penetrations; 21% for hot charging technology and 11% for bottom stirring technology. This also corresponds to the literature review we did earlier by indicating higher learning rates for technologies that have low penetration levels (i.e., assuming those are the technologies at the beginning of deployment to the market). In addition, almost the same absolute increase in cumulative energy saving in Figure 6 for sinter plant heat recovery and in Figure 8 for hot charging shows that the learning effect is more dramatic for technologies with lower penetration.

Based on our findings on learning rates, we have calculated average learning rates by technology penetration level. Table 3 summarizes the average learning rates calculated for EE technologies with different penetration levels. 50 technologies (67% of existing EE technologies considered in this study) have a learning rate of 3% or lower. The technologies that are in the lowest penetration interval have the highest learning rate of 10%. This rate drops down to 2% in the highest penetration interval. These results show that learning slows down with the increasing penetration (maturity) of the technology in the U.S. iron and steel sector.

Table 3 Penetration and average learning rates of EE technologies

Penetration	**# of Energy Efficient Technologies**	**# of EE Techs in BOF Route**	**# of EE Techs in EAF Route**	**Average Learning Rate**
[80-100%]	27 (36%)	20 (47%)	7 (22%)	2%
[60-80%)	8 (11%)	3 (7%)	5 (16%)	3%
[40-60%)	15 (20%)	9 (21%)	6 (19%)	3%
[20-40%)	19 (25%)	9 (21%)	10 (31%)	6%
[0-20%)	6 (8%)	2 (5%)	4 (13%)	10%
Total	75 (100%)	43 (100%)	32 (100%)	

(*Note*: Penetration of energy efficient technology in this analysis is defined as follows: for technologies in BOF production route, share of total U.S. integrated steel production to which measure is applied; and for technologies in EAF, share of total U.S. secondary production to which measure is applied. See Appendix B for the entire list.)

Chapter 3 Technological learning in ISEEM

This chapter describes the methodological approach used to endogenize the learning curves in ISEEM. ISEEM is a technology-oriented model. It uses a rich representation of supply and demand technologies to identify future cost effective technological options and assess their role in the energy system under different conditions. This model in standard form can assume exogenous technological change, i.e., the unit cost and efficiency of technologies can improve by constant rates over time and are independent of each other.

Incorporating learning curves as endogenous variables in bottom-up energy system models causes computational problems due to the non-convexity and non-linearity of the learning curve (Berglund and Soderholm, 2006). Most of the time there are multiple local optima which creates difficulty in identifying the global optimum. The most common way of solving this problem in linear programming models is so-called mixed integer programming (MIP), as reported in the literature for MESSAGE (Messner, 1997) and GENIE energy models (Mattsson, 1997). Such an approach consists of a piece-wise approximation of the total cumulative cost curve, using integer variables to control the sequence of segments along the curve, which enables the models to find a global optimum. However, it is very computer intensive and increases the computational complexity compared to the conventional Linear Programming (LP) models without endogenous learning. The solution time and the success to find optimal solutions depend on specific solver options. In addition, the accuracy depends on segmentation of step-wise linearization of the cumulative cost curve (Seebregts et al., 1999).

To overcome difficulties in computation in MIP, we use an iterative solution algorithm between ISEEM and the learning curve formula (see Figure 10). This approach integrates learning curves outside the actual optimization, hence it does not cause the mathematical difficulties mentioned above. ISEEM optimization is executed on periodic basis. Based on the optimum solution of ISEEM, cumulative activity (i.e., production) of each EE technology at the beginning of period *t* (excluding period *t*) is passed to the learning curve formula. With this information, learning curve-adjusted costs of the technologies at *t* are calculated. The ISEEM model simultaneously uses the costs transferred from the learning curve formula to calculate the cumulative activity of the following period *(t+1)*. This iteration continues until the end of the planning horizon. The iteration process is half-automatized. Learning curve formula is embedded into the parameter definition module of ISEEM, and cumulative activity from ISEEM optimization is internally passed to that module. New cost information from learning curves (output of learning curve formula), however, needs to be manually transferred to the ISEEM input database.

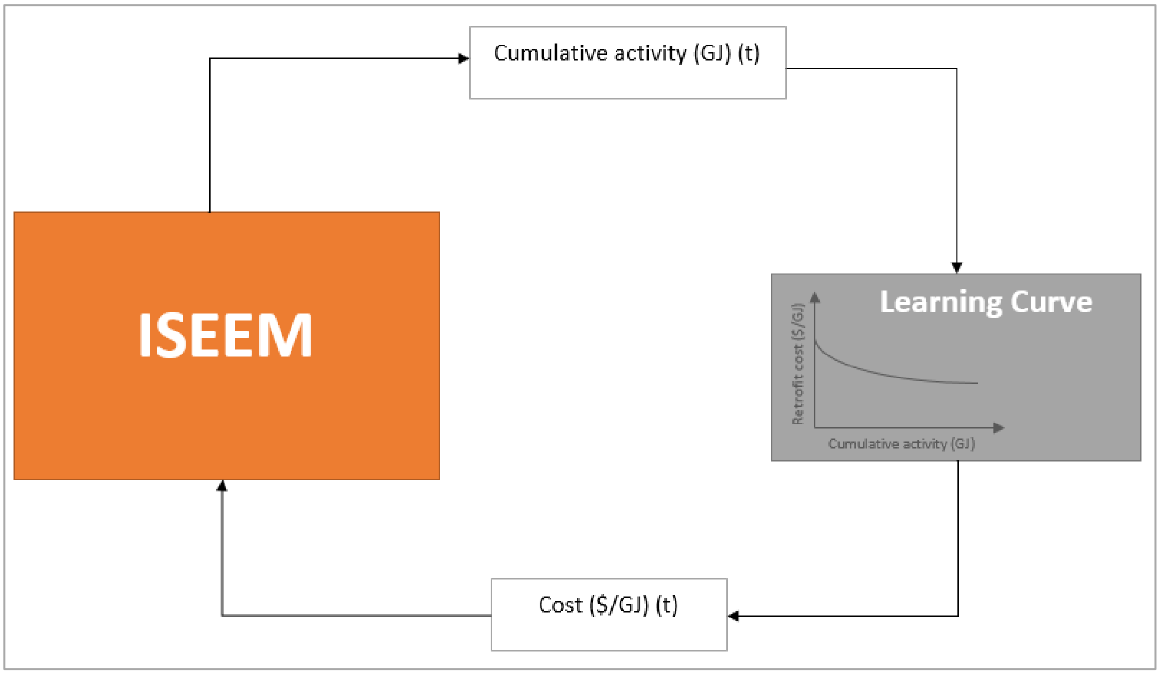


Figure 10 Iteration between ISEEM and learning curve

The iterative solution algorithm requires the following input parameters for each EE technology:

- Retrofit cost at the start period (C_1)
- Penetration rate at the start period
- Learning rate

The penetration rate enables ISEEM to calculate initial cumulative activity of the associated technology. For each EE technology, a pseudo technology is created (Figure 11). Pseudo technology is a duplicate of EE technology with no associated cost and efficiency (i.e., input/output (I/O) ratio equals to 1/1). If there is no activity on EE technology, pseudo technology would work 100% (i.e., there will be no efficiency measure implementation). If there is an activity on EE technology, the output will be shared with the pseudo technology. The share of each EE technology is fixed to penetration rate at the start year.

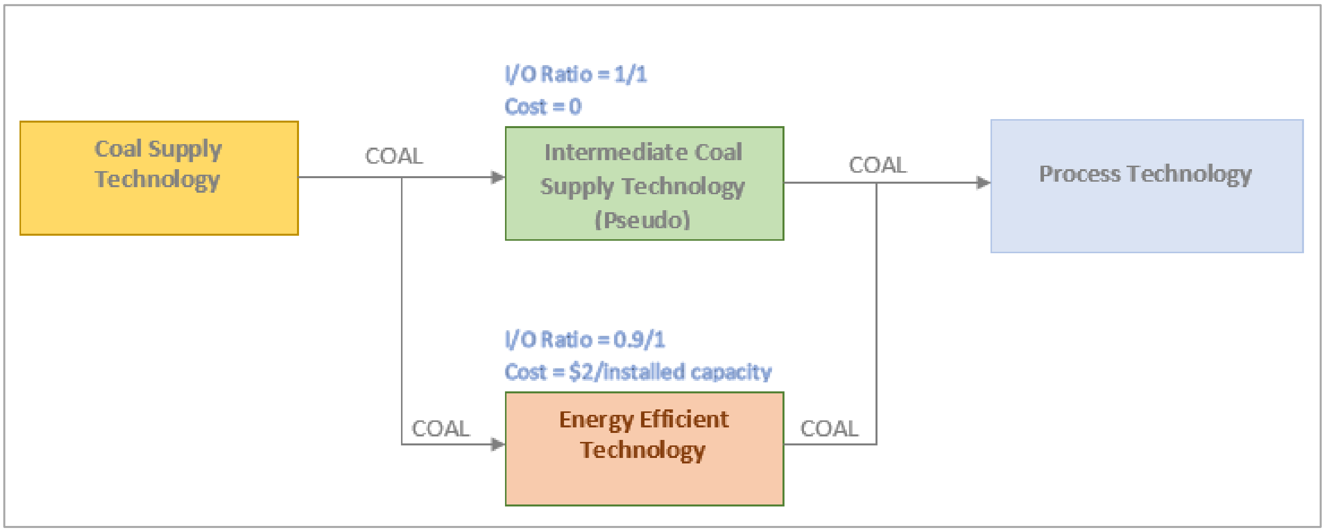


Figure 11 Schematic illustration for implementation of energy efficient technologies in ISEEM

ISEEM begins accumulating production (i.e., activity) of the EE technologies starting from the start period of the model. The cumulative production of the existing EE technologies before the beginning of the planning horizon is not taken into account. Since the cost at the start period of the planning horizon is the initial cost of the learning curve formula, this approach would not disturb the accuracy of the calculations. The learning curve formula we use is as follows:

$$Cumulative\ activity\ (t) = \sum_{i=0}^{i=t-1} Annual\ activity\ (i) \tag{3.1}$$

$$Cost\ (t) = Cost\ (0) * Cumulative\ activity\ (t)^{-b} \tag{3.2}$$

$$PR = 2^{-b} \tag{3.3}$$

where the cumulative activity of an EE technology at period *t* ($Cumulative\ activity\ (t)$ in 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 $/GJ) of the technology at period *t*, $Cost\ (0)$ is the unit retrofit cost (in $/GJ) of the technology at the start period, *b* is the learning parameter, and *PR* is the progress ratio.

For demonstration technologies, on the other hand, there is no observed penetration, thus, no associated cumulative activity, in the start period, since they've never been used before. They may or may not be adopted through the modeling periods depending on the cost minimization objective. However, as discussed in Section 2, to decrease the cost via learning curve formula a doubling of cumulative activity is needed. From this point of view, in the implementation of technological learning for a demonstration technology, ISEEM assumes a doubling of cumulative activity in the first period that the technology is available. This way, the retrofit cost of a demonstration technology decreases based on the learning rate in the following period, which is an exogenous stimuli to the

ISEEM. However, from this point onward, the system is free and the optimization procedure decides on whether further investment on the demonstration technology is needed for the cost minimization objective. If there is investment, cost continues to decrease via learning curve. If there is no investment, technology is abandoned at the end of its lifetime.

Chapter 4 ISEEM-U.S. iron and steel sector (ISEEM-USIS) model

4.1. Calibration and General Assumptions

In this study, the analyses is concentrated on the U.S. iron and steel sector. ISEEM is calibrated for the U.S. iron and steel sector for the base year 2010. 2010 is chosen as the calibration year because reliable data is available for 2010 and there were no extraordinary political, economic or social events in 2010. The planning horizon is developed in 5-year time intervals extending from 2010 to 2050. The model includes 126 process technologies, which are composed of current production technologies (18 technologies) and advanced production technologies (108 technologies). Current production technologies represent the process technologies that are currently used for iron and steel production in the U.S., such as BOF and EAF production route technologies. Advanced production technologies (i.e., newer/updated versions of current production technologies) are assumed to represent the autonomously improved versions of current iron and steel production technologies. It is assumed that those technologies would be available in the model in each year with no additional cost. We adopted an annual energy efficiency improvement rate of 0.75%, which was applied in the ISEEM model of the U.S. iron and steel sector (Karali et al., 2013). EE technologies represent the existing and emerging (i.e. in demonstration phase) energy efficiency measures in the U.S. iron and steel sector. There are 75 existing and 11 demonstration EE technologies in the model. The majority of those measures are not competing among themselves. Instead, each of them is a candidate to be adopted if *cost effective* (i.e., reducing the cost minimization objective of ISEEM-USIS). The only competing measures that are currently effective in the U.S. are different fuel injections to blast furnaces; (1) injection of 130kg pulverized coal per tonne of hot metal, (2) injection of 225kg pulverized coal per tonne of hot metal, (3) injection of 140kg natural gas per tonne of hot metal, and (4) injection of 130kg oil per tonne of hot metal.

Table B 2 in Appendix B provides the basic parameters of the EE technologies considered in this study.

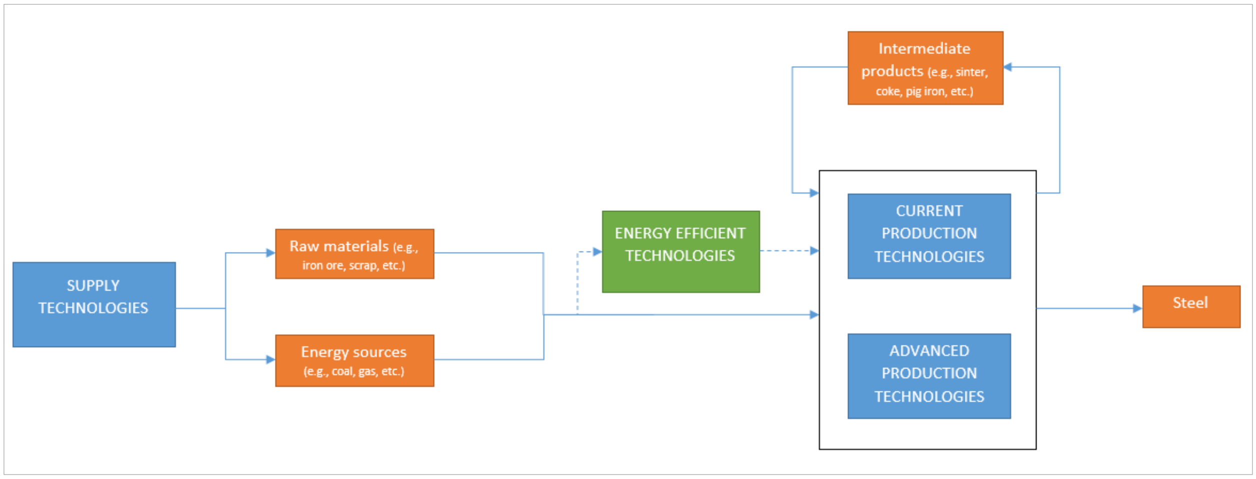


Figure 12 Production flow representations of the U.S. iron and steel sector in ISEEM-USIS

For the annual projections of the steel production in the U.S. and more details on assumptions (such as energy and raw material prices, exogenous demand growth, production constraints, and so on) and calibration included in ISEEM modeling we refer the reader to Karali (2013). A discount rate of 10% is used and a lower bound on annual production from BOF route is set to 10% of the U.S. steel production capacity. Because the total cost of steel production via BOF production route is higher than those via EAF production route, the ISEEM-USIS model's optimization process would tend to reduce the share of BOF production when seeking alternative processes with the least costs, such as EAF. However, in reality, it would be inappropriate to totally abandon BOF production route, because BOF is necessary for producing high-quality steel that EAF process just would not be able to achieve (Grobler and Minnit, 1999).

Future prices of the raw materials and energy sources used in the analysis are listed in Table 4 – 6.

Table 4 Iron ore and scrap prices used in the ISEEM-USIS model (2005 $/tonne material)

	2010	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
Domestic Iron Ore	88	115	128	140	139	133	129	132	126
Import Iron Ore	97	118	136	150	149	141	136	141	133
Domestic Scrap	284	373	423	466	461	439	425	416	404
Import Scrap	334	434	489	535	530	506	490	505	479

Source: Karali et al. (2013)

Table 5 Steam coal, electricity, miscellaneous oil, and natural gas prices considered in the ISEEM-USIS model (2005 $/GJ fuel)

	2010	2015	2020	2025	2030	2035	2040	2045	2050
Steam Coal	2.3	2.7	2.8	2.8	2.9	3.1	3.2	3.4	3.6
Electricity	16.7	15.5	15.5	15.9	15.9	16.9	16.9	16.9	17.0
Miscellaneous Oil	11.0	14.4	18.3	21.7	25.0	27.9	31.6	35.8	40.5
Natural Gas	4.5	5.0	5.4	6.3	6.7	7.3	8.1	8.9	9.8

Source: Karali et al. (2013) (*Note:* The gray shaded cells represent the prices in EIA's Annual Energy Outlook, 2011)

Table 6 Coking coal and coke prices considered in the ISEEM-USIS model (2005 $/tonne fuel)

	2010	2015	2020	2025	2030	2035	2040	2045	2050
Coking Coal	163	178	201	220	218	208	202	208	197

Source: Karali et al. (2013)

Retrofit costs of EE technologies decrease with the learning rates that we calculated in Chapter 2 and listed in Table B 2 in Appendix B). We assume that reduction of cost via learning slows down in time with increasing penetration. Thus, progress ratios (or learning rates) of EE technologies change to a higher level (or a lower level) with time. It is assumed that progress ratios (or learning rates) increase (decrease) 10% per year starting from the first year in which the learning is applied. In addition, the average *LR* rate of 0.1 calculated for the penetration interval [0-20%) (see Table 3 in Chapter 2) is used for demonstration technologies as the initial learning rate in the first year that the technology becomes available. Then, *LR* rate is changed to a lower level (listed in Table 3 in Chapter 2) as technology penetrates. For the other technologies (i.e., current and advanced production technologies) investment costs are assumed constant along the horizon (i.e., *PR* is considered equal to one). We didn't use any maximum growth constraints to control the penetration of the technologies.

As discussed in Chapter 2, there is uncertainty concerning learning rates and technology characteristics. Therefore, the analysis and the results conducted in this study should be regarded much more as what could happen if progress could be sustained at such pace. In addition, some technologies that have high penetration rates in the U.S. might have lower penetration rates in other countries, especially in developing countries such as China and India. Thus, from the global perspective, average learning rates could be higher than the ones that we obtained for the U.S. iron and steel sector.

4.2. Scenarios

Total of three scenarios are analyzed within the scope of this study. The *Frozen* scenario describes the development of the iron and steel sector where no additional production or energy policies are implemented. In addition, it is implicitly assumed that penetration levels of existing EE technologies are static at current levels until 2050, and there is no learning curve application. Production shares of

BOF and EAF, on the other hand, are not fixed and may change as a result of cost minimization objective. There is a 10% lower limit on the share of BOF production through the periods. In the *Baseline* scenario, limitations on penetration of EE technologies are eliminated. Thus, the model has the flexibility to invest in efficiency without any limitation. The other characteristics of this scenario are the same with the frozen scenario, such as no learning curve application. Learning is applied in the *Learning* scenario with flexible penetration of EE technologies. Table 7 summarizes the basic characteristics of the scenarios considered in this study.

Table 7 Scenarios defined in the ISEEM-USIS analysis

Frozen	• Penetration of existing efficiency measures/technologies is constant at 2010 levels • No demonstration technologies (that are not commercialized yet but technically feasible) • No learning
Baseline	• No limits on penetration of existing efficiency measures/technologies starting from 2015 • Demonstration technologies (that are not commercialized yet but technically feasible) available starting from 2020 • No learning
Learning	• No limits on penetration of existing efficiency measures/technologies starting from 2015 • Demonstration technologies (that are not commercialized yet but technically feasible) available starting from 2020 • Cost reductions over time according to learning curves

4.3. Results

The results from the ISEEM-USIS model presented in this section illustrate the impact of technological learning on the structure of the U.S. iron and steel sector.

Penetration (Adoption of energy efficient technologies)

Table 8 summarizes the levels of existing EE technologies in the U.S. iron and steel sector in all scenarios according to their penetration levels[3], as modeled by ISEEM-USIS. Penetrations of the EE technologies at 2015 are calibrated based on the penetration levels in 2002 (Worrell et al., 1999; Karali et al., 2013) because of limited data, and do not differentiate among scenarios in that particular year. In the Frozen scenario, the penetration levels are kept constant at 2015 levels until the end of the planning horizon (i.e., 2015-2050), thus, the number of technologies in each penetration level, listed in Table 9, does not change.

[3] As noted in Table 3, penetration of energy efficient technology in this analysis is defined as follows: for technologies in BOF (i.e., integrated steel) production route, share of total U.S. integrated steel production to which measure is applied; and for technologies in EAF (i.e., secondary steel, production), share of total U.S. secondary production to which measure is applied. See Appendix B for the entire list.)

In the Baseline scenario, where there is no learning, 57% and 89% of the EE technologies have more than 80% of penetration in 2025 and 2050, respectively (up from 36% in 2015). These results indicate that most of the existing EE technologies that are currently used in the U.S. iron and steel sector are cost effective. Penetration levels increases through the years, even though there is no technology cost reduction. In addition, none of the demonstration technologies, which are not commercialized yet but technically feasible, are adopted in this scenario. This indicates that those technologies are not economically feasible in the ISEEM-USIS model with the current cost structure, as assumed at the beginning.

In the Learning scenario, where price reduction of existing EE technologies are observed, 57% and 93% of the efficiency measures have more than 80% of penetration in 2025 and 2050, respectively. Since most of the existing EE technologies are cost effective and progressively adapted through the years as observed in the Baseline scenario, decreasing costs via the learning curve does not significantly alter results between the two scenarios (i.e., Baseline and Learning scenarios). The share of technologies that have penetration level of more than 80% in 2050 increases from 89% in the Baseline scenario to 93% in the Learning scenario. However, the results indicate that some of the demonstration technologies are adapted in the mid-term and their penetration levels increase as the prices go down in the Learning scenario (see Table 9). Furthermore, even though Blast Furnace Heat Recuperation[4] (BF-HR) is listed as a demonstration technology, it becomes economically feasible in a very short period of time and gets 100% penetration in 5 years from its initial availability in 2020).

Table 8 Penetration levels by scenario

	Frozen	**Baseline**			**Learning**		
Penetration level	**2010-2050**	**2015**	**2025**	**2050**	**2015**	**2025**	**2050**
[80-100%]	36%	36%	57%	89%	36%	57%	93%
[60-80%)	11%	11%	16%	1%	11%	16%	4%
[40-60%)	20%	20%	19%	4%	20%	21%	3%
[20-40%)	25%	25%	8%	5%	25%	5%	0%
[0-20%)	8%	8%	0%	0%	8%	0%	0%
	100%	100%	100%	100%	100%	100%	100%

[4] The heat of hot blast stove flue gases, with an exit temperature of approximately 480°F (250°C), can be recovered to preheat the combustion air of the stoves to reduce energy consumption.

Table 9 Penetration levels of demonstration technologies in the Learning scenario

	2020	2025	2030	2035	2040	2045	2050
SIN-SWGR	-	-	-	-	-	-	-
COK-APCS	-	-	-	-	-	-	-
COK-NRCO	-	-	-	-	-	-	-
SCOPE21	-	-	50%	56%	61%	62%	62%
BF-HR	-	100%	100%	100%	100%	100%	100%
BF-SHR	-	-	-	-	68%	100%	100%
BF-AUCOG	-	-	2%	-	-	-	-
BOF-ABA	-	-	7%	43%	89%	100%	100%
EAF-ABA	-	4%	52%	76%	97%	100%	100%
BOF-ISRT	-	-	100%	100%	100%	100%	100%
EAF-ISRT	-	-	34%	98%	100%	100%	100%

(*Note:* See Table B3 in Appendix B for full names of technologies)

One of the other major difference between the Baseline and Learning scenarios is the increasing penetration of 225kg pulverized coal injection (PCI225) in the Learning scenario. Currently, in the U.S. iron and steel sector, there are four competitive injection methodologies that are used in iron making (i.e., blast furnaces) to decrease the amount of coke needed[5]; (1) injection of 130kg pulverized coal per tonne of hot metal, (2) injection of 225kg pulverized coal per tonne of hot metal, (3) injection of 140kg natural gas per tonne of hot metal, and (4) injection of 130kg oil per tonne of hot metal. Those technologies have penetration levels of 21%, 26%, 21%, and 21%, respectively, in the base year. Since they are competing with each other, an increase in one's penetration results in a decrease in another's penetration. Injected fuel is replaced with coke in blast furnaces.

In the Baseline scenario, penetration levels of those injection technologies do not significantly change. In the Learning scenario, on the other hand, with decreasing prices under the impact of learning, injection of 225kg pulverized coal technology displaces with other injection technologies and reaches 100% penetration starting from 2030.

Energy Consumption

Figure 13 shows the annual steel production in the U.S. forecasted by the ISEEM-USIS model in all scenarios. The use of EAF as a low-cost steel production process dominates the U.S. steel production. Because of high production costs, the share of BOF steel production gradually decreases until the

[5] One of the main energy and cost saving measures for blast furnaces is replacing some of the coke input by injecting other hydrocarbon sources (IPPC, 2011). Coal and oil are the most commonly used injectants, while other hydrocarbons include natural gas, coke oven gas, basic oxygen furnace gas, oil and plastics (IPPC, 2011 and Worrell et al., 2010).

lower limits set in the model assumptions are reached (in 2035). This result does not differ in between scenarios.

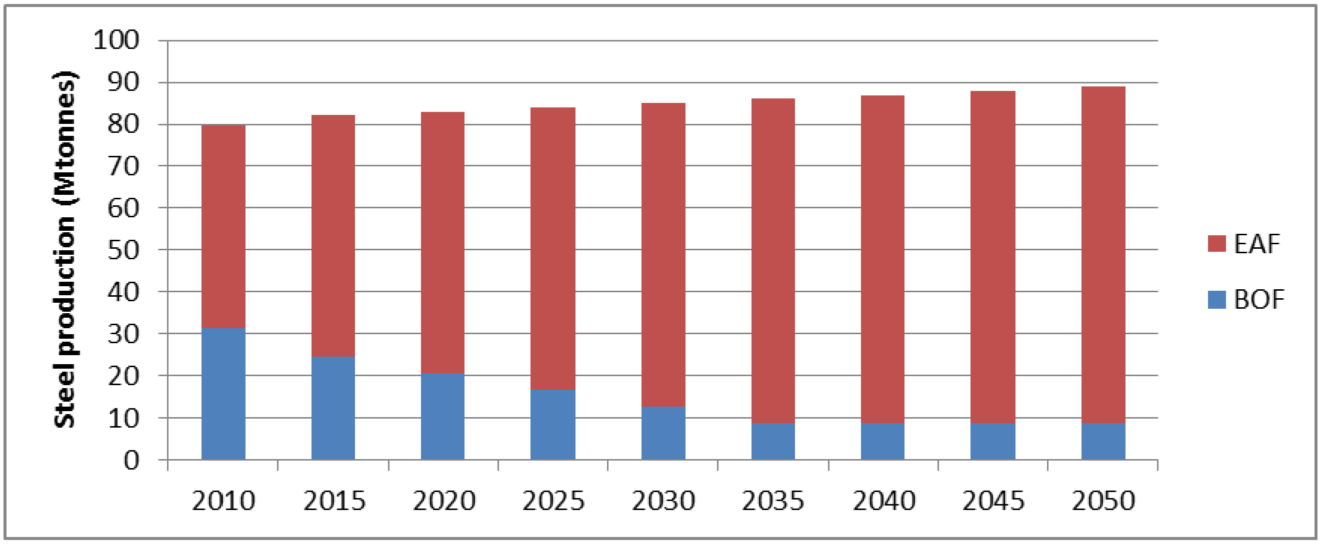


Figure 13 BOF and EAF productions in all scenarios (Mtonnes)

EAF production process requires only about one-third of the primary energy needed in the BOF production route, since the most energy intensive steps in the steel sector has been carried out in the BOF route. As a consequence of decreasing BOF share, consumptions of final and primary energy decrease in all scenarios through the years (Figure 14 - 15). In addition, lower levels of energy consumption are observed in the Baseline and Learning scenarios between 2020 and 2050, compared to the Frozen scenario (Table 10 - 11), as a consequence of an increasing penetration of EE technologies in both scenarios. As mentioned earlier, 89% and 93% of the existing EE technologies have more than 80% penetration in 2050 in the Baseline and Learning scenarios, respectively (compared to 36% in Frozen scenario). Higher penetration of existing EE technologies, particularly PCI225, in the Learning scenario further reduces the energy consumption compared to the Baseline scenario. In addition, penetration of some of the demonstration technologies (see Table 9), particularly after 2040, also contributes to the lower energy consumption in the Learning scenario.

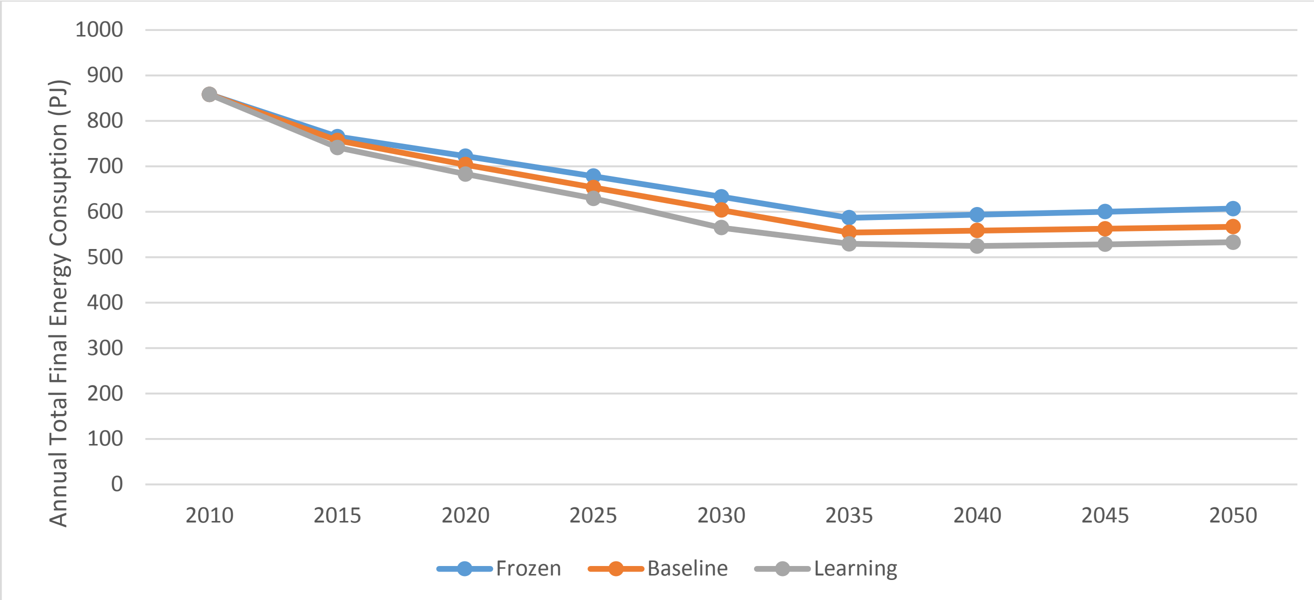


Figure 14 Annual total *final* energy consumption in the U.S. iron and steel sector in all scenarios (PJ)

Table 10 Reduction in annual total final energy consumption in the U.S. iron and steel sector in the Baseline and Learning scenarios (compared to Frozen scenario)

	2020	2025	2030	2035	2040	2045	2050
Baseline	2.6%	3.7%	4.6%	5.5%	5.8%	6.3%	6.6%
Learning	5.5%	7.2%	10.8%	9.8%	11.6%	12.0%	12.2%

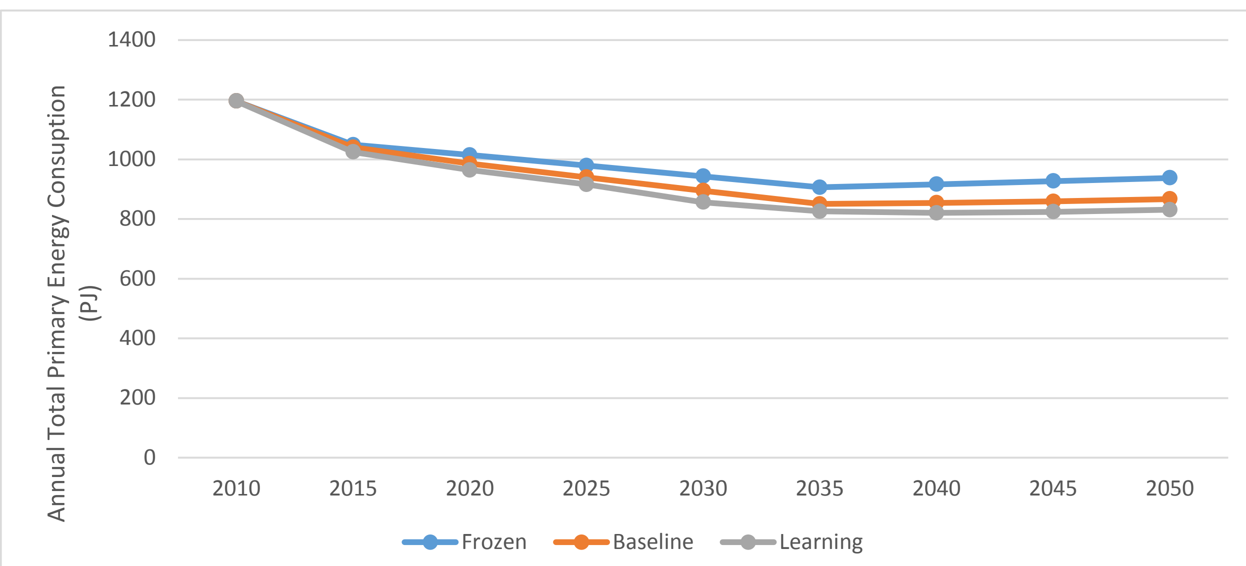


Figure 15 Annual total *primary* energy consumption in the U.S. iron and steel sector in all scenarios (PJ)

Table 11 Reduction in annual total primary energy consumption in the U.S. iron and steel sector in the Baseline and Learning scenarios (compared to Frozen scenario)

	2020	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
Baseline	2.9%	4.0%	5.1%	6.2%	6.8%	7.4%	7.5%
Learning	4.9%	6.5%	9.2%	8.9%	10.5%	11.1%	11.3%

In all scenarios, the consumption of coking coal (which is the main energy source of BOF production route) drops significantly as a consequence of the declining BOF production (Figure 16). In the Learning scenario, with increasing penetration of PCI225 and implementation of demonstration technologies, coking coal consumption decreases even more, reaching 80.1PJ in 2050, compared to the 139.4PJ in the Frozen scenario and 138.1PJ in the Baseline scenario. But in return, coal consumption increases in the Learning scenario. However, burning coal instead of burning coke in blast furnaces is more environmentally friendly than burning coking coal to make coke and then burning that coke in blast furnaces[6].

Oil injection in blast furnaces (to replace coke) is abandoned in both the Baseline and Learning scenarios, since it is not economic compared to injection of pulverized coal. This explains the decline in oil usage in scenarios. Increasing overall efficiency also contributes declining oil usage. Natural gas consumption, on the other hand, is pretty similar in all scenarios through the years. Even though there is a reduction in natural gas usage due to increasing overall efficiency and the elimination of natural gas injection in blast furnaces, some of the EE technologies that decrease electricity consumption requires additional usage of natural gas. This situation causes slightly larger natural gas consumption in the Baseline scenario compared to the Frozen scenario. In the Learning scenario, there is slightly lower natural gas consumption, while electricity consumption drops in each scenario, increasing overall efficiency (compared to the Frozen scenario).

[6] Emission factors – burning steam coal: 92.2 KgCO_2/GJ coal; burning coking coal: 94.6kgCO_2/GJ coking coal; burning coke: 107kgCO_2/GJ coke, coke production process emission: 20kgCO_2/GJ coke

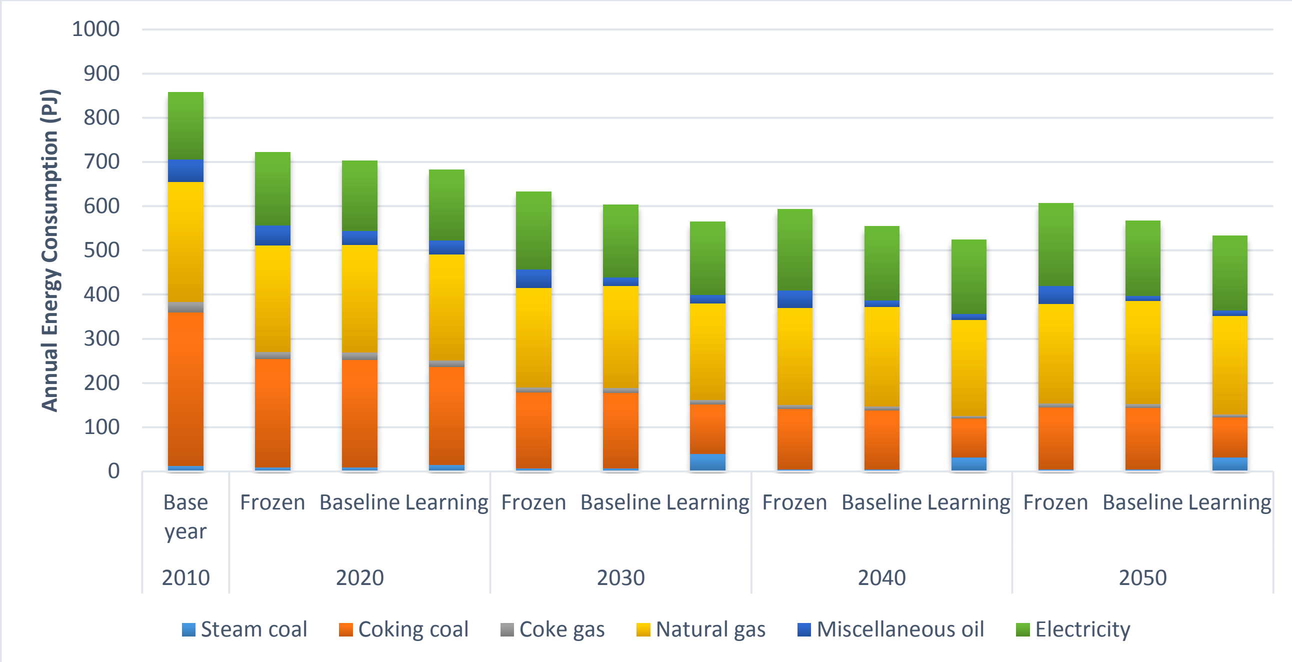


Figure 16 Breakdown of the U.S. iron and steel sector's annual final energy consumption in all scenarios (PJ)

Table 12 lists in detail where the energy savings in the Learning scenario comes from. As can be seen, increased penetration of PCI225 has a large impact. 35% and 26% of the total energy saving in 2030 and 2050 is from PCI225, and approximately 8% of the savings come from demonstration technologies after 2030. In addition, compared to the Baseline scenario, energy saving from existing EE technologies increases 34% (from 28.83PJ to 38.77PJ) in 2030 and 23% (from 39.65PJ to 48.72PJ) in 2050 in the Learning scenario.

Table 12 Energy savings in the Learning and Baseline scenarios in PJ (compared to Frozen scenario)

	2010	2020	2030	2040	2050
Frozen	858.07	722.20	632.84	593.17	606.78
Baseline	858.07	703.38	603.61	558.51	566.79
Total Energy Saving in Baseline Sce.	-	18.82	29.23	34.67	39.99
Savings from PCI225	-	0.43	0.40	0.33	0.34
Savings from existing energy efficient tech (excluding PCI225)	-	18.40	28.83	34.34	39.65
Learning	858.07	682.59	564.65	524.47	532.83
Total Energy Saving in Learning Sce.	-	39.61	68.19	68.71	73.95
Savings from PCI225	-	-	23.90	19.05	19.49
Savings from SCOPE21	-	-	1.31	1.30	1.33
Savings from BF_HR	-	-	0.86	0.68	0.70
Savings from BF_AUCOG	-	-	-	-	-
Savings from BOF_SHR	-	-	-	0.18	0.19
Savings from BOF_ABA	-	-	-	0.07	0.07
Savings from BOF_ISRT	-	-	0.41	0.28	0.28
Savings from EAF_ABA	-	-	0.65	0.70	0.72
Savings from EAF_ISRT	-	-	2.28	2.47	2.53
Savings from existing energy efficient tech (excluding PCI225)	-	39.61	38.77	44.04	48.72

Figure 17 - 18 show total energy consumptions in BOF and EAF routes separately. As seen from Figure 18, the difference of EAF route energy consumption in the Baseline and Learning scenario is very little. This result indicates that almost all of the EE technologies in the EAF production route are already cost effective, and are invested through the years without any reduction in prices. The minor difference between the two scenarios' energy consumption (i.e., Baseline and Learning scenarios) is due to implementation of two demonstration technologies (EAF-ABA and EAF-ISRT). Compared to this, learning effect on BOF production route is more straightforward. Figure 17 shows the additional energy savings in the BOF route in the Learning scenario due to reducing prices. In the Baseline scenario, there is not much difference in energy consumption compared to the Learning scenario. In contrast, in the Learning scenario, energy consumption is 15% lower than the Baseline scenario in 2050 (down from 251 PJ in the Baseline scenario to 213PJ in the Learning scenario). As mentioned above, BOF production gradually decreases until the lower limits set in the model assumptions are reached because of its high production costs. As a consequence, contribution of energy efficiency improvement in the BOF route does not make a large impact in the overall energy consumption of the iron and steel sector. A sensitivity run indicates that if BOF production has the current share in 2050 in all scenarios, energy saving via learning in the U.S. iron and steel sector would be 80% higher.

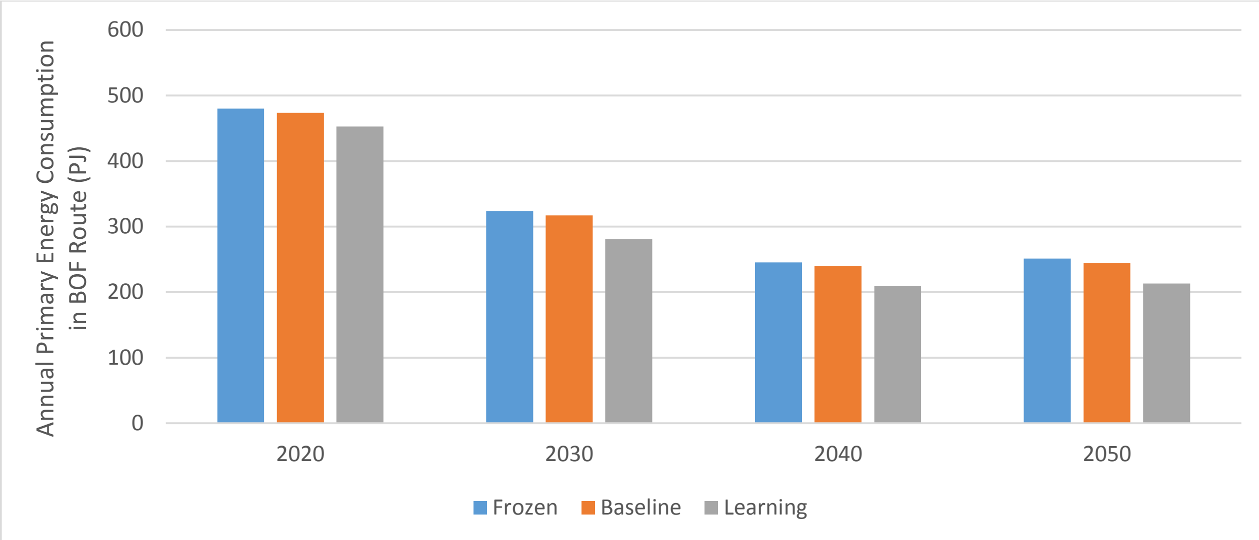


Figure 17 Annua primary energy consumption in the BOF production route in all scenarios

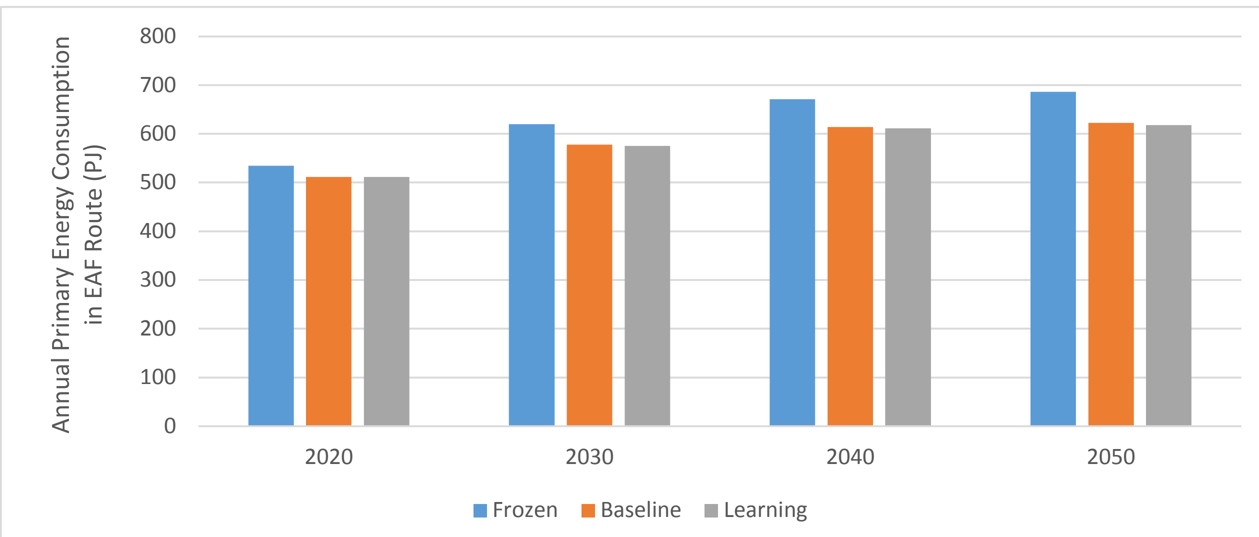


Figure 18 Annual primary energy consumption in the EAF production route in all scenarios

Table 13 - 14 illustrate the developments of the final and primary energy intensities. The Learning scenario provides the lowest energy intensity levels in all periods. Final energy intensity of the U.S. iron and steel sector decreases from10.7 GJ/tonne steel in 2010 to 6.4 GJ/tonne steel in the Baseline scenario and 6 GJ/tonne steel in the Learning scenario in 2050.

Table 13 Final energy intensity of the U.S. iron and steel sector projected in the scenarios

(GJ/tonne steel)

	2010	2015	2020	2025	2030	2035	2040	2045	2050
Frozen	10.66	9.32	8.70	8.07	7.45	6.83	6.83	6.83	6.83
Baseline	10.66	9.22	8.47	7.78	7.11	6.45	6.43	6.40	6.38
Learning	10.66	9.03	8.22	7.49	6.65	6.16	6.04	6.01	5.99

Table 14 Primary energy intensity of the U.S. iron and steel sector projected in the scenarios (GJ/tonne steel)

	2010	*2015*	*2020*	*2025*	*2030*	*2035*	*2040*	*2045*	*2050*
Frozen	14.85	12.77	12.22	11.66	11.10	10.55	10.55	10.55	10.55
Baseline	14.85	12.67	11.87	11.19	10.54	9.90	9.83	9.77	9.75
Learning	14.85	12.48	11.61	10.90	10.08	9.61	9.44	9.38	9.35

Costs

Table 15 summarizes the costs of average steel production through the years in each scenario. As mentioned above, most of the existing EE technologies are cost effective under the cost minimization objective of the ISEEM-USIS model. Increasing penetration of those cost effective technologies in the Baseline scenario decreases the total production cost of steel 2005 $0.7B in 2030 and 2005 $1.4B in 2050, compared to the Frozen scenario, even though there is no learning impact on prices associated with efficient technologies. In the Learning scenario, total steel production cost decreases even more (e.g., 2005 $1.4B in 2030 and 2005 $2.1B in 2050) due the effect of learning on technology prices. Table 1 provides the development of average steel production cost (i.e., $ per tonne steel) between 2010 and 2050 in all scenarios.

Table 15 Average steel production cost in the U.S. iron and steel sector in scenarios (2005 $/tonne steel)

	2010	2015	2020	2025	2030	2035	2040	2045	2050
Frozen	509.5	607.5	658.0	699.8	692.5	657.5	623.5	624.6	618.2
Baseline	509.5	614.0	654.9	694.2	684.4	647.1	612.1	611.2	603.0
Learning	509.5	611.6	651.3	689.6	676.4	642.4	604.4	603.0	595.0

CO_2 Emissions

In the Frozen scenario, CO_2 emissions decrease until 2035, in which BOF production reaches to the lower bound set in the model assumptions. After that year onward, emissions pretty much stabilize and reach a level of approx. 56.3 billion tonnes of CO_2 (Figure 19). BOF production route is highly emission intensive compared to the EAF production route.

In the Baseline and Learning scenarios, CO_2 emissions are 5.7% and 27.4% lower in 2050, compared to the Reference scenario. The major reason for this drastic reduction in the LR scenario is the lower demand for coking coal and coke, and so for coke production. A large share of coke used in the blast furnaces is replaced with pulverized coal. In addition, implementation of more efficient coke production technology (SCOPE21), compared to the old technology, after 2030 significantly decreases the coking coal consumption.

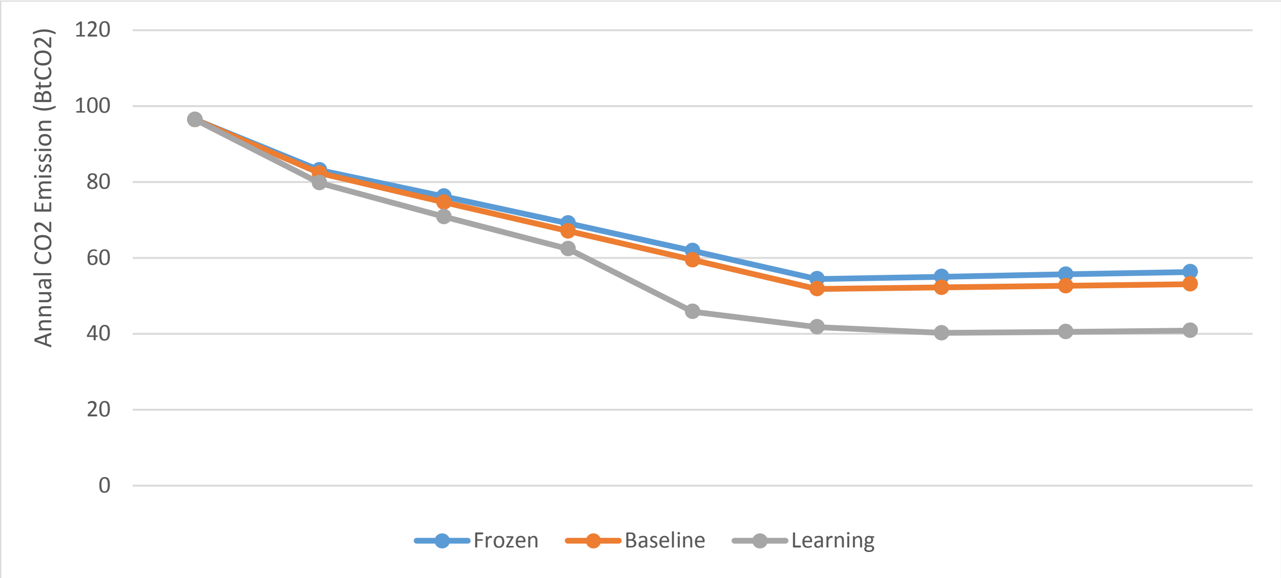


Figure 19 Annual total CO_2 emission in the U.S. iron and steel sector

Chapter 5 Conclusions and Discussions

The overall goal of this study was to analyze the learning effect on cost developments and technological progress of EE technologies in the U.S. iron and steel sector in the long term. Based on our findings on learning rates by analyzing historical data, we calculated average learning rates by technology penetration level.

The investigation was carried out using ISEEM, a technology oriented, linear optimization model for the U.S. iron and steel sector. In this study, the ISEEM model was run in an iterative fashion in combination with a learning curve function. The model, as a consequence of its structure, produces results favoring low-cost production processes, unless there are constraints limiting their activities. We conclude from our analysis that, most of the existing EE technologies that are currently in use in the U.S. iron and steel sector are cost effective for the cost minimization objective (i.e., reducing the cost minimization objective) and, thus, the model has a tendency towards increasing penetration of them, even in the absence of price reductions. However, demonstration (or emerging) technologies, which represent the technologies without a significant production history, are generally not yet economically feasible in the U.S. iron and steel sector. In contrast, adoption is forecast for some of these in the long term and their penetration levels increase as prices go down with experience. We also observe a large penetration of 225 kg pulverized coal injection, which is one of the most expensive existing EE injection methodology to blast furnaces, with the presence of learning.

The model results indicate that the energy consumption and CO_2 emissions will decline with technology learning. For example, primary energy consumption of the U.S. iron and steel sector decreases from 1195PJ in 2010 to 867PJ in the Baseline scenario (with no learning) and 831PJ in the Learning scenario (where learning is adopted) in 2050 (compared to 938PJ in Frozen scenario, in which penetration of EE technologies are constant with no learning). In addition, an increasing penetration of cost effective EE technologies in the Baseline scenario results lowers average steel production cost by $15/tonne steel compared to the Frozen scenario in 2050. With technology learning in the Learning scenario, average steel production cost decreases by an additional of $8/tonne steel (total of $23/tonne steel compared to Frozen scenario) in 2050.

Implementation of technology learning in the ISEEM modeling shows how early introduction of some demonstration technologies can accelerate their adoption as costs decline, compared to the exogenous cost projections (constant cost over time in this case).

Although the integration of learning curve with ISEEM show improvement in the results, it is important to be aware of limitations with the model to be considered in future research,

- Under the learning conditions specified here, by the end of the time horizon (i.e., 2050) the retrofit costs of some of the technologies have reached fairly low values. For example, PCI225 in this scenario have reached US$1.6/GJ tech. activity (from US$9.4/GJ tech. activity in 2010) (see Figure 21) with a constant LR of 0.06. This behavior may raise the question of whether the cost reduction of some learning technologies should be limited, for instance providing a lower bound (i.e., floor-cost) for the unit retrofit cost, in order to avoid excessive cost reductions. In the literature, different criteria have been applied to handle this situation. Messner (1997) and Seebregts et al. (1999) imposed a lower bound for the specific cost of the learning technologies, while Mattsson (1997) decided to let the natural saturation of the learning curve to control the cost reduction without imposing any lower bounds. The lower bound, where possible, should be supported by studies of the cost structure and specific potential for cost reductions in the different components, since it is tied to the expectations of the modeler as to what constitutes a "reasonable" limit value.

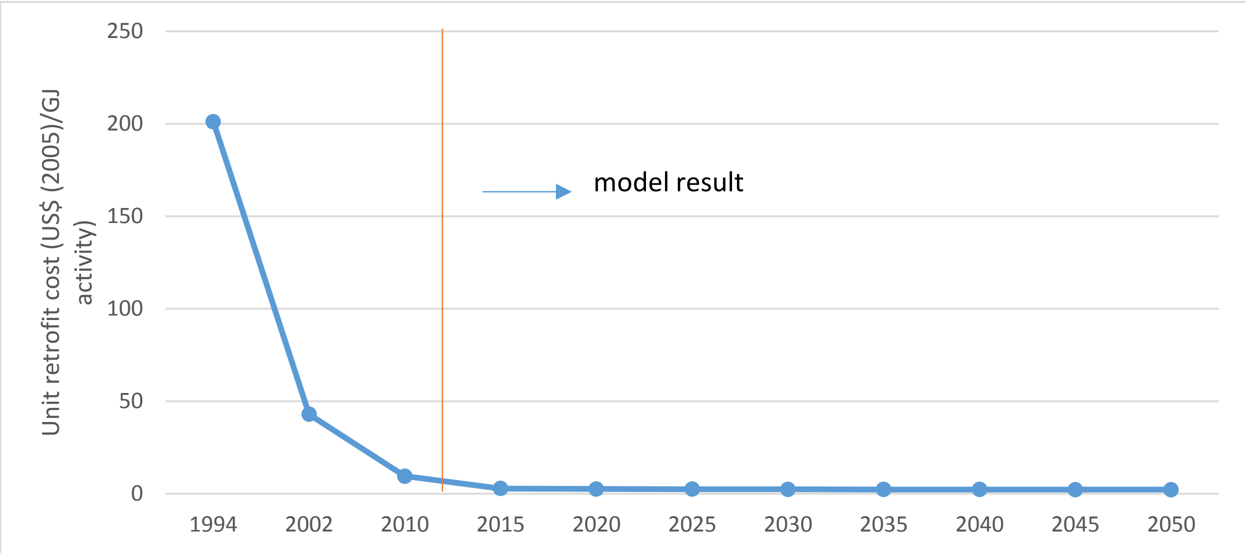


Figure 20 Evolution of unit retrofit cost of PCI225 with constant LR of 0.06

- Similarly, some studies in the literature (e.g., Seebregts et al. 1999) limit the penetration of technologies under learning with a maximum installed capacity parameter. Due to the nature of cost minimization objective, penetration of a specific technology may jump to full penetration from a very low penetration level in a very short period of time (See Table 9 for examples).

- The data that we used to calculate technology specific learning rates is subject to uncertainty. Not only the learning rate itself is uncertain, it is also uncertain if it will retain the same level over the entire planning horizon considered or if they might decline. In this study, as mentioned before we assume that reduction of cost via learning slows down in time with 1% decrease of LR every year starting from the first year in which the learning is applied.

Table 16 Development of specific retrofit cost of PCI225 with constant ad slowing down LR

(2005 $/GJ technology activity)

Constant LR (0.05)	201.0	43.0	9.43	2.72	2.52	2.41	2.30	2.26	2.22	2.19	2.16
Slowing LR (1% per year)	201.0	43.0	9.43	2.72	2.70	2.67	2.66	2.63	2.62	2.61	2.61

- Technology learning is restricted to retrofit cost only; other technology attributes like O&M costs and efficiency remain exogenous (constant in this case).

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Appendix A. Learning rates from literature

Table A 1 Learning rates for some energy technologies (Source: Kahouli-Brahmi, 2008)

Baselines	Energy technology	Dependent variable	Independent variable	Country	Time period	Estimated learning rate (%)
Fisher (1974)	Electric power production	Sale price ($/kWh)	Cumulative production ($/kWh)	US	1926–1970	25
Fisher (1974)	Coal for electric utilities	Sale price to utility ($/ton)	Cumulative production ($/ton)	US	1948–1969	25
Fisher (1974)	Crude oil	Sale price ($/bbl)	Cumulative production ($/bbl)	US	1869–1971	5
Fisher (1974)	Retail gasoline processing	Production cost ($/bbl)	Cumulative production ($/bbl)	US	1919–1969	20
Maycock and Wakefield (1975)	Solar Photovoltaic panels	Sale price ($/kW peak)	Cumulative installed capacity (MW)	US	1959–1974	22
Jaskow and Rose (1985)	Coal power plants	Investment cost ($/kW)	Cumulative installed capacity (units)	US	1960–1980	1–6.4
Jaskow and Rose (1985)	Supercritical coal	Production cost ($/kWh)	Cumulative production (TWh)	US	N/A	3
MacGregor et al. (1991)	Gas turbines	Investment cost ($/kW)	Cumulative installed capacity (MW)	N/A	1958–1963	22
MacGregor et al. (1991)	Gas turbines	Investment cost ($/kW)	Cumulative installed capacity (MW)	N/A	1963–1980	9.9
MacGregor et al. (1991)	Gas turbines	Investment cost ($/kW)	Cumulative installed capacity (MW)	N/A	1958–1980	13
Williams and Terzian (1993)	Solar Photovoltaic modules	Sale price ($/Wpeak)	Cumulative sales (MW)	Global	1976–1992	18
Lund (1995)	Wind	Investment cost (€/kW)	Cumulative installed capacity (kW)	Denmark	N/A	15
Dannemand Andersen and Fuglsang (1996)	Wind	Sale price (€/kWh)	Cumulative installed capacity (kW)	Denmark	1981–1995	20
Goldemberg (1996)	Ethanol	Sale price ($/bbl)	Cumulative production (million m3)	Brazil	1979–1995	20
Loiter and Norberg-Bohm (1999) CEC (1997)	Wind electricity	Production cost ($/kW)	Cumulative production (TWh)	California	1980–1994	20
Neij (1997)	Solar photovoltaic modules	List prices ($/kWh)	Cumulative sales (MW)	Denmark	1982–1997	20
Neij (1997)	Wind turbines	List prices ($/kWh)	Cumulative sales (MW)	Denmark	1982–1995	4
Mackay and Probert (1998)	Wind turbines	Capital cost (US$/kWh)	Cumulative sales (MW)	US	1981–1996	14.3
Mackay and	Solar	Prices	Cumulative	US	1976–	18

Probert (1998)	photovoltaic modules	(US$/Wp)	installed capacity (MWp)		1995	
Nitsch/ EU-ATLAS project (1998)	Solar photovoltaic modules	Sale price ($/Wpeak)	Cumulative production (MW)	EU	1976–1996	21
Nakicenovic et al. (1998)	Gas turbines	Investment cost ($/kW)	Cumulative installed capacity (MW)	N/A	1958–1980	13
Neij (1999)	Wind turbines	List prices ($/kW)	Cumulative sales (MW)	Denmark	1982–1997	6 and 4
Durstewitz and Hoppe-Kilpper (1999)	Wind	Prices ($/kW)	Cumulative installed capacity (MW)	Germany	1990–1998	8
Zhao (1999)	Gas pipelines onshore	Price ($/mile-inch2)	Cumulative installed capacity (mile-inch2)	US	1984–1997	3.7
Zhao (1999)	Gas pipelines offshore	Price ($/mile-inch2)	Cumulative installed capacity (mile-inch2)	US	1984–1997	24
Rabitsch (1999)	DC converters	Conversion losses (%)	Cumulative installed capacity (installed units)	Global	1976–1994	37
Claeson (1999)	GTCC power plants	Prices ($/kW)	Cumulative installed capacity (MW)	Global	1981–1991	−11
Claeson (1999)	GTCC power plants	Prices ($/kW)	Cumulative installed capacity (MW)	Global	1991–1997	26
Claeson (1999)	GTCC power plants	Production cost ($/kWh)	Cumulative production (TWh)	EU	N/A	4
Harmon (2000)	Solar photovoltaic modules	Prices ($/kWpeak)	Cumulative installed capacity (MW)	Global	1968–1998	20.2
Kouvaritakis et al. 2000a and Kouvaritakis et al. 2000b	Wind power plants	Investment cost ($/kW)	Cumulative installed capacity (MW)	OECD	1981–1995	17
Kouvaritakis et al. 2000a and Kouvaritakis et al. 2000b	Nuclear power plants	Investment cost ($/kW)	Cumulative installed capacity (MW)	OECD	1975–1993	5.8
Kouvaritakis et al. 2000a and Kouvaritakis et al. 2000b	Hydropower plants	Investment cost ($/kW)	Cumulative installed capacity (MW)	OECD	1975–1993	1.4
Kouvaritakis et al. 2000a and Kouvaritakis et al. 2000b	Coal power plants	Investment cost ($/kW)	Cumulative installed capacity (MW)	OECD	1975–1993	7.6
Kouvaritakis et al. 2000a and Kouvaritakis et al. 2000b	Lignite power plants	Investment cost ($/kW)	Cumulative installed capacity (MW)	OECD	1975–1992	8.6
Kouvaritakis et al. 2000a and Kouvaritakis et al.	GTCC power plants	Investment cost ($/kW)	Cumulative installed capacity (MW)	OECD	1984–1994	34

2000b						
Wene (2000)	Wind power	Production cost ($/kWh)	Cumulative production (TWh)	US	1985–1994	32
Wene (2000)	Wind power	Production cost (ECU/kWh)	Cumulative production (TWh)	EU	1980–1995	18
Wene (2000)	Photovoltaic	Production cost (ECU/kWh)	Cumulative production (TWh)	EU	1985–1995	35
Wene (2000)	Electricity from biomass	Production cost ($/kWh)	Cumulative production (TWh)	EU	1980–1995	15
Wene (2000)	Supercritical coal	Production cost ($/kWh)	Cumulative production (TWh)	US	N/A	3
Wene (2000)	GTCC	Production cost ($/kWh)	Cumulative production (TWh)	EU	N/A	4
Wene (2000)	Ethanol	Sale price ($/bbl)	Cumulative production (million/m3)	Brazil	1978–1995	22
Isoard and Soria (2001)	Solar photovoltaic modules	Capital cost ($/kW)	Cumulative installed capacity (MW)	EU	1976–1994	27.8
Isoard and Soria (2001)	Wind	Capital cost ($/kW)	Cumulative installed capacity (MW)	EU	1981–1995	17.06
Milborrow (2002)	Wind	Investment cost (€/kW)	Cumulative installed capacity (kW)	Denmark	N/A	15.3
Ibenholt (2002)	Wind electricity	Production cost (Euro/kWh)	Cumulative installed capacity (MW)	Germany	1991–1999	(−3)–8
Ibenholt (2002)	Wind electricity	Production cost (Euro/kWh)	Cumulative installed capacity (MW)	Denmark	1988–1999	7
Ibenholt (2002)	Wind electricity	Production cost (Euro/kWh)	Cumulative installed capacity (MW)	Denmark	1984–1988	12
Ibenholt (2002)	Wind electricity	Production cost (Euro/kWh)	Cumulative installed capacity (MW)	UK	1991–1999	15
Neij et al (2003)	Wind turbines	Price of wind turbines (EUR/kWh)	Cumulative produced capacity (MW)	Denmark Germany Spain and Sweden	1981–2000	6–8
Neij et al (2003)	Wind turbines	Total installation costs (EUR/kWh)	Cumulative installed capacity (MW)	Denmark Germany Spain and Sweden	1981–2000	4–11
Neij et al (2003)	Wind electricity	Production cost (MW)	Cumulative produced capacity (MW)	Denmark Germany Spain and Sweden	1981–2000	12–14
Neij et al (2003)	Wind electricity	Production cost (EUR/kWh)	Cumulative produced capacity (MW)	Denmark Germany Spain and Sweden	1981–2000	17

Neij et al (2003)	Wind turbines	Price of wind turbines (EUR/kWh)	Cumulative installed capacity (MW)	Denmark Germany Spain and Sweden	1981–2000	(−17)–11
Klaassen et al. (2005)	Wind turbines	Investment cost ($/kW)	Cumulative installed capacity (MW)	Denmark Germany and UK	1986–2000	5.4
Junginger et al. (2005)	Wind turbines	Investment cost (€/kW)	Cumulative installed capacity (MW)	Spanish	1990–2001	15
Junginger et al. (2005)	Wind turbines	Investment cost (€/kW)	Cumulative installed capacity (MW)	UK	1992–2001	19
Kobos et al. (2006)	Wind	Capital cost ($/kW)	Cumulative installed capacity (MW)	US	1981–1997	14.2
Kobos et al. (2006)	Solar photovoltaic	Capital cost ($/kW)	Cumulative installed capacity (MW)	US	1975–2000	18.4
Coulomb and Neuhoff (2006)	Wind turbines	German prices (€/kW)	Global cumulative installed capacity (MW)	Global	1991–2003	12.7
Jamasb (2006)	Pulverized fuel supercritical coal	Investment cost ($99/kW)	Cumulative installed capacity (MW)	Global	1990–1998	3.75
Jamasb (2006)	Coal conventional technology	Investment cost ($99/kW)	Cumulative installed capacity (MW)	Global	1980–1998	12.39
Jamasb (2006)	Lignite conventional technology	Investment cost ($99/kW)	Cumulative installed capacity (MW)	Global	1980–2001	5.67
Jamasb (2006)	Combined cycle gas turbine	Investment cost ($99/kW)	Cumulative installed capacity (MW)	Global	1980–1989	0.65
Jamasb (2006)	Combined cycle gas turbine	Investment cost ($99/kW)	Cumulative installed capacity (MW)	Global	1990–1998	2.2
Jamasb (2006)	Large hydropower	Investment cost ($99/kW)	Cumulative installed capacity (MW)	Global	1980–2001	1.96
Jamasb (2006)	Combined heat and power	Investment cost ($99/kW)	Cumulative installed capacity (MW)	Global	1980–1998	0.23
Jamasb (2006)	Small hydropower	Investment cost ($99/kW)	Cumulative installed capacity (MW)	Global	1988–2001	0.48
Jamasb (2006)	Nuclear power (light water reactor)	Investment cost ($99/kW)	Cumulative installed capacity (MW)	Global	1989–1998	36.3
Jamasb (2006)	Waste to electricity	Investment cost ($99/kW)	Cumulative installed capacity (MW)	Global	1990–1998	41.5
Jamasb (2006)	Wind energy—one shore	Investment cost ($99/kW)	Cumulative installed capacity (MW)	Global	1994–2001	13.1
Jamasb (2006)	Solar power—	Investment	Cumulative	Global	1985–	2.2

	thermal	cost ($99/kW)	installed capacity (MW)		2001	
Jamasb (2006)	Wind energy—off shore	Investment cost ($99/kW)	Cumulative installed capacity (MW)	Global	1994–2001	1
Söderholm and Klaassen (2007)	Wind power	Investment cost ($98/kW)	Cumulative installed capacity (MW)	Denmark Germany UK and Spain	1986–2000	3.1

Appendix B. Existing Energy Efficient Technologies Analyzed in the Study

Table B 1 Characteristics of 75 Energy Efficient Technologies Analyzed in the Study

	Applied Fuel Savings (GJ/tonne crude steel)	Applied Total Retrofit Costs in 1994 (2005 US$/tonne crude steel)	Applied Total Retrofit Costs in 2002 (2005 US$/tonne crude steel)	Applied Annual Operating Cost Change (2005 US$/tonne crude steel)	Lifetime of Measure	Share of total U.S. Production to which Measure is Applied/ Broken by BOF/EAF
Secondary Steelmaking						
Steelmaking Electric Arc Furnace						
Improved process control (neural network)	0	1.25	0.73	-0.552	10	90%
Fluegas Monitoring and Control	0.003	2.64	1.09	-0.524	15	51%
Transformer efficiency - UHP transformers	0	3.62	1.19	0	15	34%
Bottom Stirring / Stirring gas injection	0	0.79	0.08	-0.135	0.5	11%
Foamy slag	0	13.18	4.34	-0.221	10	20%
Oxy-fuel burners	-0.05	6.32	1.45	-0.342	10	31%
Eccentric Bottom Tapping (EBT) on existing furnace	0	4.22	1.42	0	20	5%
DC-Arc furnace	0	5.14	0.42	-0.306	30	20%
FUCHS Shaft furnace	-0.086	7.91	2.28	-0.858	30	34%
Twin Shell w/ scrap preheating	0	7.91	0.98	-0.067	30	10%

Siemens EAF Quantum with scrap preheating	-0.064		1.05 (available in 2010)	-0.536	30	34%
Recover heat from waste gas	0.025		0.78 (available in 2010)	-0.098	10	80%
Post combustion of CO gas	0		0.92 (available in 2010)	-0.441	10	80%
Increased usage of hot metal	0		0.41 (available in 2010)	-0.092	10	10%
Secondary Casting						
Efficient ladle preheating	0.005	0.07	0.04	0	10	100%
Proper sealing on ladle furnace preheating	0.021		0.05 (available in 2010)	0	10	51%
Near net shape casting/thin slab casting (TSC)	0.51	54.6	29.02	-5.574	20	26%
Use dry rolls in tunnel ovens for TSC	0.076		0.71 (available in 2010)	-0.002	20	26%
Secondary Hot Rolling						
Process control in hot strip mill	0.106	0.8	0.49	0	10	64%
Recuperative burners	0.247	2.87	1.23	0	10	64%
Insulation of furnaces	0.033	11.5	2.93	0	10	29%

Ceramic wall in reheating furnace	0.106		0.63 (available in 2010)	0	10	64%
Reduce losses from furnace door opening	0.005		0.06 (available in 2010)	0	10	64%
Controlling oxygen levels and VSDs on combustion air fans	0.008	0.58	0.25	0	15	51%
Energy-efficient drives in the rolling mill	0	0.22	0.1	0	20	90%
Waste heat recovery from cooling water	0.014	0.92	0.56	0.025	15	64%
General Technologies						
Preventative Maintenance	0.129	0.01	0.01	0.012	20	100%
Optimizing the steam system	0.086		0.55 (available in 2010)	0	20	51%
Increase efficiency of boilers	0.006		0.09 (available in 2010)	0	20	51%
Optimizing the air system	0		0.09 (available in 2010)	0	20	100%
Variable speed drive: flue gas control, pumps, fans	0	1.71	0.18 (available in 2010)	0	5	51%
Energy monitoring and management system	0.023	0.2	0.15	0	5	90%
Integrated Steelmaking						
Iron Ore Preparation (Sintering)						

Sinter plant heat recovery	0.035	0.87	0.64	0	10	101%
Reduction of air leakages	0	0.03	0.02	-0.006	10	101%
Increasing bed depth	0.005	0	0	0	10	90%
Improved process control (sinter plant)	0.002	0.04	0.03	-0.013	10	90%
Use of waste fuels in the sinter plant	0.001	0.05	0.03	0	10	10%
Improved charging method	0.005		0.055 (available in 2008)	-0.006	10	90%
Coke Making						
Coal moisture control	0.021	19.35	12.12	0	10	90%
Programmed heating - coke plant	0.018	0.09	0.05	0	10	90%
Variable speed drive coke oven gas compressors	0.001	0.12	0.08	0	15	90%
Coke dry quenching	0.152	27.65	17.31	-0.724	18	90%
Iron Making (Blast Furnace)						
Pulverized coal injection to 130 kg/thm	0.054	8.22	2.67	-0.14	20	21%
Pulverized coal injection to 225 kg/thm	0.049	6.11	4.62	-0.073	20	26%
Injection of natural gas to 140 kg/thm	0.06	5.88	2.35	-0.153	20	21%
Injection of oil up to 130 kg/thm	0.057	6.41 (available in 1998)	2.3	-0.133	20	21%
Top pressure recovery turbines (wet type)	0	23.5	14.31	0	15	80%

Recovery of blast furnace gas	0.007	0.36	0.09	0	15	31%
Hot blast stove automation	0.074	0.36	0.17	0	5	59%
Recuperator hot blast stove	0.027	1.65	1.35	0	10	101%
Improved blast furnace control systems	0.111	0.42	0.28	0	5	83%

Source: Karali et al., 2013; Worrell et al., 1999

Table B 2 Learning rates for retrofit cost for the 75 technologies examined in this study

	Learning Rate		**Learning Rate**
Secondary Steelmaking		***Integrated Steelmaking***	
Steelmaking Electric Arc Furnace		**Iron Ore Preparation (Sintering)**	
Improved process control (neural network)	0.02	Sinter plant heat recovery	0.01
Fluegas Monitoring and Control	0.04	Reduction of air leakages	0.01
Transformer efficiency - UHP transformers	0.05	Increasing bed depth	
Bottom Stirring / Stirring gas injection	0.1	Improved process control (sinter plant)	0.01
Foamy slag	0.05	Use of waste fuels in the sinter plant	0.02
Oxy-fuel burners	0.06	Improved charging method	0.02
Eccentric Bottom Tapping (EBT) on existing furnace	0.1	**Coke Making**	
DC-Arc furnace	0.1	Coal moisture control	0.02
FUCHS Shaft furnace	0.05	Programmed heating - coke plant	0.02
Twin Shell w/ scrap preheating	0.09	Variable speed drive coke oven gas compressors	0.02
Siemens EAF Quantum with scrap preheating	0.06	Coke dry quenching	0.02
Recover heat from waste gas	0.02	**Iron Making (Blast Furnace)**	
Post combustion of CO gas	0.02	Pulverized coal injection to 130 kg/thm	0.06

Increased usage of hot metal	0.1	Pulverized coal injection to 225 kg/thm	0.06
Secondary Casting		Injection of natural gas to 140 kg/thm	0.06
Efficient ladle preheating	0.02	Injection of oil up to 130 kg/thm	0.06
Proper sealing on ladle furnace preheating	0.03	Top pressure recovery turbines (wet type)	0.06
Near net shape casting/thin slab casting (TSC)	0.06	Recovery of blast furnace gas	0.06
Use dry rolls in tunnel ovens for TSC	0.06	Hot blast stove automation	0.03
Secondary Hot Rolling		Recuperator hot blast stove	0.01
Process control in hot strip mill	0.03	Improved blast furnace control systems	0.02
Recuperative burners	0.03	**Steelmaking**	
Insulation of furnaces	0.05	**Basic Oxygen Furnace**	
Ceramic wall in reheating furnace	0.03	BOF gas + sensible heat recovery	0.01
Reduce losses from furnace door opening	0.03	Variable speed drive on ventilation fans	0.01
Controlling oxygen levels and VSDs on combustion air fans	0.03	**Integrated Casting**	
Energy-efficient drives in the rolling mill	0.02	Efficient ladle preheating	0.03
Waste heat recovery from cooling water	0.02	Proper sealing on ladle furnace preheating	0.03
General Technologies		Thin slab casting	0.06
Preventative Maintenance	0.01	Use dry rolls in tunnel ovens for TSC	0.06
Optimizing the steam system	0.03	**Integrated Hot Rolling**	
Increase efficiency of boilers	0.03	Hot charging	0.05
Optimizing the air system	0.02	Process control in hot strip mill	0.03
Variable speed drive: flue gas control, pumps, fans	0.03	Recuperative burners	0.05
Energy monitoring and management system	0.01	Insulation of furnaces	0.05
		Ceramic wall in reheating furnace	0.03
		Reduce losses from furnace door opening	0.03

		Controlling oxygen levels and VSDs on combustion air fans	0.03
		Energy-efficient drives in the rolling mill	0.04
		Waste heat recovery from cooling water	0.03
		Integrated Cold Rolling and Finishing	
		Heat recovery on the annealing line	0.02
		Reduced steam use in the pickling line	0.01
		Automated monitoring and targeting system	0.03
		General	
		Preventative Maintenance	0.01
		Optimizing the steam system	0.02
		Increase efficiency of boilers	0.02
		Optimizing the air system	0.02
		Energy monitoring and management system	0.02
		Variable speed drive: flue gas control, pumps, fans	0.03

Table B 3 Demonstration technologies considered in this study

Sintering	Selective Waste Gas Recycling - EPOSINT Process (SIN-SWGR)
Coke making	Automation and Process Control System (COK-APCS)
	Non-Recovery Coke Ovens (COK-NRCO)
	Advanced coke oven (SCOPE21)
BF	Additional Use of Coke Oven Gas (BF-AUCOG)
	Blast Furnace Heat Recuperation (BF-HR)
BOF	Aluminum Bronze Alloy to Improve Hood, Roof and Sidewall Life (BOF-ABA)
	Blast Furnace Slag Heat Recovery (BOF-SHR)
	In-Situ Real-Time Measurement of Melt Constituents -BOF (BOF-ISRT)
EAF	Aluminum Bronze Alloy to Improve Hood, Roof and Sidewall Life (EAF-ABA)
	In-Situ Real-Time Measurement of Melt Constituents -EAF (EAF-ISRT)

Source: Hasanbeigi et al., 2013; Worrell et al., 2010; IPPC, 2011