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Role of technology learning in the decarbonization of the iron and steel sector: an energy system approach using a global-scale optimization model

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Abstract
The iron and steel sector, in addition to being one of the most important sources of greenhouse gas emissions on a global level (from 7 to 9% yearly) is characterized by fossil fuel-driven processes and is also one of the most difficult sectors to decarbonize, due to fierce international competition and the so-far absence of economically comparable alternatives to traditional processes. Various new technologies promise to change this, but the development of new technologies is highly uncertain. This paper aims to analyze the prospects of key low-carbon technologies in the sector, focusing on the impact of technology learning, and the sensitivity of the findings to the intrinsic uncertainty in how quickly technologies learn. An energy system optimization model was used, together with an iterative learning formulation, to understand the sensitivity of the results to different learning assumptions. The results show that learning may have only a minor impact in the short and medium term, reducing global carbon emissions of the sector by 3% (at most) in 2050, compared to a non-learning scenario. On the other hand, high learning potentials for electrolysis and hydrogen-based processes are particularly important in the long term, leading to a penetration of such technologies up to the 80% of the steel production by the end of the century. The learning potential for Carbon Capture and Storage-equipped processes, in turn, poorly affects sectoral emissions in the simulations. Early investments in the former, also through research and development, would be important to unlock the full potential of the technologies, while further, more detailed studies should be performed to better understand the impact the latter could have in the shorter term.

Keywords:

Technology learning, Energy system optimization modeling, Iron and steel, Decarbonization, TIMES model

Abbreviations

BF	Blast furnace
BOF	Basic oxygen furnace
CCF	Cyclone Converter Furnace
CC(U)S	Carbon capture (usage) and storage
DRI	Direct reduced iron
EAF	Electric arc furnace
EFOM	Energy Flow Optimization Model
ESOM	Energy system optimization model
ETM	EUROFusion TIMES Model
ETS	Emissions trading scheme
GHG	Greenhouse gas
GLOBIOM	Global Biosphere Management Model
HDR	Hydrogen direct reduction
IAM	Integrated Assessment Model
IEA	International Energy Agency
IIASA	International Institute for Applied Systems Analysis
IPCC	Intergovernmental Panel on Climate Change
LC	Learning curve
LR	Learning rate
MARKAL	MARKet ALlocation
MEDEE	A Model for Long-Term Energy Demand Evaluation
MESSAGE	Model for Energy Supply Systems And their General Environmental impact
O&M	Operation and maintenance
POLES	Prospective Outlook on Long-term Energy Systems
PR	Progress ratio
PSA	Pressure swing adsorption
PV	Photovoltaic
RCP	Representative Concentration Pathways
RES	Reference Energy System
SEWGS	Sorption-enhanced water-gas shift
SR	Smelting Reduction
SRV	Smelting Reduction Vessel
TGR	Top gas recycling
TIMES	The Integrated MARKAL-EFOM System
TL	Technology learning
TRL	Technology readiness level

ULCOS Ultra-Low CO_2 Steelmaking

VPSA vacuum pressure swing adsorption

Introduction and Background

In 2019, 2.6 Gt_{CO2} \cite{IEA3} were emitted globally to produce 1.8 Gt \cite{Worldsteel} of crude steel. This value represents 7.8% of the global CO_2 emissions in all sectors \cite{IEA4} , the highest contribution from an industrial subsector.

Despite declared efforts by several international organizations and global-scale producers during the last decades \cite{Junjie} , the decarbonization of the iron and steel sector still remains an unresolved problem\cite{Hermwille}. The very strong presence of emerging economies in the market \cite{Worldsteel} further complicates the problem, as the carbon intensity for produced steel is currently even higher in those countries, compared to the developed ones \cite{Worldsteel}.

In the context of programs such as ULCOS (Ultra-Low CO2 Steelmaking) \cite{Meijer} , however, some potentially key low-carbon technologies have been identified \cite{Junjie} and their introduction to the iron and steel production mix could help the decarbonization of the sector \cite{Birat}. These technologies are not currently at a high technology readiness level (TRL) \cite{IEA_TRL}, and are thus not yet economically competitive against the traditional and more established ones \cite{Hoffmann}. On the other hand, this picture may change in the coming decades, because of both the cost evolution of the novel technologies \cite{Karali}, and because of the expected increase in production costs for traditional, fossil-based technologies, due to the policies aiming to reduce emissions also in these sectors \cite{Fischedick}. The role of technology learning will thus be central to how this sector develops in the future, but the uncertainty in terms of the learning potentials of the key novel technologies makes it difficult to assess which technologies, when and under what type of conditions could contribute. Our study aims to investigate this, and in doing so provide information for those considering investment strategies for the sector..

Technology learning theory

Reduction in costs due to experience gained in deploying the technology, called learning-by-doing, correlates the experience accumulated with a technology to its unit cost \cite{McDonalds}. A variety of learning formulations have been used to study this phenomenon: Wright's work introduced the concept of learning curve, which was subsequently applied to the cost evolution of a number of different technologies \cite{Wright}. Instead, an exponential relationship between the number of components on integrated circuits and the cost per component was first shown in Moore's research \cite{Moore}. Goddard's paper \cite{Goddard} put out a technique for debugging the learning curve; while Sinclair, Klepper, and Cohen's study \cite{Sinclair} presented a mixed formulation for defining the learning process. A comparative paper recently examined the behavior of all these laws using historical data of 62 technologies, obtaining as a result that Wright and Moore's laws were best describing the learning of those technologies \cite{Nagy}.

Since these formulations relate decreasing costs and cumulative experience, starting from an initial value , novel technologies with little initial experience can learn rapidly, once investments are initiated, as in relative terms the experience grows very rapidly. Both learning and policy implementation are influenced by a wide range of factors, including technological \cite{Karali} and macro-economic \cite{Mayer} ones. Therefore, it is important to reflect the uncertainty in those two drivers \cite{McDonalds} in studying their potential influence on the iron and steel sector. This paper has the aim to understand if, and to what extent, learning can help in the decarbonization of the sector, which technologies are most affected by it and how uncertainty about learning rates can affect the conclusions.

In addition to technology specific, empirical analysis of learning on technology costs in the past , and their meaning for the future (e.g. Schoots et al. \cite{Schoot2} for fuel cells, Meng et al. \cite{Meng} for six different energy conversion technologies),one of the domains in which technology learning and its impacts have been introduced is energy system analysis and modeling, where, due to the decades-long temporal scales, the consideration of dynamic behaviors of technological development can improve the analysis \cite{Messner}. Learning has thus been applied to a wide variety of studies, from the assessment of its impacts on the penetration of low-carbon technologies in integrated assessment models (IAM) \cite{Carraro} (see also Krey et al. \cite{Krey} for an overview of how IAMs treat technological change, and Edelenbosch et al. \cite{Edelenbosch} for how the industrial sector is covered), to technology specific studies (e.g. Riahi et al. \cite{Riahi_add} on carbon capture and storage), and to studies using agent-based models \cite{MaT}, or sectorial models \cite{Sanchez}. In addition, while learning is usually modeled for single technologies or processes, some studies split these into core components, possibly shared with other technologies, and model learning through the learning of these components (see e.g. Anandarajah et al., \cite{Anandarajah} for future vehicle technologies). Ma et Al, \cite{MaT2}, in comparing several studies including technology learning, argued, agent-based models to be a better fit when the goal is to design predictive scenarios (see also Trutnevyte \cite{Trutnevyte}), whereas optimization models are suitable when one wants to study the impact of technology learning on the achievement of an objective (as an emission target). As our study focuses on assessing the future energy system wide impact of learning in the iron and steel sector, our approach and the discussion of literature that follows will focus on optimization models, rather than e.g. empirical, bottom-up studies of single technologies or other modeling alternatives of learning.

Implementation of learning in industry-related studies

Multiple previous works have focused on modeling how technology learning may affect the competition in specific industrial sectors \cite{Karali}. The investigated studies have been carried out using optimization models with varying complexity levels, from sector-specific \cite{Xu}, to all industry-level \cite{Karali} to the full energy system \cite{Sanchez}. In Table 1 some of these papers have been collected and divided per type of optimization model used, and the approach to sensitivity scenarios.

<table>
<tr><td rowspan="2"></td><td rowspan="2"></td><td colspan="2">Type of optimization model used</td></tr>
<tr><td>Sector/industry-level model</td><td>Energy system model</td></tr>
<tr><td rowspan="3">Sensitivity on learning rate(s)</td><td>Absent</td><td>Steel (Liu),
Cement (Strunge),
Steel (Karali)</td><td>Steel (Ren),
All industry (Sanchez2)</td></tr>
<tr><td>Binary switch ("Low" vs "High" learning scenario)</td><td>Cement (Jin-Hun Xu)</td><td>Chemicals and steel (Sanchez)</td></tr>
<tr><td>Set of scenarios (several levels of learning for each technology)</td><td>-</td><td>Olefins (Xu)</td></tr>
</table>

Table 1: Summary of key papers modeling technology learning for mitigation in the industry

While a sector-specific model can provide a very high level of detail for the techno-economic description of the problem \cite{JHXu}, using an energy system model allows one to analyze the cost-effective scenario across all sectors \cite{Sanchez2}, identify spillovers between sectors and the interactions between industry and the energy system \cite{Sanchez}. For this reason, a bottom-up, technology-rich energy system optimization model (ESOM) will be used to investigate the effect of technology learning in the iron and steel sector. This decision can be also ascribed to the high energy intensity of the steelmaking processes, which causes their development to be strongly interconnected with the development of the energy system \cite{Li}. This choice is, however, in many respects a trade-off: The description of the industrial activities and technologies contained within the sector will be less granular than it could be with tools and approaches developed only for the key technology or industry \cite{Sanchez}. Furthermore, a global-scale ESOM entails further simplifications and aggregations compared to a national-scale model, in terms of, for example, existing steel plants in different states and continents \cite{ETM}. However, a model of this scale is advantageous when investigating a primarily global-scale phenomenon such as technology learning \cite{Goddard}.

Contribution

Our work will add to the existing body of work and extend it especially in (1) the granular characterization of the impacts of uncertainty and (2) considering it for component based learning in an energy system wide context, to better understand the impact of learning on the potential development of the iron and steel industry under climate constraints. In addition to the research gap identified in the previous section, our study aims to also provide practical value by providing insights about the competitiveness of the various novel technologies under different conditions.

More specifically, and as can be seen from Table 1, most studies modeling learning in industry have paid little attention to the highly uncertain and central value of the learning rate. The benefits in focusing the analysis on the sensitivity of the results to the learning rate is that the outcomes depend less on specific, single assumptions made for this parameter. Projecting a learning rate is one of the most critical aspects in the design and analysis of a learning scenario \cite{Nordhaus}, as the values of learning rate have a very high level of uncertainty, \cite{McDonalds}, and a single estimate would be highly susceptible to ending up incorrect \cite{Nordhaus} .

Therefore, one key purpose of this work is to go beyond the single learning scenario, and provide a set of scenarios with variable levels of learning, allowing to assess the possible range of influences learning can have on the steel and iron industry and the wider energy system. In the previous work, Sanchez et Al. \cite{Sanchez} compared their “Reference” scenario to a “High TRL” one, in which all learning rates were raised, but didn’t assess how various combinations of high and low learning rates across competing technologies might affect outcomes. Similar analysis was conducted by Xu et Al. \cite{JHXu} for the Chinese cement sector. Zhongming Xu et Al. \cite{Xu} performed a broader sensitivity study, comparing a set of scenarios with different learning rates. They, however, focused on a single technology (an innovative process for olefin production) and on how the learning rate affects the penetration of the technology in the olefin production market. In the iron and steel industry there are many decarbonization alternatives, the prospects of which affect each other and thus need to be studied simultaneously. To the best of our knowledge, such a modeling study has not yet been carried out for the iron and steel industry. However, and as discussed by Jin-Hua Xu et Al. \cite{Xu} , the introduction of a second sensitivity dimension concerning environmental policy can significantly increase the meaningfulness of the sensitivity study \cite{Sanchez}, as it allows to analyze how the two sensitivities may interact \cite{Xu}: therefore, this dimension will also be introduced.

Finally, learning focused on components allows one to assess spillovers between technologies that share components, thus better capturing an element of learning. Of the reviewed papers, Karali et al. \cite{Karali}, and Jin-Hua Xu et al. \cite{Xu} model learning based on components, and of those only the former implementing it for steel. Karali et al. do not, however, consider any uncertainties in their analysis, nor consider interactions with the rest of the energy system, and thus our approach of combining component learning with our granular approach to uncertainty provides an additional element of novelty to the work.

Thus, this paper has the aim to understand if, and to what extent, learning can help in the decarbonization of the sector, which technologies are most affected by it and how uncertainty about learning rates can affect the conclusions. In doing so it also provides a datapoint for companies and policy makers planning for the decarbonization of the sector.

Structure of the work

The paper is structured as follows: in the Methods part, the model chosen for the analysis is first presented, before describing the scenario setup, and how technology learning is modeled; the Results section presents the model outputs, with a focus on four aspects: energy consumption, steel production route, costs and emissions. The Discussion and Conclusion section revisits the research questions, and how the model results provide answers to them, before closing with a discussion about the possible future work.

Methods

The Methods part contains an explanation of the model choice, followed by a description of the model itself, focusing on both its general structure, and the iron and steel sector modeling. The following two sections will illustrate respectively the scenario setup and the technology learning modeling, with a description of the selected formulation and of the data used.

The EUROFusion TIMES Model

The EUROFusion TIMES Model (ETM), a bottom-up macro-scale ESOM developed in the context of the EUROFusion project \cite{ETM}, is used to model the development of the energy system, and the role of the iron and steel sector in it. It was chosen because it covers the global energy system until the end of the current century \cite{Cabal}, allowing one to consider the learning of industrial technologies within the broader energy system in a global, long term context. Moreover, the description of its industrial sector in ETM has been recently updated \cite{Lerede}, also increasing the variety of novel technologies modeled for the iron and steel sector, based on the information developed during the ULCOS European project \cite{Meijer}.

The geographical presentation of ETM, divides the world into 19 distinct regions (\cite{ETM}), each of which is technologically characterized through its Reference Energy System (see Figure 1) and linked to socio-economic assumptions for its development. The time horizon of the model extends from 2005 (the so-called "base-year") to 2100, with the length of the time steps varying between 5 and 6 years until 2070, before extending to 15 years for the last two periods. The model depicts the development of the energy system from resource extraction to the final end use energy services through the Reference Energy System, as shown in Figure 1 \cite{ETM}.

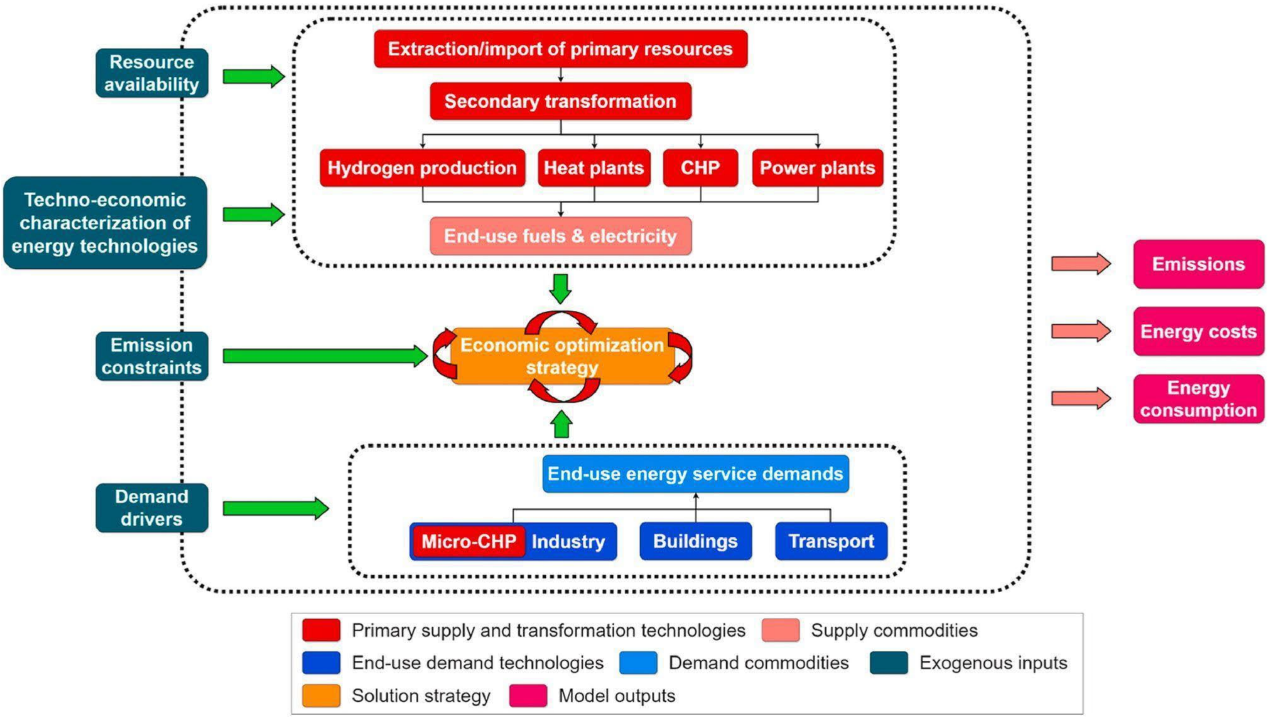

Figure 1: Reference Energy System (adopted from \cite{ETM})

The focus of the analysis presented here is on industrial technologies, and more specifically on the subsector describing the processes for the production of iron and steel. The technologies associated with this sector in ETM, with their inputs and outputs, are shown in Figure 2. Given the scope of this paper, the most important elements of the iron and steel sector are the processes reproducing steelmaking technologies, which are clustered according to their characteristics.

- the traditional and most widespread technologies, such as blast furnace and direct reduction-based technologies (light gray in Figure 2);
- novel, fossil-based technologies, such as smelting reduction and HIsarna (light blue);
- fossil-based processes with carbon capture (Direct Reduced Iron - Electric Arc Furnace - DRI EAF, Blast Furnace - Basic Oxygen Furnace - BF-BOF with and without top-gas recycling, HIsarna and Ulcored, a second generation DRI-EAF) (light red)
- hydrogen and electrolysis-based processes, i.e. hydrogen direct reduction, electrowinning and molten oxide electrolysis (light green).

The technologies in Figure 2 are described in detail in Lerede et Al. \cite{Lerede}.

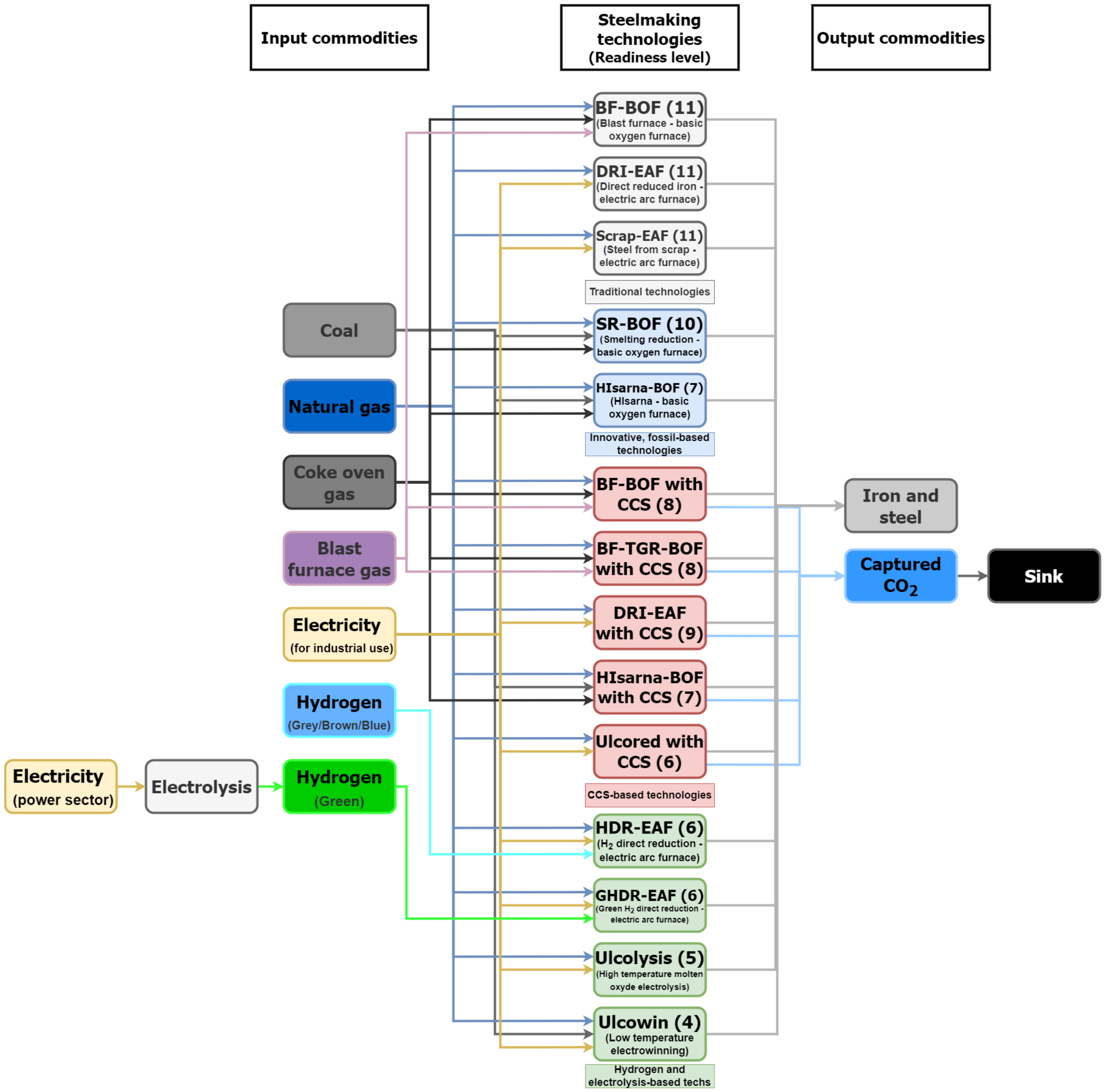

Figure 2: Iron and steel sector technologies as modeled in ETM\cite{Lerede}, together with their illustrative TRLs (in brackets) \cite{IEA_TRL}

Scenario setup

ETM is currently parametrized for three different groups of broader scenario narratives: Fragmentation, Paternalism and Harmony. The narratives and their quantifications, described in detail in \cite{Cabal}, differ in terms of their economic and social factors. For this analysis, Paternalism narrative with a 2.6 W/m2 target has been chosen: it assumes middle of the road hurdle rates, indicating a medium-term view for investments decisions, and a stringent global carbon emission target (RCP 2.6 \cite{Fischedick2}) with high level of cooperation among the global regions, reflected in a high level of commodity trading.

Policy-related sensitivity scenarios

As noted in the Background section, the specific way in which policies are implemented can have further impacts on how, when and where the energy system is decarbonised. With this in mind, the first scenario dimension added on top of the Paternalism narrative relates to sectorial emission targets. More specifically, in the default case the model has a global emissions constraint and freedom to decide how the required mitigation effort is distributed across the energy system, whereas a variant adds sector-specific constraints to the broader industrial sector, and allows the model to choose how the effort is split between the subsectors. The latter can be interpreted to reflect a case in which more targeted policies are assigned to the industrial sector. The specific constraints used reflect the industrial emissions in the results for IPCC's RCP2.6 \cite{Fischedick2}: They imply a strong effort already for 2050, with a reduction of the sector emission by the 55% with respect to 2010 levels, turning into a -90% reduction by 2070 and a net zero by 2100.

Learning-related sensitivity scenarios

Next to the modeled policies, the scenarios are differentiated based on the assumptions for the learning potentials of the key competing steelmaking technologies. To reflect the uncertainties linked to the learning rate values mentioned in the Background section, three different values for the learning rates of both CCS and electrolysis-based technologies are determined. The value of learning rate of smelting reduction is fixed: Initial modeling experiments suggested that the variations in the learning rate of this technology had little impact on the results and its relatively higher level of maturity further reduces uncertainty about its learning potential. In order to simplify the scenario structure a single learning rate for smelting reduction is used.

All the combinations of the different learning rates and the two policy variants are assessed, leading to 18 scenarios (Figure 3). Two additional scenarios without learning are also run for comparative purposes, one with and one without sector-specific emissions constraints.

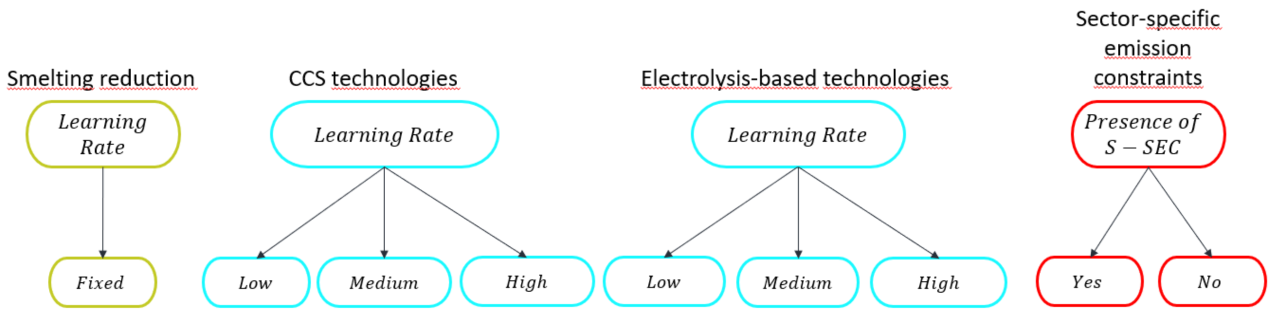

Figure 3: Sets of learning rates and sector-specific emissions, for a total set of 18 inputs.

Modeling technology learning

In ETM, technology learning can be modeled endogenously (i.e. with the learning curve internal to the model itself) \cite{Loulou}, but for this paper an exogenous approach, documented previously for both energy \cite{Riahi}, and industrial technologies \cite{Karali}, was used.

The modeling uses the so-called Wright learning curve \cite{Wright} to describe technology learning \cite{Nagy}.

$$C_t = C_0 \left(\frac{\sum_{i=0}^{t} I_t}{I_0} \right)^{\frac{ln(1-LR)}{ln(2)}}$$

Where:

- C_t is the unit cost at time t
- C_0 is the initial unit cost
- I_t is the new capacity installed at time t
- I_0 is the initial cumulative capacity
- □□ is the learning rate

The learning rate is the reduction in percentage of the specific capital cost of a technology, each time its cumulative capacity installed is doubled \cite{Argote}.

Technology learning characterization

The literature review highlighted that learning is usually not homogeneous within a technology: Different modules, or components, of the technology usually learn at different rates \cite{Berglund}. Iron and steel making processes are complex, including components at different levels of maturity, and thus the approach of Anandarajah et Al.\cite{Anandarajah} will be followed, splitting steelmaking routes into their components and modeling learning for these components. This clustered learning approach \cite{Seebregts2} allows us to also consider learning spill-overs across technologies that share the learning components \cite{Seebregts3} and reflect the role of mature components that have little remaining learning potential and are thus modeled as non-learning. Table 2 illustrates how technologies are divided into components, which of these are common across certain technologies and what is assumed for their learning (see Appendix A for the rationale for individual technologies and components). It's worth noting that while for other components learning is applied to capital costs alone, for electrolysis, which are targeted by specific R&D efforts \cite{Schoots}, also the fixed operation and maintenance (O&M) cost and efficiency will evolve. Finally, CCS is considered only in the context of the new technologies, and not as a refurbishment option for old plants. (see Appendix B for more on how learning is considered and modeled).

Technology	Ironmaking base process	Additionally added sub -technologies	Saved technologies	Carbon capture technologies	Steelmaking process	Learning component in total IC [%]
BF-BOF	Blast furnace	-	-	-	BOF	0
DRI-EAF	Direct reduction	-	-	-	EAF	0
Scrap-EAF	-	-	-	-	EAF	0
SR-BOF	Smelting reduction	-	-	-	BOF	67.4
DRI-EAF with CCS	Direct reduction	-	-	Adsorption (PSA)	EAF	7.0
BF-BOF with CCS	Blast furnace	-	-	Adsorption (SEWGS)	BOF	34.6
BF-TGR-BOF with CCS	Blast furnace	Top-gas recycling	-	Adsorption (VPSA)	BOF	11.9
HIsarna-BOF	Smelting reduction	CCF	Reduction furnace	-	BOF	61.4
HIsarna-BOF with CCS	Smelting reduction	CCF	Reduction furnace	Cryogenic distillation	BOF	65.0
Ulcored with CCS	Direct reduction	Top-gas cycle	Reformer	Adsorption (VPSA)	EAF	7.6
HDR-EAF	Direct reduction	-	Steam reformer	-	EAF	0
Green HDR-EAF	Direct reduction	Electrolyzer	Steam reformer	-	EAF	42.8
Ulcolysis	Ulcolysis	-	-	-	EAF	97.6
Ulcowin	Ulcowin	-	-	-	EAF	97.5

Table 1: Component-based decomposition of steelmaking technological routes; in red, the ones learning in their capital cost, in blue the one learning in capital cost, fixed O&M cost and efficiency

Modeling learning exogenously

The learning formulation shown above is non-linear and is thus as such incompatible with a linear optimisation model like ETM. While this can be overcome by a piecewise linearisation of the relationship \ref{Messner} , this turns the problem into a mixed integer linear optimisation problem, greatly adding to the computational burden \ref{Barreto}. Moreover, modeling learning endogenously creates incentives for the implied all-knowing decision maker (see also Keppo and Strubegger, 2010, on the impact of perfect foresight more generally) in the model to "put all the eggs in one basket" and invest heavily, and early, into a technology that through its learning potential provides the best alternative across the full timeframe. This can lead to investment patterns that do not have a clear counterpart in the real world, in which uncertainties exist and deployment is decided based on the competitiveness of technologies right now, rather than on what the deployment does to the future costs of the technology \cite{DeCarolis}.. Therefore, an exogenous, iterative approach to modeling learning has been used, in which investments in a technology reduce its costs, but the implied decision maker in the model does not have this knowledge and does not make decisions based on this relationship. The iterative procedure used is shown in Figure 4.

The investment result of a first simulation with static costs is used to calculate how, based on the investment patterns and the learning curve, costs change across time and then use this as an input in the next run of the model. This iterative procedure ends once the investment cost change between two consecutive runs is less than the predetermined threshold set for convergence. The process is described in more detail in Appendix B.3.

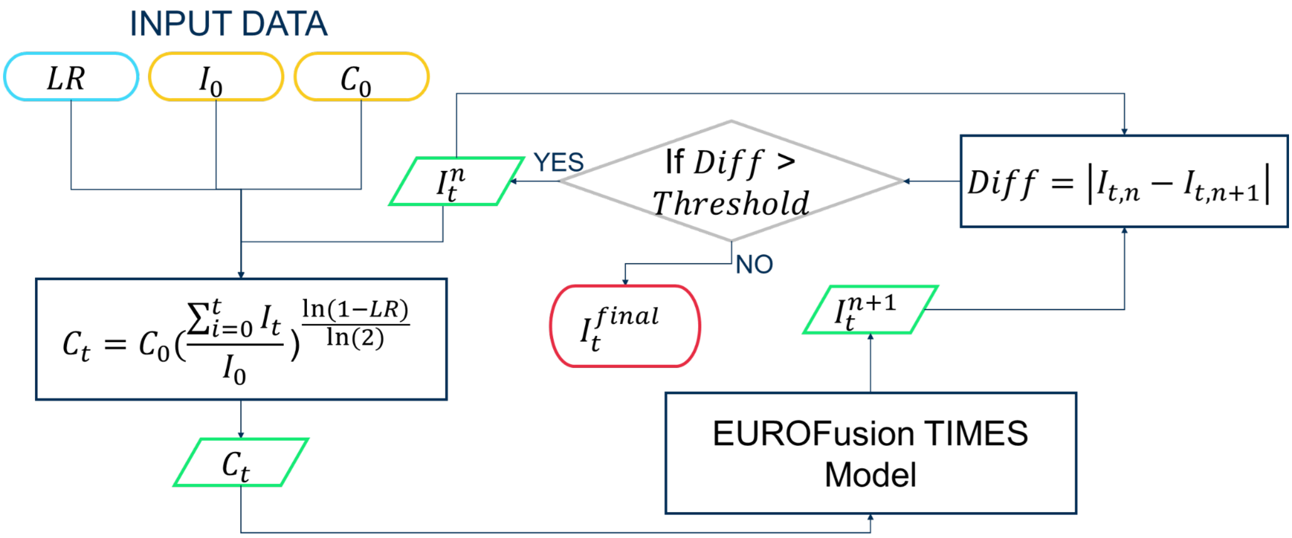

Figure 4: Flow chart of the iterative process for exogenous technology learning

Calibration of the Learning Curves

As learning creates increasing returns to scale, the results over long time periods can be highly sensitive to the assumptions of the initial values \cite{Gritsevskyi}. While learning rates are always uncertain to some extent, less attention is often paid to calibrating the initial cumulative capacity, which can be an even more important number for very novel technologies with low initial capacity. The calibration of the learning components in this study is shown in Table 3, together with the assumptions about which subtechnologies form a cluster, i.e. benefit from investments made in other subtechnologies in the same cluster. Note that each of the subtechnologies in a cluster has its own initial cost, but share cumulative capacity and learning rate with the other subtechnologies belonging to the cluster.

Sub-Technology	1) Investment cost [$/$t_{CS}$]	2) Cluster (Learning Curve)	3) Initial capacity - Unit	3) Initial capacity	4) Learning rate - mean value [%]	4) Learning rate - standard deviation [%]
Smelting reduction	351	Smelting reduction	Mt_{CS}/y	11.45	6	-
PSA-based CCS	41.5	PSA-based CCS	Mt_{CO2}/y	17.65	10.4	5.4
SEWGS-based CCS	45.4					
VPSA-based CCS + top gas recycling	78.9					
VPSA-based CCS + top gas recycling + heat recovery	286.7					
Cryogenic distillation-based CCS	46.1	Cryogenic-based CCS	Mt_{CO2}/y	0.8040	10.4	5.4
Electrolysis	411 (IC) 14.0 (FO&M)	Electrolysis	GW_e	0.2700	9.6	5.5
Ulcolysis Ulcowin	6476 6696	Electrolysis of iron ore	t_{CS}/y	18.30	9.6	5.5

Table 2: Resume of the learning curves calibration

The economic parameters have been calibrated starting from the work by Lerede et al., \cite{Lerede}, while the clustering follows from the principles described in technologically-specific papers concerning CCS-equipped technologies \cite{Kuramochi} and Ulcowin/Ulcolysis \cite{Junjie}. The calibration of the initial installed capacity has been gathered from a number of sources (see Appendix B.2) and includes all the newly installed plants for a given technology, including also some future plans until 2025 for technologies that are not available in the model from the start of the model horizon . Finally, the learning rates are based on Karali et al. for Smelting Reduction \cite{Karali}, and Bohm et al. \cite{Bohm} for the other technologies. \cite{Bohm} is a technology report focusing on comparisons of key energy technologies learning rates across studies, and therefore provides a standard deviation for the learning rate estimates. This data will be used for defining the sensitivity scenarios. More specifically,:

$$LR_{Low} = LR_{mean} - LR_{\sigma} = 5\%\ (CCS\ techs)\ and\ 4.1\%\ (electrolysis - based\ techs)$$

$$LR_{Medium} = LR_{mean} = 10.4\%\ (CCS)\ and\ 9.6\%\ (electrolysis)$$

$$LR_{High} = LR_{mean} + LR_{\sigma} = 15.8\%\ (CCS)\ and\ 15.1\%\ (electrolysis)$$

Results

All in all, 71 iterative runs were required to retrieve results for the 18 learning scenarios. Convergence was most often achieved with four iterations (9 scenarios), with the others requiring either three (5 scenarios) or five (4 scenarios) iterations.

The focus of our discussion will be on how technological learning, emission constraints and uncertainty affect the competition among iron and steelmaking technologies.

In order to provide the wider context for iron & steel sector results, the results for the global emissions (Figure 5) and for final energy (Figure 6) across the full energy system will be presented first.

As Figure 5 highlights, the share of industry as a source for global net CO2 emissions increases over time, from around one fourth in 2020, to more than a half in 2050. In fact, CO2 emissions from industry drop below 2020 levels only after 2040, and even later in the iron and steel industry. CO2 capture mainly takes place outside industry, and within industry capture in the iron and steel sector is more limited than in some other subsectors. It's also worth noting that CO2 capture, as emission reductions more generally, takes place later in the industry than in other sectors. Finally, by the end of the century most of the remaining industrial emissions originate from the iron and steel industry.

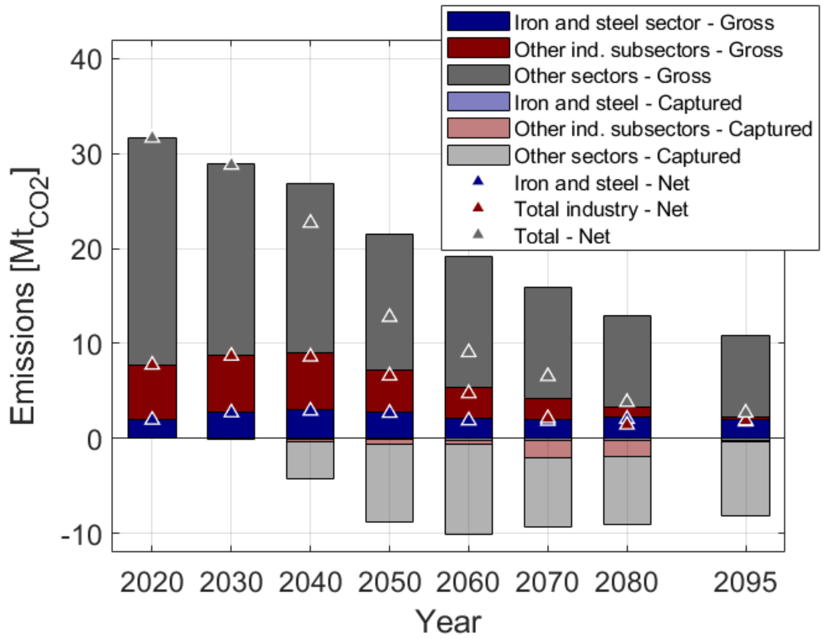

Figure 5: Global emissions, scenario with average learning for all technologies and without sectorial emission constraints.

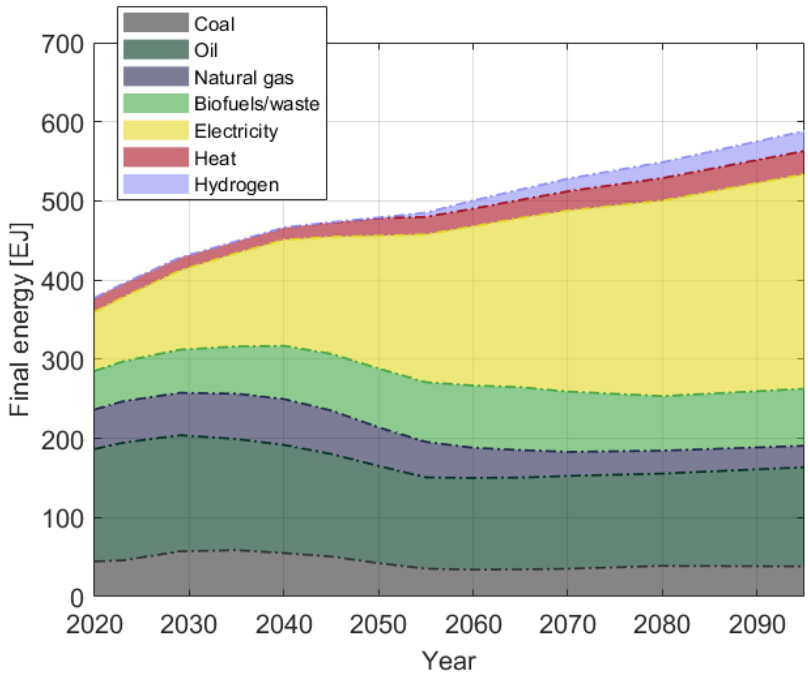

Figure 6: Total final energy consumption, scenario with average learning for all technologies and without sectorial emission constraints

The total final energy consumption (TFC) highlights the system-wide electrification, especially in the second half of the century, when also hydrogen diffusion gathers pace. It is worth noting, however, that even by the end of the century the system is far from free of fossil fuels and decarbonization is therefore reached also through an extensive use of CCS technologies. Total final energy use increases by some 50% by the end of the century.

Final energy consumption in the industrial sector

Coal continues to play an important role for the industrial sector, especially in comparison to the rest of the global energy system (See Figure 7). This trend is even more pronounced for iron and steel production, for which electrification is more muted; when no sectorial constraints are present , coal use increases to some 50% of the total final energy use in 2040 and hydrogen plays an increasingly important role only from 2050 onwards. Rest of the industrial sector is able to largely electrify its energy use, showing that decarbonization through electrification is less cost efficient for steel production than it is in the other industries. Introduction of CO2 targets for the industrial sector does change this, however, and pushes more of the fossil based technologies out of also the iron and steel industry (as shown in Figure 9).

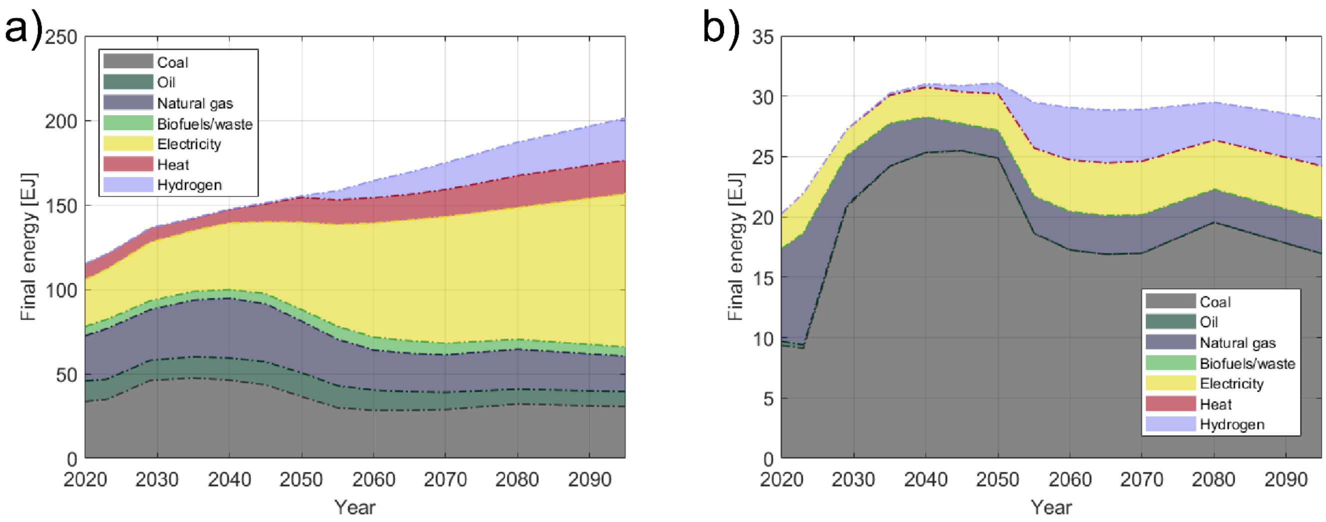

Figure 7: Total final energy consumption in the industrial sector (a) and in the iron and steel sector (b), scenario with average learning for all technologies and without sectorial emission constraints

Evolution of the steel production mix

Figure 8 collects the main results for the scenarios that do not include a sector specific constraint for the industrial sector. To simplify the illustration, the technologies have been clustered according to Figure 2 (same colors used): Some of the individual technologies within the clusters were not chosen at all by the model.

Future trends and uncertainty analysis

From a first glance, the decarbonization of the sector in the short to mid term appears challenging: Most of the demand until 2050 is covered with fossil-based technologies. From 2040 onwards both CCS technologies and hydrogen-based ones start to penetrate and after 2050 these two, especially the latter, start to cover a more significant share of the global production, and a corresponding decrease in the share of steel coming from fossil based processes. In a subset of scenarios hydrogen-based technologies, particularly green hydrogen direct reduction and Ulcolysis, start to increase their share after 2060, and become predominant by the end of the century.

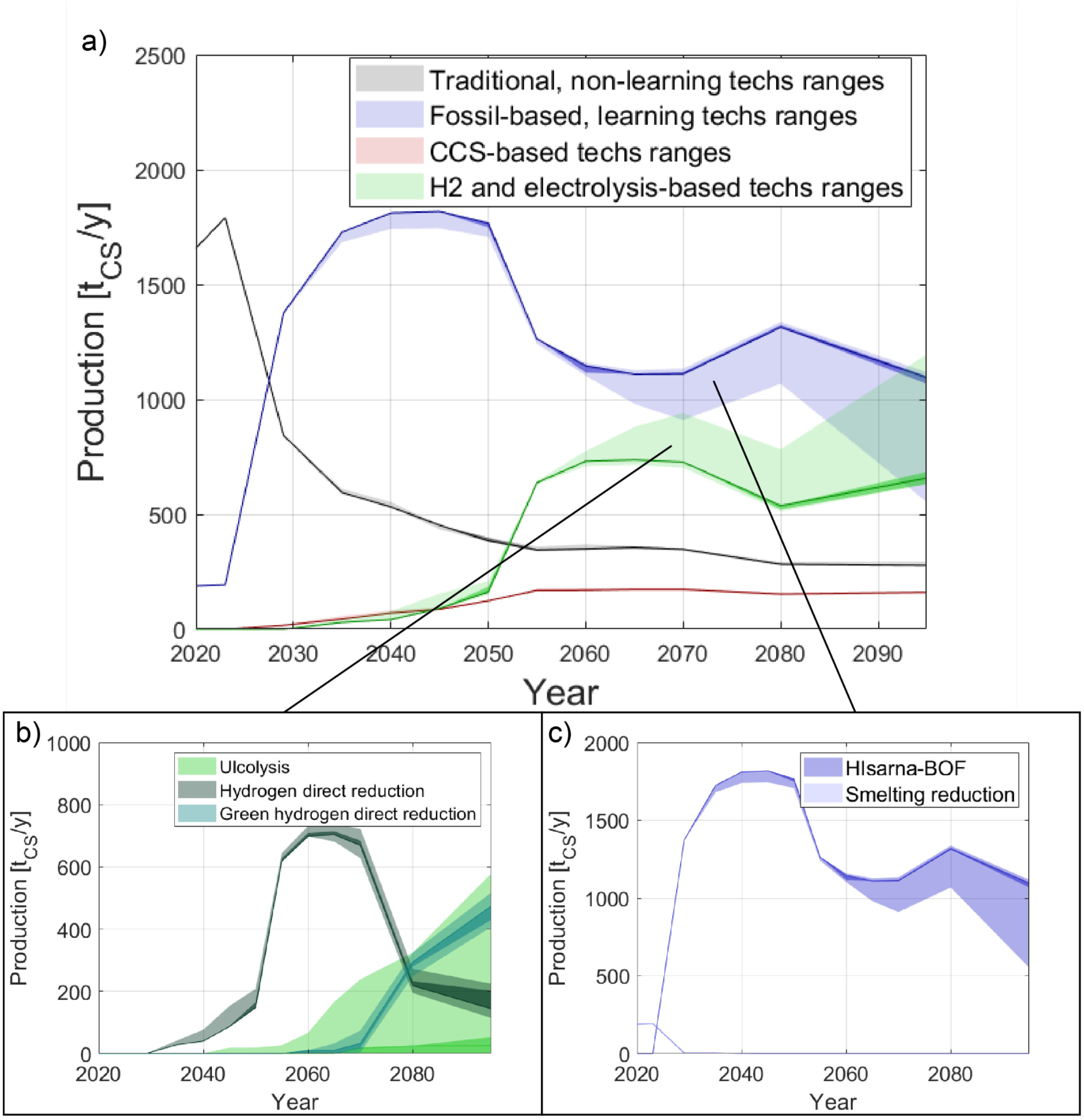

Figure 8: Steel production uncertainties without sectorial emissions constraints(a), with two detail graphs: on hydrogen and electrolysis-based technologies (b), and on fossil-based, learning technologies (c).The area filled with the light shade of each color represents the full range of scenarios, and the darker fill the central 40% of scenarios.

The impact of learning rates is very muted until the mid century. Not only is the difference across the learning scenarios non-existent, in most cases learning scenarios diverge little from the non-learning one. After 2060, however, learning starts to play a larger role and differences emerge for the scenarios. This affects especially hydrogen and electrolysis-based technologies, which as a cluster holds the largest market share by the end of the century in 30% of the various learning scenarios. Of the individual technologies particularly Ulcolysis is affected, but so is HIsarna-BOF, which relies on fossil fuels. Interestingly, the latter is not affected by learning rates related to the technology itself - these are kept constant across the scenarios - but by the changes in learning rates for the competing technologies. The results thus largely reflect uncertainties in the learning potential of Ulcolysis, with the variations for other technologies reflecting this, rather than their own learning uncertainties.

Similarly, with additional sectorial constraints (Figure 9) the contribution from conventional, non-learning technologies varies due to changes in the learning rates of the other technologies - and Ulcolysis reaches an even stronger position, leading the sector in all scenarios from 2070 onwards. It is also worth noting that the non-learning scenarios do not significantly differ from most of the learning scenarios, but fall within, or close, to the range of the latter. This emphasizes the impact of the combinations of various learning rates, rather than just the existence of learning, for defining the shape of the energy system. An interesting, and somewhat surprising, finding is that CCS-based technologies are influenced little by the level of learning, whether for CCS itself or for competing technologies. This is particularly interesting as CCS does still have a role, suggesting that it captures a niche, but is unable to break from that, no matter what is assumed for learning. Similar dynamics are seen for the non-learning technologies across the scenarios, although with sectorial constraints and certain low-learning Ulcolysis scenarios increased use of steel from scrap processes is observed.

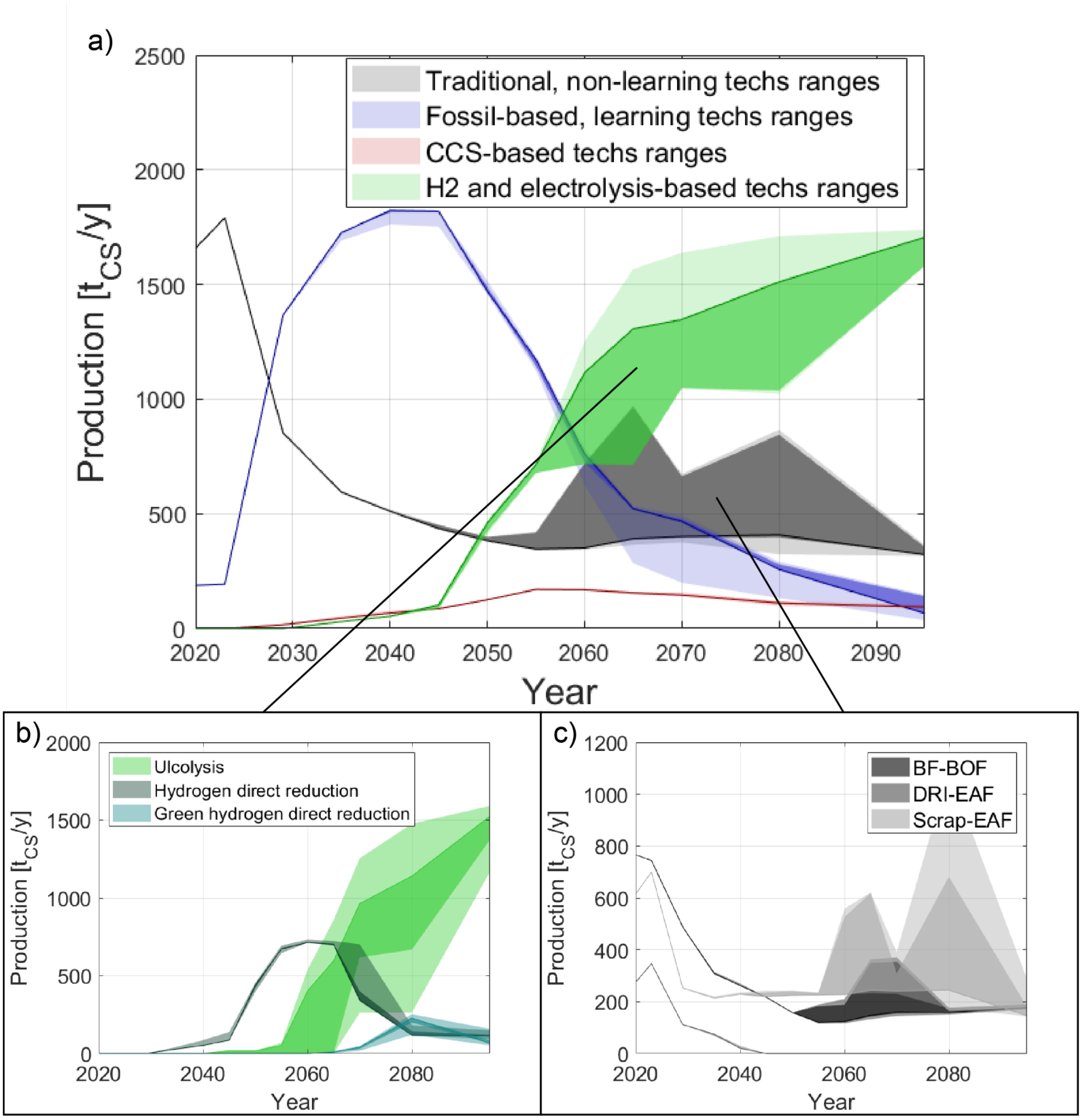

Figure 9: Steel production uncertainties with emissions constraints (a), with two detailed graphs: on hydrogen and electrolysis-based technologies (b), and on traditional, fossil-based technologies (c). The area filled with the light shade of each color represents the full range of scenarios, and the darker fill the central 40% of scenarios.

Costs evolution

In the previous section it was shown how different levels of learning produce differences for the market shares of steel making technologies. In this section, the goal is to explore how the costs of the technologies develop across time, in order to explain the observed differences in market share evolution. Figure 10 shows the cost evolution for the four main learning technologies in the different learning scenarios.

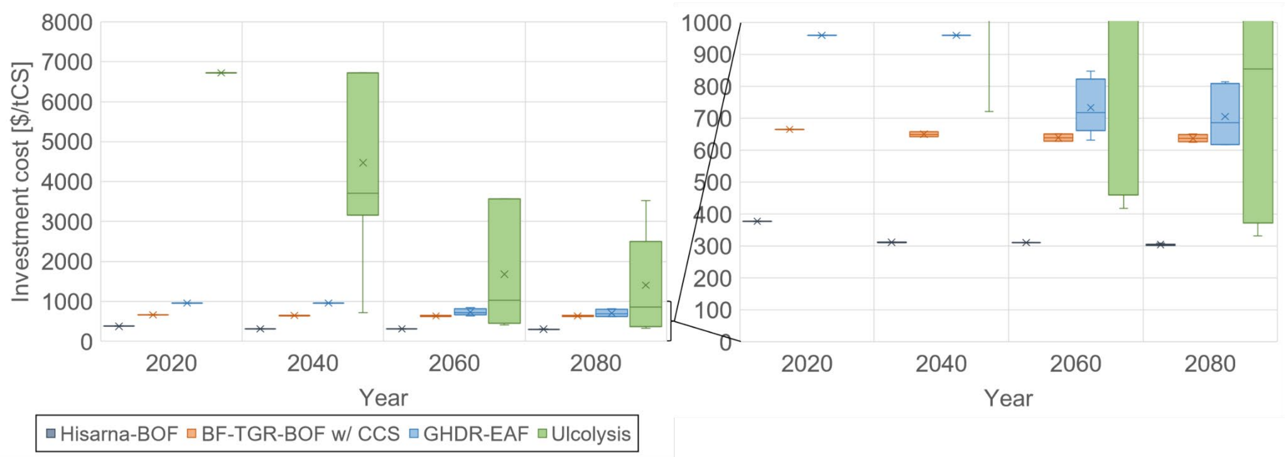

Figure 11: Evolution of the investment cost for the main learning technologies in all scenarios, for four milestone years. Bars represent the central 40% range of the scenarios and whiskers the full range. Median is shown with a line and the mean value is marked with an X.

The cost curves in Figure 11 highlight strong differences in cost reductions, but also cost reduction potentials, between the different technologies. HIsarna, Green HDR and especially Ulcolysis present high potential cost reductions, due to the innovative component covering a large portion of the capital cost (see Table 1), and consequently total capital costs are by 2100 reduced from the 2020 values by 30-32% for HIsarna, 17-38% for Green HDR and 48-96% for Ulcolysis. The significant cost reduction of Ulcolysis already in 2040 is due to the initial investments on this technology in one specific region of the model, leading to rapid cost reduction due to its very low initial installed capacity and consequent, broader deployment in other regions. On the other hand, the share of top gas recycling with CCS of the total capital cost of BF-TGR-BOF route is low, leading to a low cost reduction potential and reductions of only 3-6% in total capital cost (see Table 1). Consequently, the penetration of Ulcolysis and Green HDR strongly depends on learning, whereas the CCS technologies have almost no learning benefits from the investments in them. Being based on traditional, already established processes to which carbon capture is added, their capital costs will always be higher than for traditional technologies. Thus, the window of opportunity for these technologies would require tight policies on emissions (e.g. high carbon taxes), in parallel with high electrification costs for the system, as the latter affect the development of the competing electrolysis-based technologies (Green HDR and Ulcolysis). With this said, Figure 11, in comparing the investment costs of the competing technologies, shows that while Ulcolysis is clearly the technology most benefiting from learning, it also had by far the highest initial investment cost and still remains above the other technologies by 2080 in many scenarios. It needs also to be noted that operational costs, including implied emission permit purchases, also differ across the technologies, affect the competition and are not reflected in Figure 11.

Evolution of emissions in the iron and steel sector

Table 3 shows as a function of electrolysis technologies' learning rates, how emissions for iron & steel develop across time, for both with and without sectorial constraints for industry. In the scenarios without sectorial constraints mitigation measures in the industry compete against those in other parts of the energy system, and the model has thus broad flexibility in terms of choosing where in the energy system to target mitigation actions to. In the scenarios with sectorial constraints the industrial sector has, on top of the system wide mitigation measures, its own quota and the flexibility within this is restricted to choosing which industries and measures to target.

	Iron and steel sector global emissions [MtCO2/y]					
	Industry emission constraint: OFF			Industry emission constraint: ON		
2035	2885.5	2888.0	2890.8	2888.2	2890.9	2888.5
2050	2677.2	2676.3	2651.8	2343.7	2301.4	2317.7
2070	1853.0	1829.1	1578.5	1381.4	1059.1	707.3
2095	1789.6	1760.4	1085.9	641.5	530.8	491.6
	4.1	9.6	15.1	4.1	9.6	15.1
	Electrolysis-based technologies Learning Rate [%]					

Table 3: Sector emissions without and with sector-specific emissions constraints

Consistent with most international reports, such as IEA's Iron and Steel technology Roadmap, the emissions from iron & steel are further projected to grow in the short term , due to an expected increase in steel demand in the next decades, especially from China \cite{IEA3}. As can be seen from Figures 8 and 9, there is a strong shift to more novel technologies already by 2035, but these do not yet provide much emissions reductions in any of the scenarios, as the new technologies still rely on fossil fuels. This is due to the industrial sector, and specifically the iron and steel subsector, being costly to decarbonize and other sectors are thus prioritized for the early reductions. The new, low-carbon technologies present initially not only higher investment costs, but also higher operating costs, due to not yet advanced electrification. Also, emission prices are not yet very high during the first half of the century, and the more carbon-intensive technologies are thus not yet severely penalized for their emissions. This can be seen in Table 3, with the scenarios having nearly identical emissions in 2035 and differing around 15%, at most, in 2050.

2050 is a turning point for the development of the emissions in iron and steel, with emissions decreasing rapidly during the following decades, with the level of reductions strongly depending on the learning potential of electrolysis-based technologies.

Scenarios with a high level of learning for electrolysis-based technologies lead in 2070 to a significant reduction of emissions in the iron and steel sector, while low learning rate would produce emissions with similar levels to the current. With sectorial constraints the difference is even more significant, reductions varying as a function of the learning rate from 25% to 60% of the current sectorial emissions. As the emission constraints are formulated across sectors and separately for the industrial sector, the ranges reflect reorganization of mitigation towards the iron & steel industry, and away from other sectors.

Lowest emission levels are reached at the end of the century, following the ever tightening emission constraints. In absence of sectorial constraints and with high learning rate there is still significant reduction potential beyond the 2050 reductions (up to 60% in reduction with respect to 2050), whereas low learning rates lead to marginal additional mitigation in comparison to 2070. This trend is somewhat reversed for scenarios in which sectorial constraints are present, with more mitigation potential remaining in low learning scenarios and the difference between 2070 and 2095 thus being much greater than for the high learning scenarios in which mitigation mostly took place already by 2070.

Emission constraints for the full energy system are identical in all scenarios, and for the industrial sector in all scenarios with sectorial constraints. The latter scenarios demand more from the industrial sector, and it's thus somewhat unsurprising that in 2095 emissions from the iron and steel sector are always clearly below the level they are in the scenarios without sectorial constraints, no matter what learning levels are assumed. Interestingly, however, this is less the case for 2070, as the scenario with high learning and no sectorial constraints starts to approach the emissions of the scenario with low learning and sectorial constraints. This illustrates how learning rates affect how the model distributes the mitigation activities: High rates lead the steel industry to contribute more to the mitigation of the industrial sector, and for the industrial sector to contribute more towards the mitigation of the full system. Low rates conversely lead to the rest of the system having to do more.

Evolution of investments and marginal prices

Figure 12 shows the evolution of the annual investments in the industrial sector (panel (a)), and of the marginal price of steel (panel (b)). The focus, to illustrate the range of results, will be on four scenarios: They either assume no learning (two scenarios) or the highest level of learning for all technologies (the other two scenarios), with and without sectorial emission constraints.

The results illustrate the impact of the sectorial emissions on the sectorial investment, especially for the second half of the century, when the constraints become more stringent. High learning assumption lowers the required investments, by around 40% in 2100, due to the positive contribution of learning. Investments in the scenarios with no industry specific emission targets maintain a flat investment pattern, with learning playing only a minor role.

The marginal prices of steel illustrates the system-wide costs of producing a unit of steel, thus covering cost implications beyond direct investments. The general conclusions, however, are similar, with prices rising in the sectorial-constrained scenarios after the mid-century, and learning mitigating this price increase . The impact of the learning is, however, lower than for investments, as it directly affects the investment cost of technologies, while the marginal price is influenced also by other drivers (e.g. prices of input commodities, O&M costs, implied emission costs). As before, the price of steel remains flat, if no sectorial emission constraints are imposed.

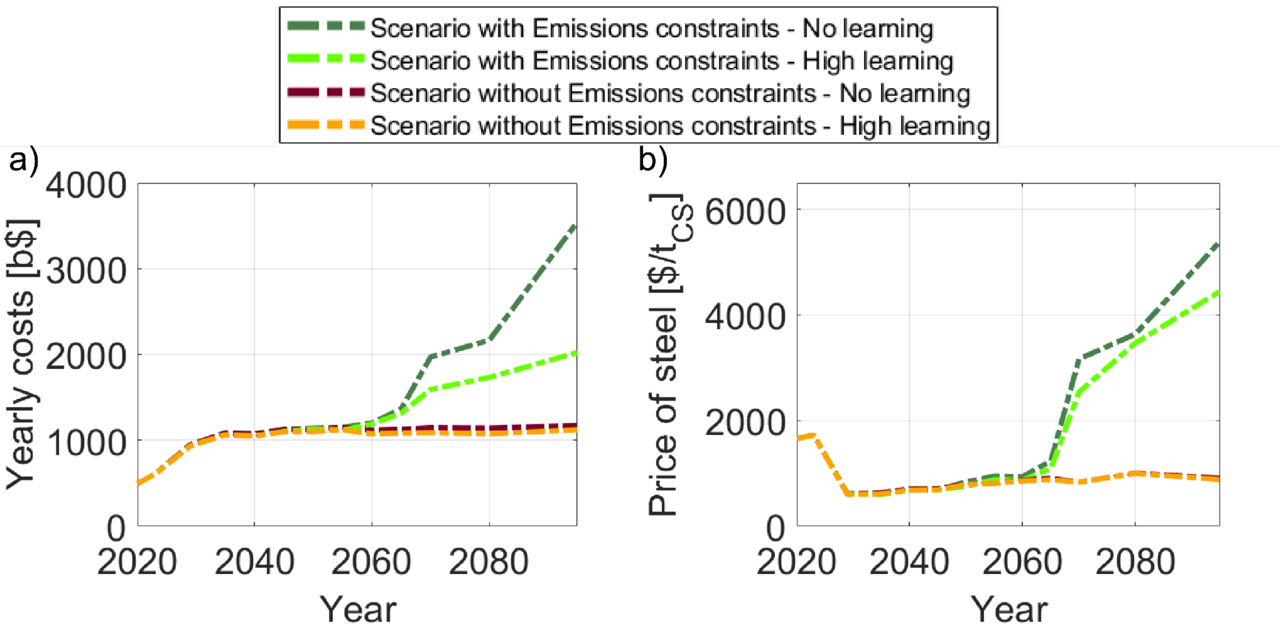

Figure 12: (a) Yearly investment cost in the industrial sector and (b) Steel price in four selected scenarios (no learning, high learning both for the sectorial-constrained and sectorial-unconstrained scenarios)

Short paragraph to be then relocated: comparison of results with other TL studies

- In \cite{Liu}, \cite{Strunge}, \cite{Ren}, \cite{Sanchez} no mention of the impact on the results
- In the work by Jin-Hua Xu \cite{JHXu}, which studies the impact of technology learning on innovative technologies for cement production, the technology benefiting the most from learning is one with high learning rate assumed and in development stage (low TRL).
- In \cite{Sanchez2}, where the analysis is realized on the iron and steel and chemicals sectors only until 2050 and a comparison is realized between two scenarios, which differ for the level of learning, no sensible differences can be noted between the two, except for one very specific process for syngas production.
- In \cite{Karali}, where the impact of technology learning of some technologies and energy efficiency measures applied to fossil-based steelmaking processes on the sector's energy consumption is studied, the larger impact, by 2050, can be seen only on already established technologies, while only few of the emerging ones are affected by the effect of learning.

Discussion and Conclusions

The results above demonstrate how decarbonization of the industrial sector remains an ambitious and complex goal to achieve, compared to other sectors; without an ad-hoc sectoral policy, no significant reduction in the use of fossil fuels could be achieved in our modeling.

The results also highlight that the decarbonization of the iron and steel sector can be positively influenced by the improvement of innovative, carbon-free technologies, but only in the long-term. Before 2050 learning does not affect the decisions much and at least 70% of the global production would still be provided with fossil fuels-based processes in 2050. The remaining portion would be covered with non-green hydrogen direct reduction and blast furnace-based process with top gas recycling and CCS. This outcome is consistent with the results obtained by IEA for 2050 projections in the latest Technology Roadmap \cite{IEA3} and suggests that if an earlier low carbon transition is desired also for the iron and steel sector, measures targeting specific technologies may be required..

The low impact of learning on the sector up to 2050 is ascribed to a series of factors: Firstly, the electrification of the energy system, a key element for the new technologies also in the iron and steel sector, becomes predominant only in the second part of the century and variation of assumptions for the iron and steel sector alone does not change this. Secondly, the investment costs for electricity and hydrogen-based technologies are in relative terms higher in the sector compared to the other sectors, e.g., electrolyzers become a commercially-widespread solution around 2045, but first in other industrial processes, such as ammonia production. Thirdly, the introduction in 2025 of an innovative, cost-effective technology based on fossil fuels (HIsarna-BOF), leaves less room to the introduction of less carbon intensive technologies in the short-medium term. Finally, this result differs in nature from those produced with similar models , but using an endogenous learning formulation: The iterative, exogenously-defined learning approach reflects learning as a co-benefit of investments made based on competitiveness on the day, rather than based on future prospects, as is the case with endogenous formulations with perfect foresight. This also means that in this formulation learning is simulated, rather than optimized across time, and different investment patterns could have led to a lower cost across time for the full system. Also, the range of learning rates would have, in all likelihood, led to a wider range of outcomes, as the strategies would have been specifically optimized for the combination of learning rates. Considering the high uncertainties and the “all eggs in one basket” strategies that, due to the increasing returns to scale, endogenous learning encourages, the information about optimal results has been traded off against the more realistic simulation of investment behavior. With that said, the results do also emphasize the need to encourage and incentivize through targeted policies early investments into pilot projects and R&D, as the purely market driven mechanism modeled here does not bring the low carbon technologies to the market as early as would be needed. It is also of note that Sanchez et Al. \cite{Sanchez}, studying the impact of several factors, including technology learning, on the decarbonization of the steel and chemical sector, obtained a comparable result: No significant effect of technology learning was found, given 2050 as a time horizon. Our results therefore emphasize the previous findings about how learning and framework level policies (e.g. a system wide carbon price) alone may not give adequate incentives to introduce new technologies in the sector rapidly.

Contrary to the insensitivity of results to learning before 2050, during the latter half of the century technology learning becomes an important driver for the decarbonization of the sector. By lowering the investment costs of low-carbon technologies, and consequently the price of low-carbon steel, learning leads to a deeper decarbonisation of the sector, with up to 40% less emissions from the iron and steel sector by the end of the century, compared to a scenario with the same global or industry wide emission constraint, but no learning. An ambitious, industry-specific emission policy will further drive technological improvement of electrolysis-based technologies, making them even more cost effective. These technologies, and in particular Ulcolysis, benefit the most from learning due to their high learning potential, which significantly reduces the high initial cost in some learning scenarios. This leads to significant changes in the market shares of the technologies in the sector, and to an almost complete decarbonization of iron and steel production. A similar outcome emerges from \cite{JHXu}, in which the impact of technology learning on innovative technologies for cement production is studied. The technology benefiting most from the learning is the one with a high learning rate and an early development stage (low TRL), as these two elements generate a very high potential for cost reduction. For CCS, another technology available for reducing emissions in the sector, the message is different: The influence of the learning is low for these technologies, as most of the costs are in already mature components of the technology and thus even high learning potential for the novel components does not lead to high absolute cost reductions for new installations. The granular sensitivity study confirms this, as CCS deployment remains largely identical across the sensitivity scenarios.

The impact of uncertainty on technology choice in the sector is perhaps smaller than expected: While the level of the learning rates have an impact on the speed with, and extent to, novel technologies diffuse, the general storyline remains the same: Conventional technologies are phased out quickly, initially replaced by more advanced fossil based technology that then peaks before 2050 and gives way to the low carbon technologies. The largest differences for the storylines are, instead, observed between the scenarios with or without sectorial emission constraints, with the sectorial constraints bringing about a much deeper decline for the novel fossil based technologies, further emphasizing the role of innovative technologies, and relying more heavily on Ulcolysis rather than green hydrogen direct reduction. This outcome is likely to be at least partially driven by our approach to modeling learning, as noted above.

While this work shows how the effects of technology learning will become more evident in the long term, a further development could, instead, focus on the coming one or two decades, in order to understand what strategies could help a faster roll out of low carbon technologies in the short and medium term. In particular, it may be interesting to focus more closely on the CCS technologies, and the drivers that could possibly bring them in in the short term, both regulatory (e.g. support mechanisms such as subsides and R&D funding) and technological (e.g. focus more on the various retrofit possibilities for using CCS in existing processes). From a methodological perspective, a parallel, endogenous learning formulation could provide additional insights about the inefficiencies of the markets in investing in technologies that have the greatest prospects in the long term.

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A - Innovative aspects of learning sub-technologies

This appendix describes the ways in which the sub-technologies in Table \ref{table:cluster} could potentially improve and reduce their costs.

A.1 - Smelting reduction

While this technology is already mature, with several large-scale plants installed worldwide, a range of ways to improve its cost-effectiveness remains, starting from some lack of theoretical knowledge on the process, to more practical aspects. \cite{Zhou}

The stratification of the slag inside the melting-gasifier is poorly understood, and it would be important to understand how the different layers interact and how this depends on the operation conditions. By fully understanding the process, a more optimized design of the melting-gasifier could be realized, decreasing the investment cost per ton of output for this type of plant. \cite{Zhou}

Other problems observed in this type of plants concern the air vent, which often gets damaged, and the poor control on the tuyere area (where the oxygen is input in the melting-gasifier). This last problem has been solved with coal injection through tuyere, in a way that stabilizes the temperature, making the area more controllable.\cite{Zhou} \cite{Zhou2}

Finally, further scale-up in the size of the facilities would further reduce the costs, even if Mt_{CS}/y-sized plants already exist worldwide.

A.2 - PSA-based CCS technologies

The pressure swing adsorption-based carbon capture and storage technologies represent an innovative alternative to already-established CCS technologies, such as the amine-based ones.

PSA based technologies bring advantages such as the lower energy consumption, a lower environmental impact of the sorbent used, and less sorbent used for the process \cite{Rochelle}.

By comparing PSA-based CCS and relative amine-based counterparts, however, the former show lower electrical efficiencies and CO_2 recovery \cite{Riboldi}. By raising the input temperatures, the gas cleanup could be performed with less energy losses, raising the overall efficiency \cite{Riboldi}; an evolution of the PSA-based process towards the SEWGS-based ones, could help their penetration in the

CCS market. This is another reason why, PSA-, VPSA-, and SEWGS-based processes have been coupled in this study.

A.3 - Cryogenic distillation-based CCS technologies

Cryogenic distillation presents problems mainly in terms of high energy expenses for the cooling of CO_2 to condensation temperatures. Alternative strategies can, however, be applied to reduce the consumption of energy, such as cyclic distillation, heat-integrated distillation column, reactive distillation and thermally coupled columns \cite{Song}. These solutions are promising in terms of energy consumption reduction, but a scale-up of such applications is important in order to practically prove the theoretical gains \cite{Song}. In addition to operative expenses savings, the scale-up would bring significant reductions to the overall investment cost of the CCS system.

A.4 - Electrolysis

Electrolysis, unlike most other technologies in this study, shows very high learning potential for different parameters and is thus described in more detail:

A.4.1 - Electrolysis investment cost

According to different studies \cite{Anderson} \cite{Saba} \cite{Smolinka}, the investment cost of a PEM electrolyzer shows cost reduction potential in the following components:

A.4.1.1 - Flow fields and separators

Flow fields cover almost 30% of cost and the separators are designed according to the minimization of entropy generation, which is computed through very complex CFD simulations. For this reason, they are subjected to a continuous design improvement (around 40% reduction in cost from 2009 to 2015, with an enhanced production of hydrogen up to 15%). During the same time span, material related improvements, such as new manufacturing process and nitride coating, were achieved. The lower exposure to hydrogen over the lifetime ensures a longer lifetime. Even after these improvements, these components still represent the highest percentage of the total cost.

A.4.1.2 - Membrane electrode assembly

Membrane electrode assembly covers roughly 25% of the cost, with the cost especially driven by the cost of noble metals. In particular, PGM – platinum group metal – covers more than 50% of material cost. The use of these costly materials has been limited in more recent applications, through no longer using PGM. In addition to reducing costs, this also leads to a decline in raw materials cost volatility. Catalysts also play a central role in potential cost reductions, with two key characteristics to be enhanced: Firstly, the Oxygen Evolution Reaction (OER) activity should be improved, together with the process to enhance electronic structure, and secondly, the conductivity should be improved as well. The aim of both these improvements is to increase the current density. Moreover, manufacturing scale-up would also drive to higher reductions in cost. Finally, by redesigning the cell and using a reinforced hydrocarbon for the membrane, 4x current density can be reached, with an increased durability to 10000 h at 80°C

A.4.1.3 - Labor

Higher levels of automation in the manufacturing process can reduce labor costs, which currently cover a bit more than 20% of the total cost.

A.4.2 - Electrolysis fixed O&M cost

A large part of fixed O&M costs for large-scale plants represents labor. This cost can be reduced with increased operational automation.Second element of fixed O&M costs in PEM electrolysis plants reflects continuous activities of testing and maintenance, partially due to the poor scientific knowledge available about degradation modes and failure paths of such plants. \cite{Ayers} Improving the knowledge under this point of view could drive the fixed O&M costs to very low levels compared to the current ones. Finally, various sources \cite{Ayers} \cite{Mazloomi} agree with the fact that materials durability, especially in the separator, can have a great impact on the fixed O&M costs, lowering maintenance-related expenses.

To conclude, in papers such as the one by \cite{Ayers} it is underlined how such improvements will allow a decrease in fixed O&M costs even far below 50% with respect to the current trends. These considerations, as a consequence, drove the choice to model the technology learning of the fixed O&M costs in electrolyzers, unlike what had been done for steelmaking technologies that do not present such cost reduction potentials.

A.4.3 - Electrolysis efficiency

The efficiency of the process is dependent on a series of interdependent factors, each of which can be improved separately, or the configuration of which can be optimized to increase efficiency.

Mazloomi \cite{Mazloomi} distinguished three elements to focus on for increasing efficiency: electrode, electrolyte and separator material.

Electrode, in addition to being strongly influencing the investment cost of an electrolyzer, a further increase in efficiency can be reached by changing its material, or the size and alignment, or the space between those (which should be minimized). The *electrolyte* is vital for determining the efficiency of an electrolyser, and in particular its electrical resistance and quality are very important; by changing the electrolyte, Taner \cite{Taner} obtained a significant increase in the overall efficiency of a PEM electrolyzer. Finally, the *separator* is responsible for a large part of power losses, being an obstacle to the free movement of electrons and ions, and having electrical resistance much higher than the one of the electrolyte. Several researches are focusing both on the material itself, and on the pressure and temperature conditions to minimize the losses.
Depending on the choices above, some working parameters, such as temperature pressure and applied voltage waveform, can be optimized, with the aim of maximizing the efficiency.The working temperature for PEM electrolyzers is around 50-80°C, with an increase usually beneficial for the efficiency, as the splitting reaction potential of water decreases, together with surface reaction and ionic conductivity of the solution. Higher temperature can, however, can lower the durability of materials and their stress resistance. Pressure has a direct effect on the power losses due to voltage drops, that are lower when the electrolyte is compressed. Recent research has shown how, by compressing the inlet water, an even higher gain in efficiency can be reached, both in the electrolysis phase (5%) and in hydrogen compression phase (50%) \cite{Mazloomi}. Finally, the applied voltage waveform plays a significant role: applying a simple DC power supply lowers the efficiency, especially by increasing the power rating of the electrolyzer. As a consequence, research is moving towards ultra-short pulse power supply, with very positive results.

It is particularly difficult to predict the possible increase of electrolyzers efficiency because newer designs will be required to respect very strict constraints also in terms of durability and cost effectiveness (some short-term solutions in design innovations prioritize this aspect with respect to the efficiency, trying to reduce the cost while keeping reductions in energy efficiency to a minimum \cite{Ayers}). The majority of publications in this field do, however, agree that increases in efficiency can still be expected, which is why increase in efficiency is modeled as part of the learning process.

A.5 - Electrolysis of iron ore

This technology, being particularly innovative and technologically immature, presents a large variety of aspects to be improved, and as a consequence has high learning potential. Similarly to the water electrolyzer, two main aspects to be improved are the cell design and the electrolyte, with the third relating to the characteristics of the metal ore Potential improvement for cell design have been discussed in detail in a paper by ArcelorMittal researchers \cite{Lavelaine}, and concern the internal distribution of current density, as well as the steadiness of the process. The electrolyte represents also a very critical element, as it should maintain its physical properties when subjected to high voltages, and therefore many research efforts are aimed at finding a better performing solution \cite{Wiencke}. Finally, the input products mix should, in the right proportion, enhance the efficiency of the reaction: this is why researchers are oriented to find the optimized mix of hematite and iron ore \cite{Maihatchi}. Finally, the scale-up of the technology is of vital importance, as existing plans are for small scale plants, in the order of few kg_{CS}/day, whereas economies of scale are expected to exist for the process.

B - Technology learning methodologies

This appendix will describe, (1) the computation of the initial installed capacities for the different clusters of technologies presented in Table \ref{table:cluster}, and (2) the operative details of the technology learning implementation.

B.1 - Calibrating initial installed capacity for the learning technologies

The initial installed capacity of the different technologies have been computed as follows:

B.1.1 - Smelting reduction

For this technology, the Corex© and Finex© investments are considered, leading to a total capacity of around 11.45 Mt_{CS}/y \cite{Siemens}, split as follows:

1) Corex:
   a) 2 x C-2000 plants by JSW, India
   b) 2 x C-2000 plants by Essar, India
   c) 1 x C-2000 plant by ArcelorMittal, South Africa
   d) 2 x C-3000 plant by Baosteel, China
   e) 1 x C-2000 plant by Posco, Korea
2) Finex:
   a) Demo plant by Posco, Korea
   b) 1 x F-1.5M by Posco, Korea
   c) 1 x F-2.0M by Posco, Korea
3) HIsarna: Not considered, as not yet established and a demo plant is planned to be built only in next years

B.2.2 - CCS technology (physical adsorption)

For this technology, all the CCS-based plants in the world are being considered, distinguishing the plants using this type of technology \cite{CCUS}. At the moment, the only CCS-based iron and steel plant active is the Abu Dhabi CCS1 (DRI-EAF with CCS), with no other plants planned until 2025, the year in which all CCS technologies become available within the model.; for all the other technologies, other types of plants are considered:

- Air Products plant in Texas (hydrogen production plant) stores 1 Mt_{CO2}/y using VPSA technology
- Emirates steel project comprehends a DRI plant with amine adsorption, so it would not be included normally, but dealing exactly with the same technology,it is possible to include it as well (0.8 Mt_{CO2}/y)

- LafargeHolcim Cement CCS system will be based on Svante's technology (Canada manufacturer of PSA filters); the predicted carbon capture rate will be of 0.72 Mt_{CO2}/y
- HyNet North West is planning to build a 1.50 Mt_{CO2}/y plant in the UK which produces hydrogen using ATR technology which includes a PSA
- Lake Charles Methanol plant in US is planning to build a plant within 2025 where CO2 is sequestrated via a PSA; it is predicted to capture 3 Mt_{CO2}/y
- NetZero Teesside is a UK project which aims at developing a non-amine based CCUS integrated within a CCGT; project size: 6 Mt_{CO2}/y
- Drax BECCS Project uses an alternative technology applied to power generation (presumably PSA); size of the project: 4 Mt_{CO2}/y

B.2.3 - CCS technologies (cryogenic distillation)

The initial capacity has been computed based on the data found in different papers reviewing the capacity installed of innovative CCS technologies \cite{CCUS} \cite{vanderStel}:

- There is one planned plant by Tata steel for the integration of HIsarna with CCS to be built by 2022 (and by 2025 it is assumed that the first demo plant will have been built, producing 0.5-1.0 Mt_{CS}/y);
- In China, Yulin, there is a 50.000 t_{CO2}/y capture facility using cryogenics-based technology

B.2.4 - Electrolyzers

The most recent data for the cumulative capacity are dated 2019; according to IEA \cite{IEA2} the total installed capacity of PEM electrolyzers accounted 270 MW_e

B.2.5 - Electrolysis of iron ore (Ulcowin - Ulcolysis)

The pilot plant, which was to be built in2022, is being considered. There is no information about subsequent plants, and it is likely that also the pilot plant is delayed, due to the current Covid crisis. The pilot plant will produce roughly 50 kg_{FE}/day = 18.3 t_{Fe}/y \cite{Birat}

B.3 - Exogenous learning technology: operative details

This subsection will discuss the operative details of the implementation of exogenous technology learning, focusing on two problems are assessed: (1) the convergence conditions for the iterative procedure, and (2) the practical implementation of the procedure.

B.3.1 - Convergence condition

As highlighted in the flow chart describing the iterative procedure, there is, at every iteration, a check on the difference between the result of the prior iteration and the current one; if the difference is above given thresholds, another iteration is started, if below, at least the absolute error (see below) the iterative procedure is stopped.

In order to consider the convergence also across the model time horizon, the check is performed for each model time step. The difference between two subsequent iterations is computed as shown in Equations \ref{eqn:ae} and \ref{eqn:re}.

$$RelErr_t = \frac{\sqrt{\sum_{i=1}^{num_{technologies}} \{(I_{t,i}^{n+1}\} - I_{t,i}^{n})^2}}{\sqrt{\sum_{i=1}^{num_{technologies}} \left(I_{t,i}^{n+1}\right)^2}}$$

$$AbsErr_t = \sqrt{\sum_{i=1}^{num_{technologies}} \{(I_{t,i}^{n+1}\} - I_{t,i}^{n})^2}$$

Where i indicates the technologies, and n the iteration number. The first check calculates the relative error, which should be below 5%. As in some time steps the newly installed capacity is small compared to the existing one, a check on the relative error can produce high percentages considering the newly installed capacity in the denominator, but if compared to the global sector (where the existing capacity may be higher, even by an order of magnitude) could be negligible. As a consequence, a double check system was designed: If the relative error check is above the 5% threshold, a second check on the absolute error will be performed, with a threshold of 30 Mt/y.

This procedure is adopted also for the newly installed capacity of electrolysis technologies, with a 5% maximum admitted relative error and 300 PJ/y maximum absolute error.

B.3.2 - Operative implementation

1) The procedure starts with the first run, in which constant costs over time are used (no learning).;
2) The newly installed capacity from the run for each time step and used with the exogenously defined learning curves to calculate the new investment cost trajectories. Some notes on specific technologies:
    - Smelting reduction: the newly installed capacity of Smelting Reduction, HIsarna-BOF and HIsarna-BOF with CCS are summed ;
    - PSA-based CCS technologies: the newly installed capacity of BF-BOF with CCS, BF-TGR-BOF with CCS, DRI-EAF with CCS and ULCORED with CCS are taken, in Mt_{CS}, and converted into the units of the learning curve formulation (Mt_{CO2}/y) by using the capture rate of the different CCS technologies;
    - Cryogenic distillation-based CCS technologies: the newly installed capacity of HIsarna-BOF with CCS, in Mt_{CS}/y, is converted as for the other CCS technologies into Mt_{CO2}/y;
    - Electrolysis: the newly installed capacity of electrolyzers, in PJ/y, is converted into MW_e for the learning curve;
    - Electrolysis of iron ore: newly installed capacities of Ulcolysis and Ulcowin are summed for the learning curve
3) The costs in the model are updated and the model is run again;
4) The outputs of the second run are checked against the convergence criteria; if the criteria is fulfilled, the procedure is stopped, otherwise, the procedure will go on, restarting from point 2 of this list.