POLITECNICO DI TORINO

Master's Degree
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Master's Thesis

Role of technology learning in the decarbonization of the iron and steel sector: a global approach using a TIMES energy model

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Abstract

The iron and steel sector, in addition to being one of the most impacting for greenhouse gases emissions at a global level (from 7 to 9% yearly), is one of the most difficult sectors to decarbonize, due to fierce competition and the absence of economically comparable alternatives to traditional processes, based on the use of fossil fuels. This thesis therefore aims to analyze the impact that future investments in decarbonizing technologies may have on their technological development, taking into account the uncertainty intrinsic to their correlation (called technology learning), and consequently, on the decarbonization of the sector, combined with the presence of policies for the reduction of emissions on a global scale.

Using an appropriate energy system model (EUROFusion TIMES Model), a learning model (Wright curve), and having supposed different levels of learning, a series of simulations were run. The results showed that a significant impact can be played by such phenomenon in the long term, as the decarbonization results particularly enhanced when the levels of learning are maximized for electrolysis and hydrogen-based processes, while CCS-based processes may play only a marginal role in the short term. Therefore, long-term investments on the former technologies are recommended, while further, policy-centered studies should be performed to understand the impact the latter can have in the short term.

Acknowledgements

I would like to thank, for the realization of this thesis, all the professors who followed and supported my work through the past months: I will treasure their teachings in my future experiences.

I would like to thank my family, and in particular my sister Irene, for all the help and support that I received.

Finally, I would like to thank all the contingencies that made this experience possible: in fact, despite all the difficulties dictated by the Covid-19 pandemic,carrying out this work at Aalto University gave me the opportunity to live an unforgettable experience, the best possible to conclude my Master's path.

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Andrea Moglianesi

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List of acronyms

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
ESM	energy systems model
ETM	EUROFusion TIMES Model
ETS	emissions trading scheme
GET-LFL	emissions trading scheme
GHG	greenhouse gas
GLOBIOM	Global Biosphere Management Model
HDR	hydrogen direct reduction
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 model
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
ULCOS	Ultra-Low CO_2 Steelmaking
VPSA	vacuum pressure swing adsorption

Chapter 1

Introduction

In 2019, 2.6 Gt_{CO2} [1] were emitted globally to produce 1.8 Gt [15] of crude steel: this value, if compared to the global CO_2 emissions in all sectors (around 33.3 Gt_{CO2} according to IEA [2]) represents the 7.8%: it is the highest contribution for a single industrial subsector.

Despite strong efforts by several international organization and global-scale producers in the last decades, the decarbonization of the iron and steel sector still remains a crucial as well as unresolved problem for the GHGs emissions mitigation. In fact, the price elasticity of the sector, together with the very strong presence in the market of emerging economies, whose carbon intensity in processes is even higher than in developed countries [15], increase the problem complexity.

However, in the context of programs launched by the mentioned stakeholders, such as ULCOS [20], some key low-carbon technologies have been individuated: their introduction in the iron and steel production mix could therefore assist the decarbonization of the sector. Such technologies are not at an acceptable readiness level, and thus are not as cost effective as traditional and more established ones [32]. Nevertheless, in the upcoming decades the cost of technologies in the iron and steel sector may not remain on the same level as now, both because of the development of the low-carbon, innovative technologies themselves, which could lead to a reduction of the cost per produced unit, and because of the possible increase in cost of traditional, fossil-based technologies in case of imposed sector emission targets.

The first phenomenon can be described by an econometric principle called technology learning, or learning-by-doing, which correlates the experience accumulated with a technology, and its unit cost [3]; the second is determined by a variety of possible emission reduction strategies: the most common ones are the emissions trading schemes (ETS) and carbon taxes.

Both phenomena are influenced by a wide range of factors, both technological and macro-economic. Therefore, in studying the influence they bring to the iron and steel sector, it is equally important to take into account the level of uncertainty they generate [3] [4].

1.1 Aim of the thesis

This thesis has thus the aim to understand if, and eventually in what extent, these two factors can help in the decarbonization of the sector, taking into account the uncertainty they bring (especially concentrating on the uncertainty that technology learning phenomenon generates).

In fact, while several papers exist in assessing the impact of technology learning applied to energy technologies [94], but also to the same industrial sector [11], none of them tries to analyse the uncertainty generated by such phenomenon. Instead, in this paper, the focus is set on how the uncertainties connected on such phenomenon can drive the evolution of the iron and steel sector: what would be the key technologies if hypotizing faster or slower performance improvements, and as a consequence how this can be beneficial, or detrimental, for the reduction of the carbon footprint of the sector.

In other words, this work tries to answer to the questions:

Can investments on new, technologically uncertain processes impact the iron and steel sector decarbonization under strict emissions targets? If so, to what extent? And which technologies, considering the effects of investments and their uncertainty, would affect the most the decarbonization?

In order to answer to these questions, an energy systems model (ESM) will be used: a thorough discussion on this type of models will be performed in a literature review, which will also contain a part concerning a technical characterization of the iron and steel sector, and a theoretical background on technology learning concept.

The literature review represents only the bibliographic research aimed at formulating the operative choices that will then be reported in the Methods section, where instead the procedure itself for the realization of the work will be presented. Afterwards, the results will be presented and discussed, with the deriving conclusions. Finally, the conclusions will sum up the work, connecting in a more direct way the starting questions and final answers.

Chapter 2

Literature review

The literature review, as briefly anticipated, will mainly cover three topics: starting from the *object* of the analysis, namely the iron and steel sector, which will be technically characterized in both the traditional and innovative technologies, moving to the *mean* of the analysis, i.e. the theory of energy systems models (ESMs), shortly arguing on which typologies could best suit for the current analysis, and concluding with the *main actor* of the analysis, the technology learning theory, with its principles, strong points and weaknesses.

2.1 Iron and steel sector technical characterization

The iron and steel sector is a very energy and carbon intensive sector for the world energy system. Introduced on an industrial scale since the ending of the 14th century and successively become a heavy industry sub-sector with the second industrial revolution, it is responsible nowadays for a large percentage of global GHG emissions, from 7 to 9 percent yearly. [2]

It is important to underline the difference between steel and iron: steel is composed by iron and a small percentage of carbon; in fact, pure iron's mechanical properties are poorer. As a consequence, all the processes used to produce steel aim at obtaining a mixture of iron and carbon at the right concentration in order to enhance its mechanical properties. [13]

In order to obtain these products, different processes can be used; in this analysis, the processes will be differentiated between the traditional and innovative ones. The traditional processes cover almost the entire sector production [15] and are technologically well established, having been used since many decades. [13]

Besides the most widespread and most commercially established technologies, in the last decades several innovative technologies have been developing and, with different stages of technology readiness [28], are starting to approach the market in the very last years, and in the future. These necessity of exploring new possible paths in steelmaking is driven by the necessity of reducing the energy intensity of the process, and its operation costs with it, but also the greenhouse gases emissions, being the sector, as previously stated, one of the most impacting in this sense.

The variety of innovative technologies in this sector is very large, and the distinction between the different technologies is sometimes difficult, as different steelmaking companies call the same process with different names, and the complexity is further increased by international institutions, who add their nomenclature to the processes.

In order to put order on this very complex context, the innovative technologies that will be analyzed in this section are taken with the nomenclature and descriptions coming from the "Ultra-Low CO2 Steelmaking" project by the European Union [20].

It is possible to divide the innovative technologies into four macro-categories:

- Fossil-based technologies, that optimize the already established processes in terms of energy efficiency and cost effectiveness;
- Fossil-based technologies with Carbon Capture and Storage (CCS) devices, able to abate the emissions without the necessity to disruptively change the design of plants;
- Hydrogen-based technologies;
- Electrolysis of iron ore-based technologies, at the moment in a very early stage, but with a high potential in the future, due to very low direct emissions and the possibility to be powered by green electricity.

2.1.1 Traditional processes

Studying the currently used steelmaking processes, it is possible to distinguish between primary and secondary steelmaking. The former represents the group of processes that use new iron ore as a feedstock for steel production, while with the latter, new steel is produced using scrap iron [82]. For the primary steelmaking, the main processes to take into account are blast furnace-basic oxygen furnace and direct reduced iron-electric arc furnace.

Blast furnace - Basic oxygen furnace (BF-BOF)

The Blast furnace - Basic oxygen furnace route (BF-BOF) is the most widespread technology in the sector, with more than 70% [15] of world production coming from it. In the blast furnace, at a temperature of around 1700°C, both iron ore and coke (obtain by introducing coal in appropriate, air free, ovens) are input, and in presence of oxygen from the air, the obtained reaction consists in a reduction of the iron ore, with the release of carbon dioxide and the so-called "pig iron", an intermediary of steel, composed by iron and carbon, with a concentration of this last one of 4%. Inside the blast furnace, a series of chemical reactions take place, all of which can be summarized with the following:

$$Fe_2O_3 + 3CO \rightarrow 2Fe + 3CO_2 \tag{2.1}$$

The pig iron is then introduced in a refractory-lined element called ladle. Once there, a lance is inserted in the ladle, and it blows oxygen at a pressure around 7-10 bars, on a first step just above the pig iron, and then inside the bath. These two operations have different purposes: the first one lowers significantly the content of sulphur, silicon and phosphorous, while the second one causes the combustion of the carbon still present in the pig iron, rising the temperature internally and melting the iron. At this point, fluxes (dolomite or lime) are added to the ladle, before letting the steel flow into a ladle furnace, where the additives are input, and finally the desired steel is obtained.[16]

Direct reduced iron - Electric arc furnace (DRI-EAF)

The DRI-EAF route, instead, has been increasingly used only in the last decades, and nowadays around the 10% [18] of the produced steel comes from it. It is overall a more energy-efficient process, where syngas (a mixture of carbon monoxide and hydrogen, obtained via steam reforming of natural gas) or coal are added to iron ore in a shaft furnace, at a temperature that is below the melting one (800-1200°C), contrarily to what happens in blast furnaces. In this way, the iron ore is reduced, and the result of the process is a 97% pure iron. The reduction reaction takes place in multiple phases, as shown below:

$$3Fe_2O_3 + CO/H_2 \rightarrow 2Fe_3O_4 + CO_2/H_2O \tag{2.2}$$

$$Fe_3O_4 + CO/H_2 \rightarrow 3FeO + CO_2/H_2O \tag{2.3}$$

$$FeO + CO/H_2 \rightarrow Fe + CO_2/H_2O \tag{2.4}$$

The output to this process is the Direct Reduced Iron (DRI), which is then input into an electric arc furnace. There, DRI (most of times with at least a small portion of steel scrap) is melted thank to the very high temperatures reached by the furnace, and thank to the injection of oxygen with a lance inside the bath, rising furtherly the temperature, and forming ferrous oxide and slag on the top of the bath, which acts as a thermal barrier and enhances the melting. Moreover, the introduction of oxygen burns impurities such as silicon, sulfur, phosphorus, aluminium, manganese, and calcium. Successively, the slag layer is removed, and the steel is extracted for further processing [17].

For what concerns the secondary steelmaking, the main route is represented by steel from scrap-electric arc furnace.

Steel from scrap - Electric arc furnace (Scrap-EAF)

it is performed via using an electric arc furnace as for the direct reduced iron, and the scrap is directly input in it. With this process, almost 20% of the steel has been produced in 2019. [15] Through the re-use of scrap steel, a large portion of energy is saved from the reduction part of the process.

2.1.2 Innovative technologies for steelmaking - Fossil-based, energy efficient processes

In this section, it is possible to find primarily two technologies, one of which is the evolution of the other: the smelting reduction-based process, and HIsarna.

Smelting reduction - Basic oxygen furnace (SR-BOF)

Smelting reduction is a process that takes inspiration by the traditional blast furnace, but with the difference that it aims at not using coke, but directly the raw material, coal. In order to do so, the process has been designed with three main parts, namely:

- Iron ore reduction furnace
- Melting furnace
- Gas distribution system

The iron ore furnace (also called shaft furnace) is fed with high-quality lump ore, limestone and dolomite, with a small amount of coke, and reducing gas at the temperature of 800-850°C. Iron ore pellets are now reduced, and shaft furnace gas is formed, at a temperature of 250-300°C. At this point, the shaft furnace product enters the melter-gasifier (also alled melting furnace) with non-coking coal. The non-coking coal burns with oxygen blown by the tuyere, melting the shaft furnace product, together with the flux. The working temperature range is around 980-1050°C. In the hearth of the melter-gasifier, then, hot metal and slag are formed: the former will be input in the basic oxygen furnace. Finally, the hot gas formed on top of the melter-gasifier is input, together with a cooling gas, in a hot gas cyclone, that reduces sensibly the dust content, and the purified gas is supplied in the reduction shaft as a reduction gas [21].

HIsarna - Basic oxygen furnace (HIsarna-BOF)

HIsarna technology is based, in principle, on smelting reduction, but with further evolution in design. In fact, in this technology, only two components are present, namely the Cyclone Converter Furnace (CCF) and the HIsmelt Smelt Reduction Vessel (SRV).

The CCF plays a similar role to that played by iron ore furnace in Smelting Reduction, as iron ore is fed in it together with hot offgas coming from the SRV; the difference, in this case, is that also oxygen is injected in this phase, rising sensibly the temperature (to around 1450°C), melting and partially reducing the ore, which, at this point runs into the SRV under gravity [22].

Coal is injected in the SRV, causing that around 4% of carbon dissolves in the metal bath, where, in this phase, very low quantities of impurities are present comparing to the blast furnace. Thank to the injection of oxygen from above, the upper part of the vessel reaches higher temperatures and causing the formation of an interface between metal and slag, with droplets of the latter falling downwards, rising the temperature also in the lower part of the vessel, where however the environment remains strongly reducing, allowing the smelting reaction. In the meanwhile, on top of the vessel, carbon monoxide is formed from the reaction of oxygen with the slag, forming the hot gas used in the CCF [22].

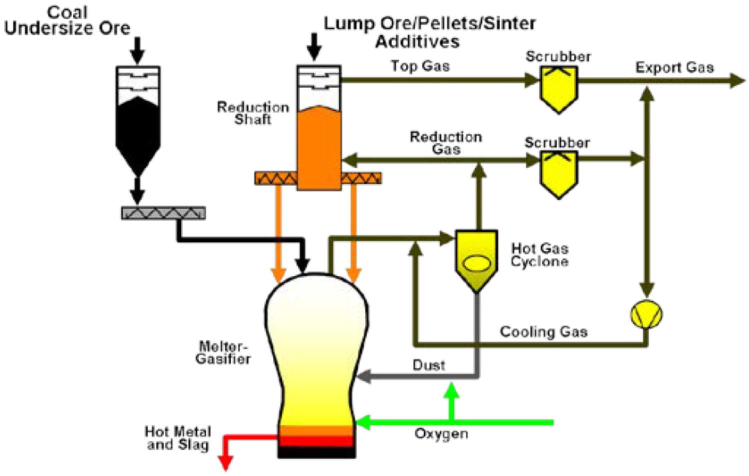

Figure 2.1. Smelting reduction process [21]

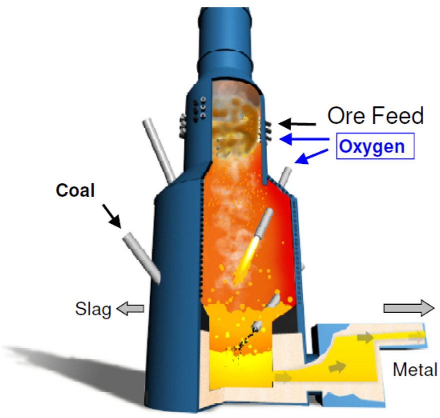

Figure 2.2. Graphical representation and schematics of HIsarna process [22]

2.1.3 Innovative technologies for steelmaking - Fossil-based processes with integrated CCS devices

One strategy individuated by most expert in iron and steel sector to drive the mitigation of the future years is to apply Carbon Capture and Storage appliances to iron and steel plants. This has very strong advantages, because this would allow a strong reduction of emissions, without the necessity to change disruptively the technologies involved in the sector [20].

However, some drawbacks in adopting such strategies are represented by issues related to the storage of carbon dioxide, as well as its cost effectiveness [23].

In the framework of iron and steel sector, several solutions have been designed applying CCS to different typologies of plants.

Direct reduced iron - Electric arc furnace with CCS (DRI-EAF with CCS)

Within this production path, the carbon capture is possible in the Direct Reduction part of the process. As previously discussed, the direct reduction involves the use of a reduction gas that transforms the iron ore into metallic iron. The reduction gas is usually natural gas, converted into CO and H_2. As a consequence, the carbon capture can happen in the pre-combustion phase, when the syngas is obtained through steam reforming, or in post-combustion, using technologies such as PSA or VPSA [28].

The PSA (Pressure Swing Adsorption) is an adsorpion-based innovative CCS technology, as the reference, more established technologies are the absorption-based ones. The chemical-based absorption involves the presence of aqueous amine absorbent which make the CO_2 react, forming, in a reversible way, ammonium carbamate, ammonium carbonate and ammonium bicarbonate. Instead, the physical adsorption-based process does not include any reaction; instead, they involve the use of an adsorbent (typically zeolites and metal-organic frameworks - MOFs), able to physically capture CO_2 molecules. The adsorbent, however, need also to be discharged of the captured CO_2: this is performed by inputting a given pressure to the device [59].

Blast furnace - Basic oxygen furnace with CCS (BF-BOF with CCS)

This application is an obvious development of the most traditional steelmaking technology. In order to apply CCS to the BF-BOF, no modifications are performed on the plant itself, except for the addition of the capture and storage system. In a BF-based process, around 70% of the carbon introduced flows in the blast furnace; as a consequence, in order to abate the emissions, the greenhouse gases must be removed from the BF gas. It contains roughly 17-25% of carbon dioxide, 20-28% of carbon monoxide, 1-5% of hydrogen and 50-55% of nitrogen [24]. At the pressure of 2-3 bar, it enters a turbine, with the aim of recovering some power from its heat, before being distributed as a fuel. Two solutions are possible at this point:

- Capture CO_2 directly from BF gas
- Capture CO_2 after having converted CO

If the second option guarantees higher capture rates (being, in the first case, CO directly freed in the atmosphere) it represents the most capital expensive option [25]. In any case, the most recommended technology for CCS in this application is SEWGS (Sorption Enhanced Water-Gas Shift). This is an adsorption-based CCS process, which represents an evolution of the PSA process: in this case, the adsorbent is the K-promoted hydrotalcite, to which the flue gas is input at a higher temperature (400°C), and, as a product, gas with higher concentration of CO_2 is obtained. Moreover, it allows the use of one single type of adsorbent [45].

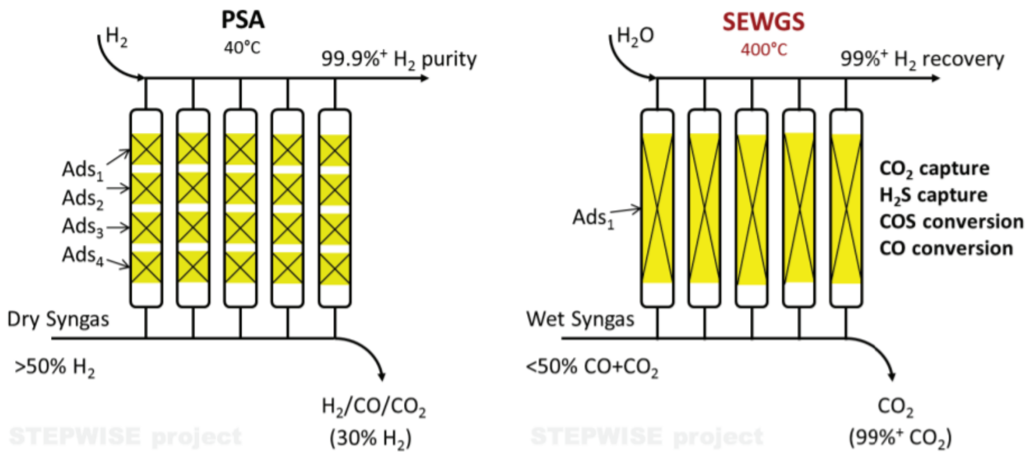

Figure 2.3. Compared PSA and SEWGS adsorbing processes [45]

Blast furnace - Basic oxygen furnace with top gas recycling (BF-TGR-BOF with CCS)

This system represents an improved version of the traditional blast furnace, thought and designed in order to reduce the consumption of coke in the process. In fact, by recycling the top gas, which is rich in CO (40-50%) and in CO_2(35%), allows to reduce the consumption of reducing element, the coke itself. After having removed the dust from the top gas, by removing the CO_2 present in it before its reuse, a large portion of greenhouse gas emissions will be avoided.

At the moment, for what concerns the carbon capture technology, the research is oriented on vacuum pressure swing adsorption (VPSA) [25]. The VPSA is an alternative to PSA, with the only difference consisting in the fact that, instead of applying a positive relative pressure on the adsorbent, the vacuum is generated in order to discharge it.

HIsarna-Basic oxygen furnace with CCS (HIsarna-BOF with CCS)

Removing CO_2 from smelting reduction-based processes' gas results to be much easier than for blast furnace gas, being the CO_2 concentration much higher. According to different sources [28], the yield for CO_2 captured in HIsarna-BOF with CCS would overcome the 80% [27]. Differently from the other technologies, having higher concentration of CO_2 originally, a cryogenic distillation-based technology is recommended [28].

Cryogenic distillation-based CCS system is based on the separation of CO_2 by thermal means; in particular, a distillation column is filled with pre-cooled flue gas. There, thanks to a large number of vapor-liquid contact devices, which divide the flue gas into top and bottom products; the latter will be composed by a large part of condensed CO_2, which, after having flown through other distillation post-processes, has a high level of purity. At

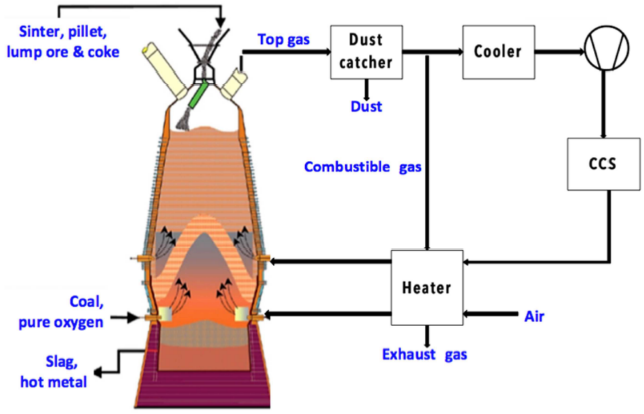

Figure 2.4. Simplified scheme of the BF-TGR-BOF process [26]

the moment, this technology results to be the best suitable for high CO_2-concentration flue gases, but presents a high cost mainly due to the energy necessary for the condensation of CO_2 [60].

New Direct Reduction Process (ULCORED) with CCS

ULCORED is one of the innovative processes promoted by ULCOS program, from which it takes the name. It is substantially a direct reduction process, which uses natural gas to reduce iron ore and produce direct-reduced iron (DRI), which is then input in an electric arc furnace (EAF). The innovative elements with respect to the traditional production path are [26]:

- Presence of a top gas recycle system
- Presence of a pre-heating system of the input natural gas, deploying the excess of heat in the top gas
- Presence of a CCS device

For what concerns the carbon capture technology, it is suggested to use VPSA or PSA as in direct reduction with CCS.

2.1.4 Innovative technologies for steelmaking - Hydrogen-based processes

This typology mainly contains one technology type, namely the Direct Reduction using hydrogen as a reducing gas; only this technology will be discussed in this paragraph, despite, as it will be shown in the RES discussion part, two different technologies are present in the model to represent it, that however differ only in the production path of the hydrogen gas.

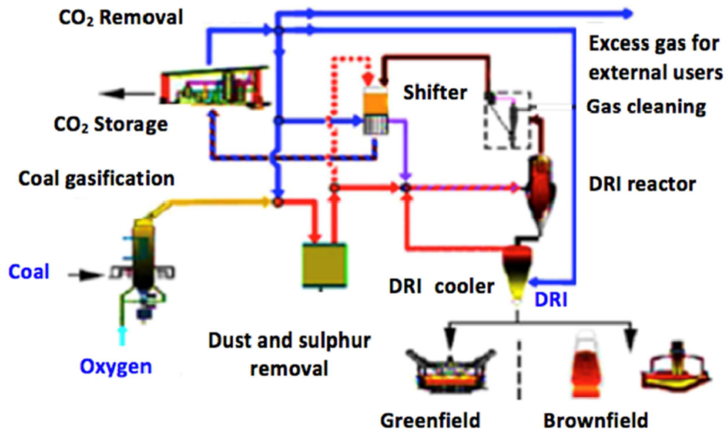

Figure 2.5. ULCORED process schematics [26]

Hydrogen direct reduction - Electric arc furnace (HDR-EAF)

This technology shares many similarities with the Direct Reduced Iron production path. In fact, in addition to the fact that both use the electric arc furnace for completing the steelmaking process, also in the ironmaking part, one reducing element, namely the hydrogen, is present. If, in fact, in the traditional production path (DRI) syngas (a mixture of CO and H_2) was used, after having obtained it from the steam reforming of natural gas, in this case the hydrogen is used as the only reducing element. Hydrogen can be obtained with different processes, both fossil- and non fossil-based: for the former, besides natural gas steam reforming, coal and biomass gasification, for the latter electrolysis. The hydrogen is then input in a shaft furnace with pelletized iron ore, with a temperature lower than the melting one (around 800°C). Here, the reduction of the ore takes place, in the form of the two reactions below:

$$Fe_2O_3 + 3H_2 \rightarrow 2Fe + 3H_2O_{(g)} \tag{2.5}$$

$$Fe_2O_3 + H_2 \rightarrow 2FeO + H_2O_{(g)} \tag{2.6}$$

The water, representing the output of the reducing process from the shaft furnace, is then used to partially recover the heat, rising the temperature of the input hydrogen to the furnace. Besides of the problematic related to the high costs with respect to more already-established production routes, another issue for HDR-EAF is represented by the reducing power of hydrogen, which needs to be tested more thoroughly, and for this reason process modelling papers, such as the one by Vogl [29] opted for taking into account an oversupply of hydrogen in the shaft furnace. Despite these uncertainties, most papers [30] and international institutions agree with its importance in the decarbonization of the iron and steel sector [32].

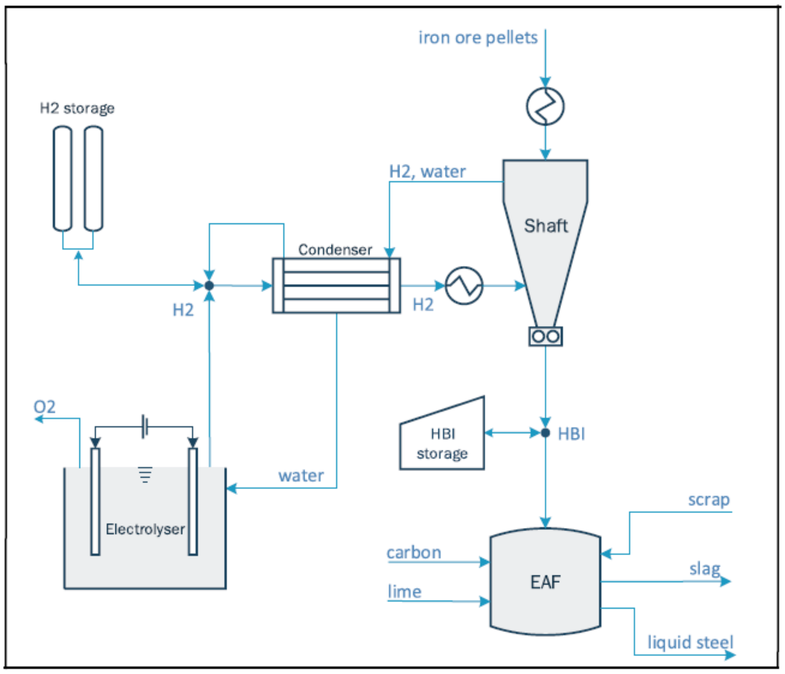

Figure 2.6. Schematic of the HDR-EAF process design [29]

For what concerns the electrolyzer, it is important to perform a technical characterization of the device, to be able to understand, in the next sections, the nature of its possible future developments and improvements. First of all, it is important to underline that the main technology considered for this type of electrolysis application is the proton exchange membrane (PEM) electrolyzer. This is due to its very rapid response in production, which makes it able not to waste istantaneous over-productions of energy by renewable-based plants (solar and wind overall). The PEM electrolyzer is a device which uses electrical power to perform a water electrolysis reaction, obtaining oxygen and hydrogen as outputs. It originally used Iridium ad the anode and Platinum at the cathode, despite more advanced applications are trying to limit their use with the aim to reduce the investment cost. It also has a solid polymer electrolyte, which allows the passage of the protons from the anode to the cathode. The scheme of the cell is reported below, with the relative reactions [62].

2.1.5 Innovative technologies for steelmaking - Electrolysis of iron ore-based processes

Since the ULCOS project has been launched, in 2004, steelmaking technologies based on the direct use of electricity to perform the smelting of iron ore had been considered crucial in the medium-long term, being their potential, in terms of cost and emissions reduction,

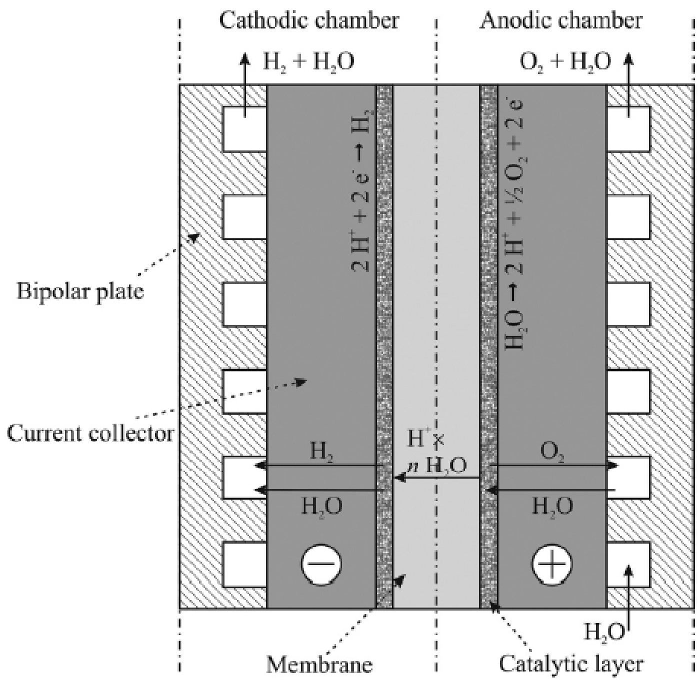

Figure 2.7. Scheme of the principle of the PEM electrolysis cell [62]

very high, but being very immature technologically. After 17 years these technologies have been refined and improved by different institutions, and the interest on their potential has not decreased.

Low-temperature electrowinning for steelmaking (ULCOWIN)

This electrowinning process, which is namely a low-temperature electrolysis process (it is performed at an operating temperature of 100-110 °C) [33], sees the introduction of iron ore (hematite - Fe_2O_3) in form of suspended particles in an alkaline electrolyte solution [26]; when an electrical current flows through the solution, the oxygen is attracted by the anode (being freed on the surface of the solution) and the metallic iron crystallizes on the cathode [35].

Once obtained the metallic iron, it is input in an electric arc furnace, where, with the addition of some carbon-based component (namely coke or natural gas), steel is obtained (in this last part of the process, the addition of some scrap steel or direct reduced iron in the EAF is possible).

At the moment, the technology is still at an early development stage, with some demonstration plants realized at a pilot stage by ULCOS and Siderwin [33], but its entrance in the market is not expected before 2030.

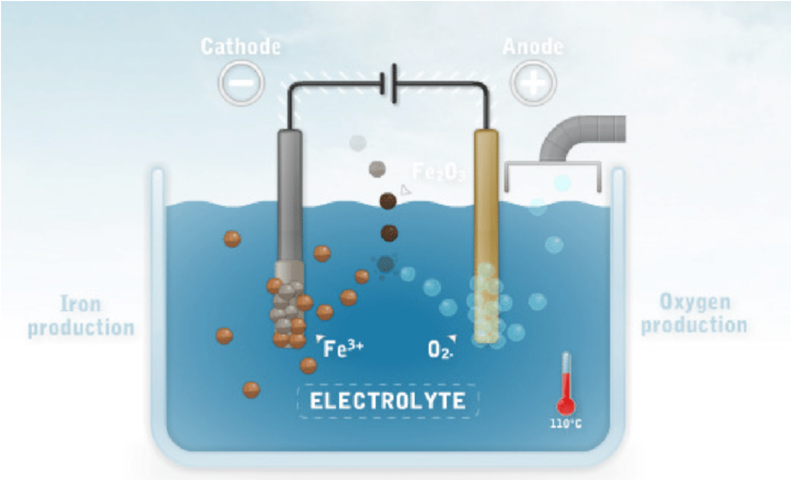

Figure 2.8. Electrowinning cell simplified scheme [36]

High-temperature molten oxide electrolysis for steelmaking (ULCOLYSIS)

Differently from ULCOWIN, ULCOLYSIS is an electrolysis-based process that has as an object the molten iron oxide; as a consequence, the working temperature should be sensibly higher (in the order of 1600°C). The molten iron oxide is then dissolved into a liquid electrolyte solution and the electrical current is used to actuate the smelting process. In this process, only an anode is needed in order to perform the electrolysis, as the cathode is represented by the liquid iron bath. At this stage, the iron ore is reduced and liquid iron is obtained as a result of the endothermic reaction [34].

Subsequently, and similarly to what has been described for ULCOWIN, the liquid iron is input into an electric arc furnace, where, with the addition of a carbon-rich element (pulverized coal, or steel scrap), the liquid steel is obtained.

This process is at a laboratory stage and, as for the ULCOWIN, will not be commercially available before 2030 [34]. Currently, steel producers such as Boston Metal [26] and ArcelorMittal [37] are investing on this technology.

2.2 Energy system models

Given the high complexity of the problem to be solved in order to answer the question presented in the introduction, it is essential to have a means capable of relating the steel sector with elements external to the sector itself, and reproducing its evolution over the coming decades [11].

This is for a number of reasons: first of all, the steel sector, being extremely energy intensive, cannot be disconnected from the energy system itself [11], as the economic and technical evolution of energy vectors could influence its future development in a decisive way. Moreover, being the analysis centered on the technology learning, it is not possible to exclude *a priori* that learning of some technologies internal to the sector will influence other external technologies, or viceversa, that technologies exogenous to the sector will influence the learning of steelmaking technologies.

As a consequence, the possibility to use energy systems models is considered; they are models which analyze the energy system (or a sub-system) at different geographical scales, with the purpose of understanding future trends in the energy market, or to analyze different energy policies [73].

2.2.1 Generalities and classification

Energy system models start to be introduced in the 1970s, subsequently to the oil crisis, when the topic of energy use optimization disruptively became of global interest; however, in the successive decades the attention shifted to the interaction between energy sector and environment, and one of the main aims became to assess the impact of energy sector on the emissions of greenhouse gases (GHGs) [72].

The common feature of all the energy system models is the capability they should have to reproduce the energy system itself, which should therefore comprehend the energy production/extraction, conversion, distribution and use [74]. This need has led most energy modelers to build a network-like description of the energy system, called Reference Energy System (RES), which allows to reproduce the supply chain by describing the technological characteristics of the energy system itself, both in the existing and future technologies [72].

The models, however, present a large variety of different characteristics among themselves, and it is possible to classify them under different points of view, such as the aim (e.g. models to study the links between energy sector and environment, or the economy), or the purpose (e.g. models for an improved design of an energy supply system, or models for the prediction of an energy-related market), or the spatial scale (local, regional, national, global scale) [74]. More often, nevertheless, the classification is performed basing on the modelling technique. In this framework, there are three main classes of interest:

- Macroeconomic top-down models
- Bottom-up accounting models
- Bottom-up optimization models

In general, the difference between top-down and bottom-up approach is the different focus on the main influencing factor to the energy sector: while top-down models focus on the influence of price and markets, bottom-up ones concentrate on the technological detail of the energy sector; as a consequence, if the former requires a good description of the macro-economic factors influencing the energy sector, the latter has to be characterized by a RES with very high detail in technological description. While optimization models use the Reference Energy System description, and the linear programming to find the solution to the problem, the accounting models use a different, namely *accounting*, approach, on the supply side, with the aim of answering to "what if"-type of questions [72].

Criteria	Bottom-up, optimisation	Bottom-up accounting	Top-down, econometric
Geographical coverage	Local to global, but mostly national	National but can be regional	National
Activity coverage	Energy system, environment, trading	Energy system and environment	Energy system and environment
Level of disaggregation	High	High	Varied
Technology coverage	Extensive	Extensive but usually pre-defined	Variable but normally limited
Data need	Extensive	Extensive but can work with limited data	High
Skill requirement	Very high	High	Very high
Capability to analyse price-induced policies	High	Does not exist	High
Capability to analyse non-price policies	Good	Very good	Very good
Rural energy	Possible but normally limited	Possible	Possible but normally limited
New technology addition	Possible	Possible	Difficult
Informal sector	Difficult	Possible	Difficult
Time horizon	Medium to long term	Medium to long term	Short, medium or long term
Computing requirement	High end requires commercial LP solvers	Not demanding	Econometric software required

Table 2.1. Energy system models typologies and characteristics [72]

The Table 2.1 sums up the different characteristics of the models typologies described above.

After a quick review on ESMs in general, bottom-up optimization-based models probably result to have more adherent requirements to those necessary for the analysis, thank to their higher level of technological detail, which cover the entire energy supply chain; as a consequence, a further literature review specifically on this typology of ESMs will be performed.

2.2.2 Bottom-up optimization-based models

Bottom-up optimization-based models are usually based on linear programming, through which the optimal solution, according to different criteria, depending on the specific model, is computed. Some of them are based on the equivalence theorem guiding demand and production, with the former computed either exogenously, or internally but with drivers' projections computed externally [72].

In the following subsections, some examples of bottom-up optimization-based models are reported, with a short discussion on their characteristics and application to analysis of decarbonization strategies.

MESSAGE

The Model for Energy Supply Systems And their General Environmental impact, or MESSAGE, is a type of model, which works by minimizing, through linear programming, the total costs of energy supply over a time horizon. It has originally a global scale, despite it can be used by taking into account only one or some regions inside it. Inside the model, demand and supply are disaggregated into several sectors; the former is built exogenously, using another model, namely MEDEE-2. Then, a series of constraints are provided to the model, on the annual build-up of technologies, resources availability and technologies relationships [77]. Its primary purpose was to study the IIASA global energy scenarios, but it has been used in several researches with different aims. In particular, it is used in many papers to assess the feasibility of mitigation strategies [80] on the agricultural sector [79], often coupled with the land-use model GLOBIOM (or to assess the impact of different greenhouse gases on agriculture [78]).

EFOM

The energy flow optimization model, or EFOM, is an example of bottom-up optimization-based model, designed for the first time in 1970s. It is based on linear programming, with the aim of minimizing the total discounted cost, in order to meet the demand, which is linked exogenously. It is multi-period based, and can be used to analyze one specific sector, or the whole energy system. It is particularly focused on the electricity industry [75]. It is used in some papers to assess the impact of different mitigation strategies on air pollutants, at local [82] and regional level [81].

MARKAL models family

The market allocation models family, shortly MARKAL, is probably the most famous and used family of optimization models. It also uses linear programming to minimize the supply cost, and it covers the entire energy system, with a high level of detail. It is used for a large variety of purposes, among which the environmental effect of energy policies [72], but also for designing mitigation strategies of a country, such as Taiwan [83], or the US power sector [84]. The building blocks of the model can be seen in the Figure 2.9.

TIMES models family

The integrated MARKAL-EFOM system, or TIMES, is a new family of models born from MARKAL and EFOM ones. The demand, in this family, is computed starting from exogenous assumptions (ad-hoc drivers, forecasted exogenously); in particular, the following equation is used:

$$D\left(d,r,t\right)-D\left(d,r,t_{i-1}\right)=D\left(d,r,t_{i-1}\right)\cdot\left[\delta\left(d,r,t_{i-1}\right)^{e(d,r,t_i,s)}-\delta\left(d,r,t_{i-1}\right)^{e(d,r,t_{i-1},s)}\right] \quad (2.7)$$

Where D is the demand, and is dependent on time and region, δ is the driver, and e is the elasticity, which is dependent also on the storyline s.

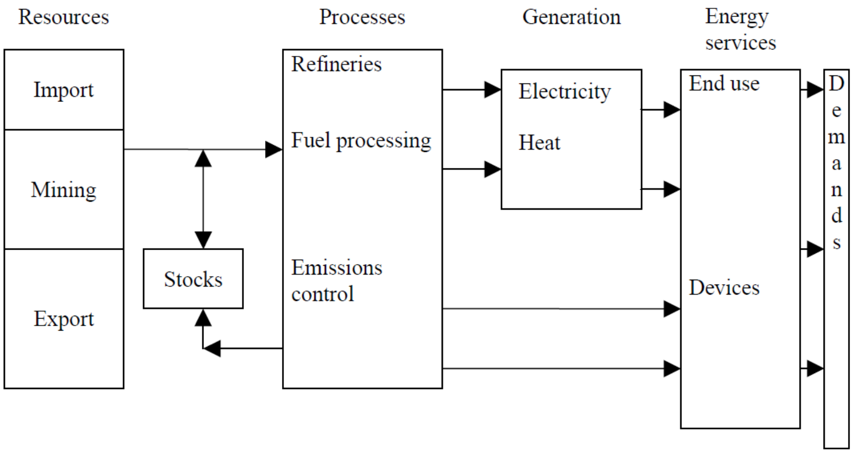

Figure 2.9. MARKAL building blocks [76]

A peculiarity with respect to MARKAL and EFOM is the optimization procedure, which aims at maximizing the total surplus [8] (consumer plus producer surplus), after having built multi-stepped supply curves (as shown in Figure 2.10) [72]. TIMES model have already been used for studying mitigation strategies for industrial sector [85], but also specifically of iron and steel sector [86].

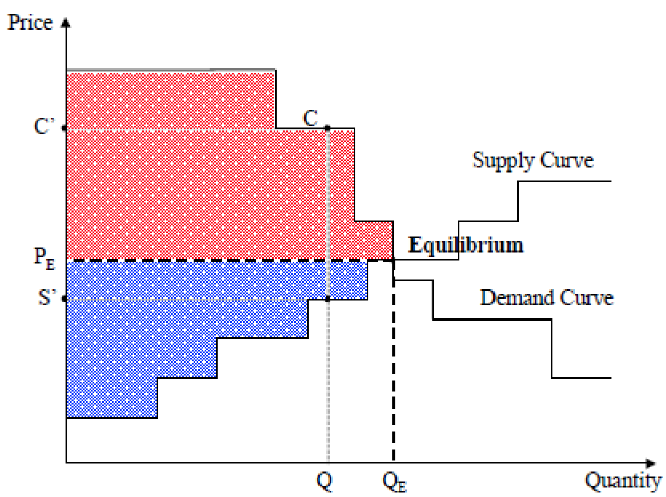

Figure 2.10. Producer and consumer surplus in the Supply-Demand curve graph [8]

2.3 Theory of technology learning

The technology learning concept, as previously anticipated, is an econometric phenomenon correlating the experience gained with a technology and the improvement in its production performance. It was studied the first time by Wright in 1936, when he correlated the number of produced airplanes with the number of direct labor hours required to assemble one [87].

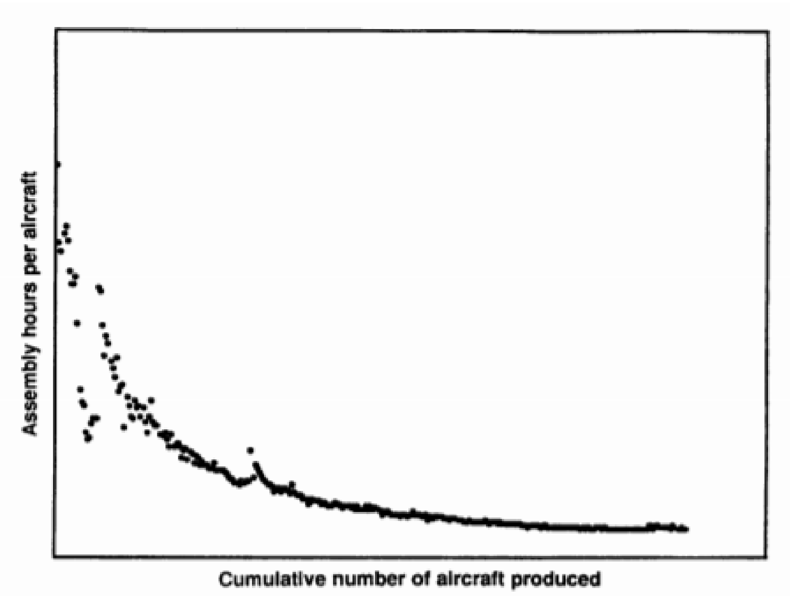

Figure 2.11. First example of learning curve by Wright [87]

Technology learning is a theory which has been object of great discussion in the academic world, for its formulation, applications and limitations. As a consequence, this section is developed with this purpose: starting from the theoretical formulation, described by the so-called learning curve, moving to the applications in energy system models, and finally reporting the criticisms and limitations of the theory.

2.3.1 Learning curve

As previously anticipated, the first study trying to theorize the technology learning concept was performed by Wright: he managed to correlate cumulative capacity and time employed for the assembly of air crafts according to a power law [87]:

$$y = ax^{-b} \tag{2.8}$$

With:

- y number of direct labor hours to produce the x-th unit

- a number of direct labor hours to produce the first unit
- b is a parameter connecting number of labor hours and number of units produced, later named learning elasticity

Subsequently, the object of study shifted towards the unit cost decrease as a dependent variable of cumulative capacity produced for technologies. The formulation above, therefore, proposed also in a paper by Argote and Apple [88], can be reformulated when applying the same concept to the link between cumulative capacity in general, and unit cost of the technology learning:

$$C_t = C_0 (\frac{\sum_{i=0}^{t} I_t}{I_0})^{-b} \tag{2.9}$$

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; as a consequence, the summation of all these components gives the cumulative installed capacity at time t
- I_0 is the initial cumulative capacity
- b is the learning elasticity

Often, the definition of learning elasticity is replaced with the one of learning rate. It is obtained starting by considering that, if the capacity is doubled over time, the cost is reduced of a factor $PR = 2^b$. PR is defined as the “progress ratio”, while $LR = 1 - PR$ is the learning rate.

The learning rate is, in other words, the reduction in percentage of the specific capital cost of a technology, once its capacity installed is doubled [88].

At this point, it is possible to rewrite the equation above in function of the learning rate itself:

$$C_t = C_0 (\frac{\sum_{i=0}^{t} I_t}{I_0})^{\frac{\ln(1-LR)}{\ln(2)}} \tag{2.10}$$

However, this is not the only theorized formulation to describe the learning phenomenon; the most notable alternative theory, in fact, was worded by Gordon Moore in 1965, where he suggested an exponential law guiding the new capacity of an innovative technology (starting with the observation of the number of transistors in a chip) [90]; a consequence he derived in his work was then the exponential cost reduction when increasing the capacity of a technology.

At least, other three laws describing the phenomenon can be individuated, such as the ones by Goddard, Sinclair et al. [89], and Nordhaus [4]. However, a comparative paper recently confronted the behavior of all these five laws on the historical data of 62 technologies, obtaining as a result that Wright and Moore’s law were describing in the best way the technology learning of those, with a similar accuracy. As a consequence, the paper recommended these two methods for the forecasting of cost evolution of innovative technologies [89].

2.3.2 Technology learning in energy modelling

According to the IPCC Special Report on Emissions Scenarios in 2000, the technology learning is the main driving force of the world energy system, even higher than all the other demographic and economic drivers [91].

As a consequence, technology learning has been included in many energy models through the endogenous implementation of the curves inside an energy model, allowing the model itself to have a less myopic view on the different technologies and to give importance also to longer-term investments. This approach, being the learning curve implemented inside the model itself, is called endogenous technology learning [11].

The endogenous technology learning has been adopted by most of bottom-up energy models, and applied to the capital cost of many energy technologies: models such as MARKAL, MESSAGE (and MESSAGE-MACRO), POLES include this feature. Only one bottom-up energy model, GET-LFL, uses the learning curve approach to model both the capital cost evolution and the energy conversion activities evolution [11].

This approach was first applied in 1968 by Boston Consulting Group to 24 industrial products [11], and then used in a number of applications, from manufacturing [88] to products for large consumption [92]. However, what is of greater interest for this literature review are the papers specifically focusing on the implementation of technology learning to energy technologies.

Many examples of this type of application can be found in literature: some of them focus on PV technologies (with basic studies [100], or to estimate the learning rates [94] and exogenous learning factors [102]) , as well as on wind power technologies [96] and their cost dynamics [97], while others on fossil-fuels based systems [95] with CCS technologies [98], but also studies on learning of hydrogen-based technologies can be found [103], as well as on hydrogen production [101].

The concept of technology learning, however, can also be applied to industrial technologies; recent papers, in fact, applied it to the ethanol production [93], to the Chinese industrial sector [99], and, most relevantly for this work, to the U.S. iron and steel sector [11].

2.3.3 Weaknesses and limitations

If on one hand the implementation of technological learning inside energy system models provides a significant improvement in considering the technological evolution in the future, several drawbacks, criticisms and limitations have been individuated in the adopted methodology.

The main problem individuated by the papers assessing the problematics is the estimation of the learning rate. In fact, being the technology learning endogenous to the model, a value for the learning rate has to be provided by the modeler; therefore, it is usually computed by taking into account historical data of installed capacity and cost reduction of the technologies, and checking the power law (and consequently the power factor) connecting them. This approach presents (at least) two problematic points:

- The values of learning rate have a very high level of uncertainty [3], depending on the computing method of the learning rate itself (considered period, cumulative capacity calculation etc.) [104]
- If the estimation does not take into account a series of econometric issues such as the scale effects, the estimation of learning rate can be biased; as an example, in a paper by Söderholm and Klaassen [105], these effects caused a change in the learning rate of wind technologies from 1.8% to 7.9%. A paper by W. Nordhaus also shows how the impossibility to separate endogenous learning from exogenous phenomena drives modelers to an overestimation of the learning rate [4]

Another issue of technology learning in its original concept is strictly linked to this last point: learning, in the real world, is not only driven by cumulative capacity (or investments) and/or R&D expenditures, as would be pointed out by the technology learning theory; instead, it is largely influenced by phenomena such as costs of inputs, scale effects, but also policies [104]. For instance, the paper by Söderholm and Klaassen [105], showed how feed-in prices for wind power can have a negative impact on the learning of wind power technologies.

One further criticism is about the integration of technology learning in bottom-up optimization-based energy models: in fact, if the latter concentrates on finding the *optimal* solution, the former is a phenomenon that does not apply to an optimally designed energy system, but rather to an *actual* one. In fact, the penetration of an innovative technology will also depend, besides than the cost minimization (in which learning has an influence), also on very important aspects such as transaction costs, inertia of the sector to accept innovative technologies, and market imperfections such as information costs [104].

Finally, from a more merely technical point of view, the implementation of endogenous technology learning in bottom-up models, makes the problem non-linear; this means that the computational expense, and consequently the resolution time will increase sensibly [11].

Chapter 3

Methods

In this section, the specific methodology applied for the analysis will be explained and justified, making some consideration on the basis of the studied subject in the literature review. This section will be structured as follows: it will start with the choice of the model, which will be then introduced and described, with a particular focus on how the iron and steel sector is modeled inside it. Then, the successive subsection will design the modelling of technology learning, which will be shaped accordingly to the strong points and limitations highlighted in the literature review. Finally, the details of the set of inputs will be discussed and summarized.

3.1 Model choice and setup

This subsection, as anticipated, is structured with the following order: on a first step, discussing the choice of the energy system model, from the typology to the family of models, up to the single model, then describing it in its more general features, such as purpose, Reference Energy System, scenarios and storylines, and ending with a more systematic description of the iron and steel sector inside it.

3.1.1 Choice of the model

The choice of the model was based on considerations deriving from the content of the literature review. In particular, taking into account the advantages and disadvantages of the different types of model, in view of the analysis to be carried out, a choice was made that would minimize the latter. As previously anticipated, the bottom-up energy models would probably represent in general the best choice to technologically analyze a very specific subsector, given its higher level of technological detail. This although in some papers [104] , the conceptual incorrectness in integrating technology learning into a bottom-up model has been highlighted [105]: in fact, almost all papers with study purposes similar to this one used models of this type [98], being the focus on energy technologies [99] or on industrial processes [11].

However, as previously seen, many different bottom-up models families exist: among the others, MESSAGE, MARKAL, EFOM, TIMES families can be considered; however, this last family presents some advantages, as it has some models in its family which cover multiple countries (until reaching a global scale), which is an advantage in order to model a global phenomenon as technology learning is [104], and, it is the only family of bottom-up model which include modules on energy trading and economic transition [72], which could partially compensate the problems in implementing technology learning on bottom-up energy models presented in the paper by Berglund et al. [104].

As a consequence, a model belonging to TIMES family is chosen to be the best suited: in choosing the exact model, however, it must be considered that not all the models were available. Among the available ones, the EUROFusion TIMES Model resulted to be the best possible fit with the analysis: it has a global scale, a good level of technological detail, especially for the industrial sector, which has recently been updated [19], and allows long-term simulations, which could better show the impact of technological learning [6].

3.1.2 EUROFusion TIMES Model: characterization

The EUROFusion TIMES Model is a model owning to the TIMES family, developed by EUROFusion from 2004, in order to assess the impact of introduction of nuclear fusion technologies in the world energy system in the long term.

ETM structure

As all the TIMES models, it is based on the concept of maximization of the net total economic surplus, assuming a perfectly competitive market (with the possibility to implement market imperfections such as taxes, subsidies, hurdle rates..), by also satisfying all the given constraints (environmental, resources availability-related, etc.).

Its Reference Energy System (RES) has to describe with the same level of detail both the demand and production sides; it is built on three main elements, namely Commodities, Processes and Commodity flows.

- Commodities: they represent energy carriers (NRG in the model), energy services (DEM), materials (MAT), monetary streams (FIN) and emissions (ENV) [5]; as an example, the steel produced, within the iron and steel sector, is modeled as a Commodity

- Processes: they represent technologies of various types, that convert the different commodities into other ones; for instance, the different steel production paths modeled in ETM, are reported as Processes;

- Commodity Flows: they represent the connection between Commodities and Processes, allowing the interaction between the two; in particular, it can be the input, output or the efficiency connected to a Process.

In the Figure 3.1, the RES of ETM is reported [6].

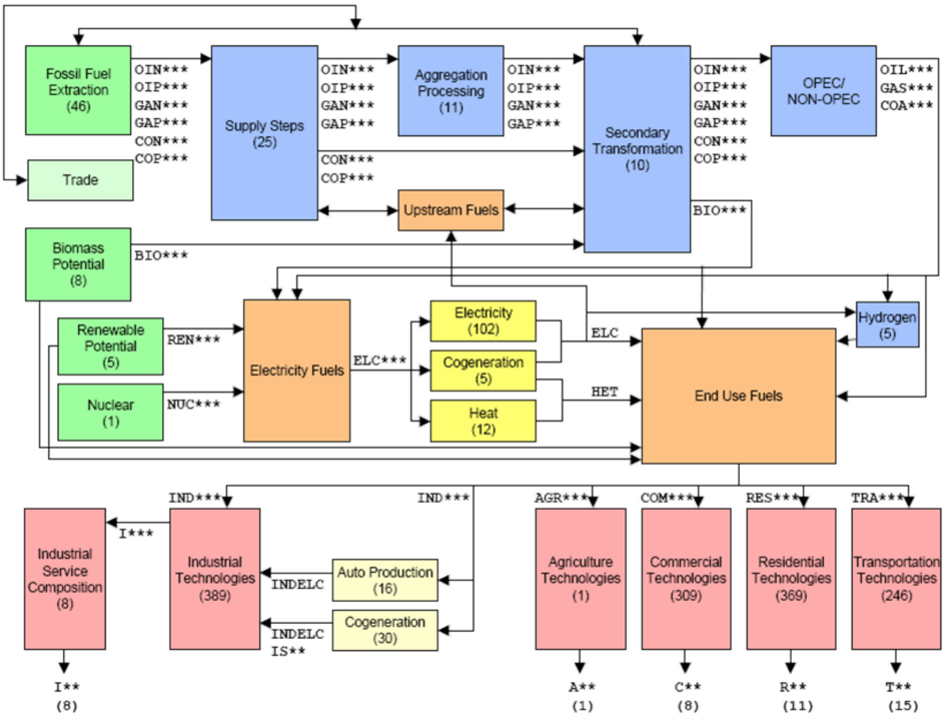

Figure 3.1. Reference Energy System of ETM [6]

Spatial horizon

The model, as previously introduced, has a global scale, and divides the world in 17 different macro-regions, some of which covering one single country (for the major world countries for extension and economy) and the remaining grouping together countries that are geographically close and have similar economic characteristics. In the Appendix A, both a map with the macro regions (Figure A.1), and a Table which lists the macro-regions, A.1, are reported

Although it is possible, internally to the model, to perform simulations only considering a part of the regions, for the reasons explained above, the modelling choice is to include all of them in the simulations, in order to have a global-scale picture of the phenomenon.

Time horizon and discretization

The ETM has a time horizon that goes until 2100: it is one of the longest-term models, and this choice is driven by the necessity of representing a future where reactors based on the EU-DEMO concept [106] will be commercially available (this is assumed to happen from 2070 on).

Besides the time horizon, however, the discretization is equally important and has to be defined. The original time discretization provided in ETM is present in Figure 3.2: after the base year (2005), other 11 time slices of similar length (alternating 9 and 11 years from 2010 until 2080, and then two time slices of 10 years arriving to 2100).

~TimePeriods		
PeriodsDef		
1	2005	
9	(2006-2014)	2010
11	(2015-2025)	2020
9	(2026-2034)	2030
11	(2035-2045)	2040
9	(2046-2054)	2050
11	(2055-2065)	2060
9	(2066-2074)	2070
11	(2075-2085)	2080
10	(2086-2095)	2090
10	(2096-2105)	2100

Figure 3.2. Time steps - base case

However, this time discretization presents a major issue, especially in the framework of a technology learning-focused problem: in fact, very long time steps in the closest future would act against the evolution of the technology cost, as the cost in every time step depends on the installed capacity in the previous one. If ideally the time step length should be reduced to reduce the granularity, on the other hand the computational expense would increase too much, no allowing to reach the convergence of the results in a reasonable time.

As a consequence, having to maintain reasonably low the number of time steps, it would be possible, also for the minor weight of technology learning evolution, to impose longer time steps in the longer term. Taking into account all these elements, the new time discretization is reported in Figure 3.3.

Storylines and choice

Accordingly to the fact that some major parameters that determine the future development of the energy system are largely unpredictable, three different storylines were built in the model. They are designed basing on different assumptions on a large variety of economic and social factors, that have consequences on the shaping of the energy system in the upcoming years, and, as a consequence, on the environmental impact.

- Fragmentation: this storyline is characterized by very high elasticity of energy service demands to their drivers, leading to higher demand projections. Moreover, investment choices are performed with short−term view (following the higher values of hurdle rates), and the scenario is characterized by “weak environmental responsibility”, being poorly regulated by regional partial agreements on carbon emissions; [6]

- Paternalism: in this storyline, instead, there is a mixed and regionally differentiated elasticity of energy service demands, leading to medium values globally; the

~TimePeriods		
PeriodsDef		
1	2005	
9	(2006-2014)	2010
6	(2015-2020)	2017
6	(2021-2026)	2023
6	(2027-2032)	2029
5	(2033-2037)	2035
5	(2038-2042)	2040
5	(2043-2047)	2045
5	(2048-2052)	2050
5	(2053-2057)	2055
5	(2058-2062)	2060
5	(2063-2067)	2065
5	(2068-2072)	2070
15	(2073-2087)	2080
15	(2088-2102)	2095

Figure 3.3. Time steps chosen for this analysis

investment choices are driven by medium−term perspective (with hurdle rates at a medium level): the result is that, also thanks to a global carbon emissions target, the environmental responsibility is on average levels; [6]

- Harmony: storyline characterized by low elasticity of energy service demand (justified by high levels of energy efficiency and environmental responsibility); this, together with investment choices performed with a long−term perspective (low hurdle rates), drive the high level of environmental responsibility of this storyline, declined also in the form of stringent global carbon emissions target, agreed by different world regions. [6]

For what concerns the definitions of the environmental (emissions) constraints, the scenarios are built accordingly to the Representative Concentration Pathways, designed by IPCC in their 5^th Assessment Report [9]. The constraints are based on the maximum values of radiative forcing, that "is defined by the net radiative flux change induced at the tropopause (by the presence of a gas). It is interpreted as a gain (positive) or a loss (negative) for the surface−troposphere system as a whole". [10]

In this framework, four scenarios for emissions reduction have been built:

- RCP 8.5: scenario in which the emissions continue to rise until the very end of the century, causing an increase in the concentration of CO2 up to almost 1000 ppm;

- RCP 6: scenario where some environmental policies are applied, but the emissions start decreasing only after 2060, causing that CO2 concentration increase remains steady and overcomes 650 ppm

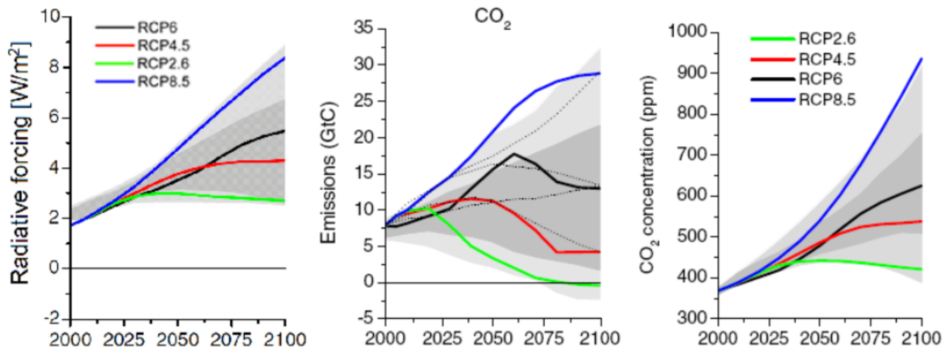

Figure 3.4. Radiative forcing, global carbon emissions and CO_2 concentration in the atmosphere according to the different RCPs [6]

- RCP 4.5: scenario with more stringent constraints, that drive the decrease in emissions starting from 2040, with CO2 concentration that stabilizes below 550 ppm
- RCP 2.6: scenario with the most stringent conditions, requiring that all the regions (comprehending developing countries) have a strong reduction of emissions already starting from 2020; in order to reach this goal, all the carbon negative technologies need to be used. The result is that CO2 concentration remains below 450 ppm.

The Fragmentation storyline comprehends the RCP6 emission scenario, while Harmony embodies RCP2.6. For what concerns Paternalism, it is possible to design two different storylines depending on the emissions constraints, namely Paternalism2.6 (with RCP 2.6) and Paternalism4.5 (with RCP4.5).

To sum up, in choosing among the different storylines, the following elements are determined:

- **Higher** or lower **stringency in CO2 emissions reduction objectives**
- Sensitivity and responsibility of the investors and consumers, leading to a lower or **higher growth of the demand**
- Short, **medium**, or long **term-based decisions**
- High, **medium** or low **grade of interconnection and cooperation between the different regions**

The bold parts highlight the choices made; in fact, for our analysis, the Paternalism 2.6 storyline is chosen, for a series of reasons:

1. Paternalism storyline underlines the diversification of the choices in the different regions, and this results to be a very important aspect in our case, as we are modelling

the iron and steel sector's technology learning on a worldwide scale, so the differences among the regions represent a very precious characterization;

2. Paternalism storyline is focused on medium term-based decisions, which perfectly reflect the point of view of investors in iron and steel sector, where the lifetime of a plant is in the order of 20 to 30 years;

3. Paternalism 2.6 storyline is characterized by two aspects: the strong increase in electrification, and the intermediate level of the demand, due to the controversial acceptance of the environmentally-driven decisions by the consumers. As a consequence, both electrified and CCS-based solutions are overall considered in order to satisfy the demand: this is a very interesting point, as all the technologies modeled in our technology learning analysis represent either the implementation of CCS technologies on currently existing technologies (BF-BOF with CCS, HIsarna-BOF with CCS, Ulcored with CCS) or solutions based on electrification of the sector (Electrolysis-based HDR-EAF, Ulcolysis, Ulcowin).

Scenarios and choice

Once the storyline has been defined, different scenarios can be built according to technological development obtaining, as a result, 24 possible combinations. The technological development options build the so-called scenario tree, which is shown in figure 3.5. The options are the following:

1. Fusion availability: Nuclear fusion availability from 2070 (in Europe region);

2. Fusion cost: For the branch that assumes the existence of nuclear fusion, a further distinction is performed on the costs, that are assumed at two different levels, a Reference one, and a High one;

3. CCS availability: Carbon Capture and Storage technologies are available from 2030;

4. Nuclear fission: two possible pathways are assumed in the improvement of this technology (High and Low), depending on the grade of social acceptance;

5. External cost of fusion: two pathways are considered also in this case, only one taking into account the external costs of fusion

The choices that can be made on the points 1, 3, 4 and 5 are of really poor importance, as they concern fusion and fission technologies, that can have a very low impact on the price of electricity, generating very small differences in the sector of our interest (iron and steel). On the other hand, the availability of CCS is a key point (being present also internally to the sector) and has to be set to the reference value. It has been decided to choose a high cost of fusion with a high development of both fission and fusion (in order to have a low changes in the overall cost of electricity, but a development of fusion and fission coherent with the concept of technology learning applied within the iron and steel sector), obtaining the scenario number 9.

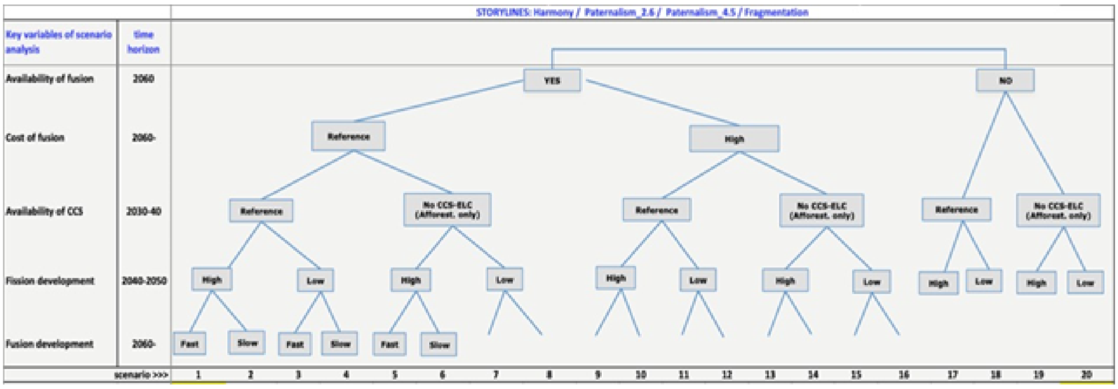

Figure 3.5. Scenario tree in EUROFusion TIMES Model [6]

Sector-specific emissions constraints

The only emission constraints originally present in the model are related to the Scenario file implementing the RCP2.6; it is referred to the global emissions, aggregating the emissions from every sector.

As anticipated in the introduction, however, this analysis aims at understanding the impact of policies specifically targeted for the emissions of the industrial sector. As a consequence, it was decided to assume two different scenarios in the analysis: one only with global emissions constraints, and one adding sector-specific constraints to the industrial sector, which would represent the case in which appropriate emissions reduction strategies are designed, tailored for the industrial sector.

The constraints related to this last scenarios were built by taking into account the levels of emissions from industrial processes necessary, according to the IPCC, to reach the results for the RCP2.6 [68]: they are specifically shown in Figure 3.6.

3.1.3 Iron and steel sector in ETM

The Iron and steel sector in the ETM Reference Energy System is included in the industrial sector, and is characterized by the following elements:

- Input commodities (Fuels and reducing elements)
- Steel-making technologies
- Type-specific steel output
- Technology that transforms the output commodity into service commodity (IIS000)
- Service commodity (IIS)

The iron and steel sector part of the RES is represented in Figure 3.7.

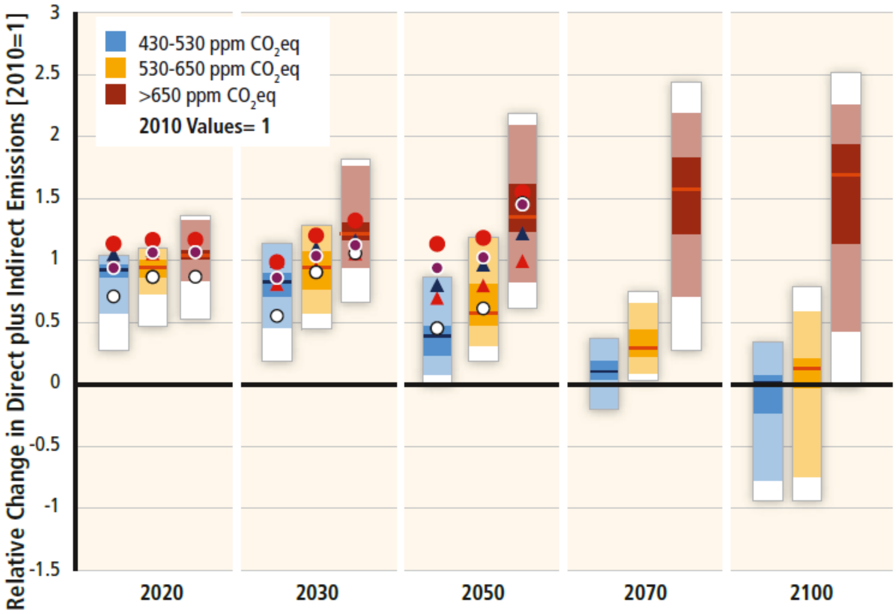

Figure 3.6. Industrial sector emissions evolution - RCP2.6 in blue [68]

The RES of the sector has been represented with the selected burdens for the technology learning analysis; as the reader can see, the electrolysis has been included in the analysis despite not being directly part of the iron and steel sector, as it feeds the Green HDR-EAF process. On the other hand, no external CCS technologies to the iron and steel sector have been considered: this choice comes as a consequence of a peculiarity of the CCS technologies used in the iron and steel sector, which are mainly physical processes-based (in particular, PSA, SEWGS and Cryogenic distillation technologies), while in most of the other sectors where CCS is modelled (power sector, hydrogen production, other industrial applications) in most cases, amine-based CCS technologies are preferred [61]. As a consequence, the learning of the two typologies of carbon capture and storage is assumed to be unrelated.

At this point, it is important to explore more analytically the different commodities and processes, to have a better understanding of the iron and steel sector.

Input commodities

The input commodities to the iron and steel sub-sector are mainly composed by fuels and reducing elements; the iron ore, that is also an input in the real processes, is not modeled due to its poor energy content:

- Natural Gas Mix (INDNGA): it is used in most of processes, and represents a major reducing element; in many traditional processes (such as in DRI), its use is limited in the real energy system, despite its penetration is increasing in the latest years;

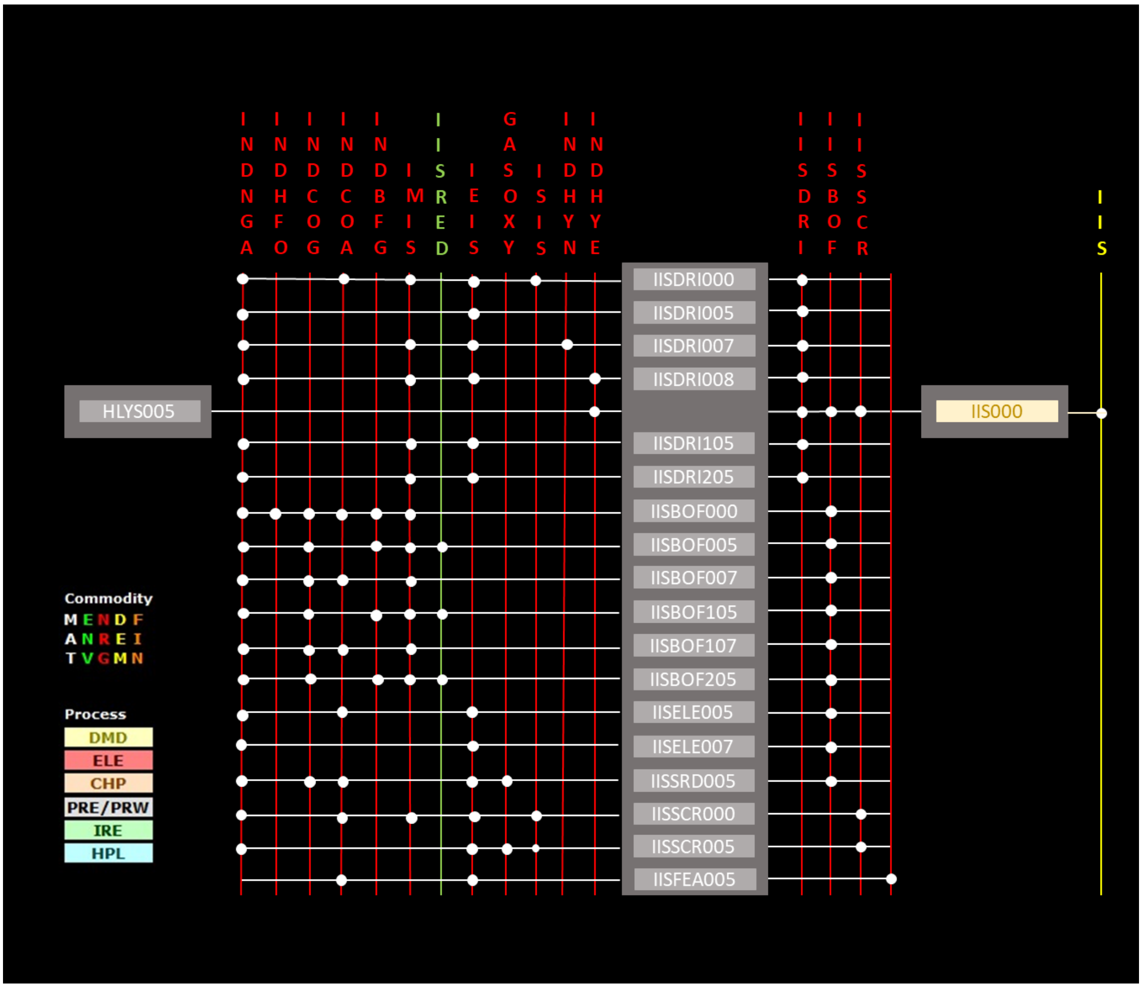

Figure 3.7. Iron and steel sector (+ electrolysis process) in ETM

- Oven Coke Gas (INDCOG): coke gas is obtained as a by-product of the coking process, from which is produced in very large quantities (360 m^3/t_{Coke}), and can be used, besides as a fuel for all blast furnace-based processes, as a feed stock for hydrogen production [39];
- Coal (INDCOA): coal represents a cheaper alternative to coke, as, in order to use it, no coking process has to be performed; steelmaking technologies such as HIsarna and smelting reduction directly use it, sensibly reducing the capital cost of the technology; finally, it is also used as an input to ULCOWIN, as a carbon rich element for the steelmaking part of the process;
- Blast Furnace Gas (INDBFG): the blast furnace gas is a by-product of blast furnaces, which has a very low heating value: it is mostly re-used within steelmaking processes,

or, if properly post-processed, it can be used in power plants [40], but sometimes it is flared without any power or heat production; in the model, it represents an input of the blast furnace-based processes, after having been pre-processed in an appropriate technology (namely INDBFG000 or INDBFG005), that transforms the GASBFG commodity (output of all blast furnace-based technologies) into INDBFG;

- Machine Drive (IMIS): this commodity represents the electricity needed for the machine drive of the steelmaking technologies; it is input in all the blast furnace and shaft furnace-based technologies;
- Blast Furnace Reductant (IISRED): it is the reductant specifically used for blast furnace; in the model, it is produced by using coke, coke oven gas, coal, natural gas and heavy fuel oil, and being specific for blast furnace processes, it is input only to Traditional BF-BOF, BF-BOF with CCS and BF-TGR-BOF with CCS;
- Electricity (IEIS): the electricity for industrial uses (IEIS) commodity represents the electricity used as an input to the industrial processes, excluded the portion used for machine drive; as a consequence, in the iron and steel sector, only Electric arc furnace and electrolysis-based processes have it as an input;
- Oxygen Steel Furnace Gas (GASOXY): similarly to the blast furnace, where the reducing gas is modeled on its own, the oxygen that is input in the basic oxygen furnace is modeled as an independent commodity in the ETM;
- Steam (ISIS): energy content of the input steam to the processes: in the iron and steel sector, it is input to all the blast furnace and smelting reduction-based technologies;
- Hydrogen from fossil-based processes (INDHYN): the hydrogen in input to the direct reduction process (HDR-EAF) is modeled exogenously to the iron and steel sector, so that a distinction is possible between DRI obtained with green hydrogen, and DRI obtained using hydrogen coming from fossil-based processes; in the latter case, the commodity is called INDHYN and is input to an appropriate technology - DRI-EAF with hydrogen reduction (IISDRI007); it is important to underline that INDHYN can come from different hydrogen production paths in the model, namely:
  - Natural Gas Steam Reforming
  - Natural Gas Steam Reforming with Carbon Capture and Storage
  - Hard Coal Gasification
  - Hard Coal Gasification with Carbon Capture and Storage
  - Brown Coal Gasification
  - Brown Coal Gasification with Carbon Capture and Storage
  - Biomass Gasification
- Hydrogen from electrolysis (INDHYE): this commodity, instead, represents hydrogen produced from non-fossil sources, the so-called Green Hydrogen, coming from water electrolysis; it enters as an input an alternative technology to IISDRI007 - DRI-EAF with green hydrogen reduction (IISDRI008).

Steelmaking technologies

In the Table 3.1, all the input and output commodities to the different technologies are specified, also by quantifying the energy intensity of the flows; in Figure 3.8, instead, the carbon intensity of every process is reported.

Technology	Input energy intensity [GJ/t_{CS}]											Output EI [GJ/t_{CS}]	
	BF Reduct.	BF Gas	Coal	Coke oven gas	Nat. gas	Elec.	Mach. drive	Steam	O_2	H_2	Total	Rec. off-gas	Steam
BF-BOF (BY)	13.3	3.06		0.9	0.7		0.6	0.2			18.7		
BF-BOF (2050)	11.7	2.7		0.8	0.6		0.5	0.2			16.5		
DRI-EAF (BY)					21.2	1.2					22.4		0.2
DRI-EAF (2050)					17.5	1.0					18.5		
Scrap-EAF (BY)					3.4	2.8			0.5		6.7		
Scrap-EAF (2050)					2.2	1.8			0.3		4.3		
Smelting reduction-BOF			15.9	0.4	0.4	0.4		0.1	1.2		18.4	0.4	
BF-BOF with CCS	13.3	3.06		0.9	0.7		1.0	0.2			19.1		3.1
BF-TGR-BOF with CCS	10.9	3.06		0.9	1.8		0.5	0.2			17.3		
DRI-EAF with CCS					17.5	1.0	0.4				18.8		0.2
HIsarna-BOF			13.1	0.8	0.6		0.6	0.2			14.3	0.7	
HIsarna-BOF with CCS			13.1	0.8	0.6		1.0	0.2			15.6	0.7	
Ulcored with CCS					17.5	1.0	0.7				19.2		
HDR-EAF					2.2	1.8	1.3			6.1	11.4		0.2
Green HDR-EAF					2.2	1.8	1.3			6.1	11.4		0.2
Ulcowin			0.9		2.27	12.6					15.7		
Ulcolysis					1.2	14.5					15.7		
Ferroalloys				0.06		15.59					15.7		

Table 3.1. Input and output commodities to the different technologies [19]

As noticeable, the prior technological characterization of the sector was performed following the same rationale as the model; as a consequence, the technologies included in the EUROFusion TIMES Model are the same which were previously discussed.

They both follow the characterization presented in the recent update by Lerede et Al.[19], which extended the number of steelmaking technologies to 15. All data presented in this section, except for minor modification which will be underlined below, make reference to the reference paper by Lerede et Al. [19].

With respect to the reference paper, the following changes have been implemented:

- Green HDR-EAF technology has been added, with the same inputs and emissions levels as HDR, being the only difference between the two in the origination of the input hydrogen;

- The BF-BOF with CCS energy intensity improvement in 2050 (present in the original document) has been removed because the technology learning of the BF-BOF will be modeled exogenously as explained in the section 3.2.2

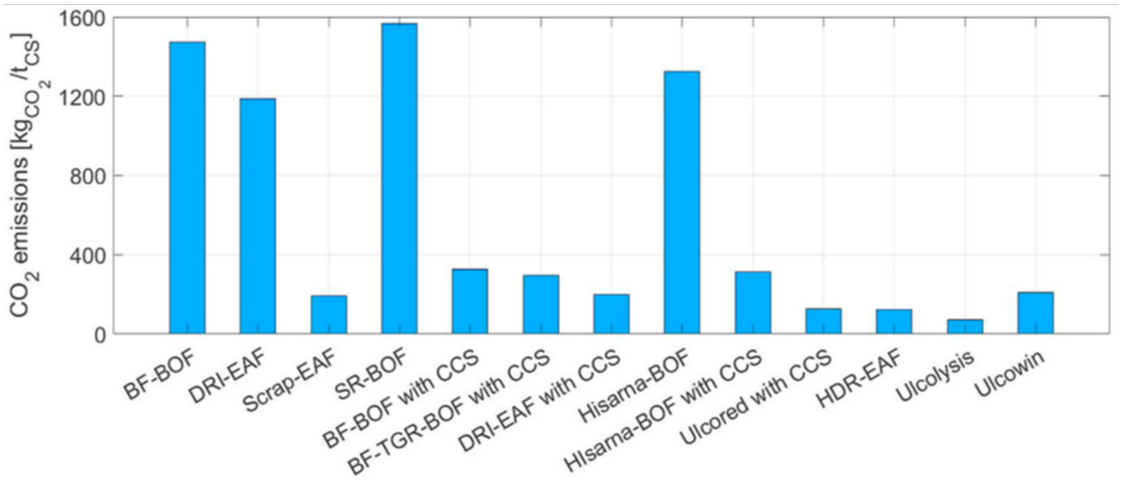

Figure 3.8. Emissions related to each steelmaking process [19]

Moving to the technological development of the processes, which is one of the most relevant aspects for the analysis performed in this paper, here below the different technologies are presented with their related readiness level and year of introduction in the model.

Steelmaking technology	TechName	Deployment state	TRL [41]	IntroYear
Traditional BF-BOF	IISBOF005	Traditional	11	2005
Traditional DRI-EAF	IISDRI005	Traditional	11	2005
Traditional Scrap-EAF	IISSCR005	Traditional	11	2005
Smelting reduction-BOF	IISSRD005	Innovative, commercial	10	2006
DRI-EAF with CCS	IISDRI105	Demonstration phase	9	2025
BF-BOF with CCS	IISBOF105	Demonstration phase	8	2025
BF-TGR-BOF with CCS	IISBOF205	Demonstration phase	8	2025
HIsarna-BOF	IISBOF007	Demonstration phase	7	2025
HIsarna-BOF with CCS	IISBOF107	Demonstration phase	7	2025
Ulcored with CCS	IISDRI205	Demonstration phase	6	2030
HDR-EAF	IISDRI007	Demonstration phase	6	2030
Green HDR-EAF	IISDRI008	Demonstration phase	6	2030
Ulcowin	IISELE005	Pilot plant	5 [33]	2030
Ulcolysis	IISELE007	Pilot plant	4 [34]	2030
Ferroalloys production	IISFEA005	Traditional	11	2005

Table 3.2. Steelmaking technologies and their development status [19]

The content of the Table 3.2 will be of vital importance in the Methods part, as it will guide the sensitivity analysis, together with the economic data on the various technologies, which are presented below, in Table 3.3.

Also in this case the data used come mainly from the reference paper, with some minor changes:

- HDR-EAF: being the hydrogen an input of the process, the investment cost of this

Steelmaking technology	Investment Costs [€/t_{CS}]	Fixed O&M Costs [€/t_{CS}]	Plant Lifetime [years]
Traditional BF-BOF	586	438	30
Traditional DRI-EAF	549	418	20
Traditional Scrap-EAF	244	418	20
Smelting reduction-BOF	521	438	30
BF-BOF with CCS	825	426	30
BF-TGR-BOF with CCS	665	424	30
DRI-EAF with CCS	594	418	20
HIsarna-BOF	440	435	30
HIsarna-BOF with CCS	486	448	30
Ulcored with CCS	595	393	20
HDR-EAF	549	418	20
Green HDR-EAF	549	418	20
Ulcowin	6945	403	20
Ulcolysis	6722	340	20
Ferroalloys production	600	1800	30

Table 3.3. Fixed costs and lifetime of the different technologies [19]

technology has been lowered, excluding the investment cost for the hydrogen generation technology, which has been modeled exogenously (this aspect will be more thoroughly discussed in the Methods part)

- Green HDR-EAF: the cost of this technology is assumed to be the same as in the previous case, with the investment cost of the electrolyzer modeled exogenously (see Appendix C.1)

Type-specific steel output

The technologies studied in the previous subsection generate different types of output commodities, but in this paragraph only the ones representing iron and steel products are taken into account, excluding the various by-products.

Three different steel output commodities are produced by the processes above, depending on the main technology the process is based on. The process-specific commodities are the following:

- IISBOF: steel produced from basic oxygen furnace (BOF) processes (+ steel produced by means of Ulcowin and Ulcolysis)
- IISDRI: steel produced from direct reduced iron (DRI)-based processes
- IISSCR: steel produced from scrap-based processes
- IISFEA: produced ferroalloys

The production shares of the mentioned process-specific commodities is driven, besides of the economic competition, by some constraints, which are regionally specified in the industrial characterization sheet for each region. The constraints on the shares result to be large enough to let the model be driven in large portion by economic competition between the different technologies.

This is however not applied for the last presented commodity, IISFEA: in fact, the ferroalloys, resulting to be a completely different product, have a predetermined and fixed input value to the final service demand, as it is possible to see in the figure below.

For this reason, the production output of IISFEA results to be completely independent on the technologies costs and environmental constraints; moreover, IISFEA represents effectively a different final product with respect to the other three process-specific commodities. As a consequence, the technology connected to the production of this commodity, IISFEA005, has been excluded from the following analysis on technology learning, differently from all the other 14; this aspect has been already taken into account when designing the RES of the sector, in Figure 3.7.

IIS000

This technology merely transforms the already-mentioned process-specific commodities into the final service commodity (IIS).

It has an unitary efficiency and production capacity, and is defined for every region singularly, as it is possible to see on the right-hand side of the figure above.

Final service commodity - IIS

The final service commodity, namely IIS, satisfies the final demand, which is built accordingly to the already-mentioned formula, with one only driver (PISNF, namely the "Driver for Iron, Steel and Non-Ferrous Materials" [42]) which is built on the basis of the Total Final Consumption of iron, steel and non-ferrous materials. [43]

3.2 Technology learning

The technology learning concept has already been explained in the previous sections, but in this part the focus will be on the application of the already illustrated concepts to this analysis. In particular, the drawbacks and limitations discussed in the literature review subsection on technology learning (2.3.3) will guide the choices in this part, in order to obtain results that are as meaningful as possible for this analysis.

3.2.1 Technology learning characterization

A problem underlined in the literature review, in the part dedicated to the limitations of technology learning theory, concerned the fact that the learning is usually not homogeneous in a technology: different modules, or components, usually learn at different rates [104]. As a consequence, the most indicated way to perform the analysis is to spread the steelmaking technologies present in the Reference Energy System of ETM into subtechnologies, with the aim of individuating those subtechnologies which, being innovative, are subject to learning. The following paragraphs will show the characterization performed in this sense; the results are then resumed in the last paragraph of this subsection 3.2.1.

Blast furnace - Basic oxygen furnace (BF-BOF)

Given its very large diffusion in the world as a technology (more than 70% of the world production in 2019 was obtained through its process), it is considered as a well-established technology, which is no more subjected to learning; in fact, taking into account the Wright formula, if the initial installed capacity (I_0) is already very high, the cost reduction with respect to the initial one (C_0) will be very small, even if the new investments (I_t) are increasing (and this is not the case, being a highly pollutant and carbon intensive technology, whose use is projected to decline in the upcoming decades).

Being the whole technology classified as non-learning, neither its sub-technologies will learn: as a consequence, both the blast furnace and the basic oxygen furnace will be considered as non-learning.

Direct reduced iron - electric arc furnace (DRI-EAF)

A similar consideration can be done for DRI-EAF; in fact, being already quite spread in the world, with a production which is close to the 10% globally, the initial cumulative capacity I_0 is high enough to prevent very steep reductions in unit cost; moreover, exactly as for BF-BOF, the spread of this technology is projected to decrease in the upcoming decades [1].

As a consequence, also direct reduction of iron and electric arc furnace are considered as non-learning technologies.

Steel from scrap - electric arc furnace (Scrap-EAF)

Steel from scrap is the only "traditional" technology which is projected to have an increase in share in the upcoming years [1]; however, being already been used for decades, covering more than the 20% of the global yearly production, its learning can also be neglected.

Thus, the steel from scrap sub-process is also considered as non-learning.

Blast furnace - basic oxygen furnace with CCS

This technology presents two traditional subprocesses (namely the blast furnace and the basic oxygen furnace), to which a carbon capture and storage technology is added. The CCS device, based on a Sorption Enhanced Water-Gas Shift technology (SEWGS) [45], represents an innovative sub-process for its scarce diffusion.

Economically speaking, it has an impact on the investment cost, due to the presence of the device, but it does not afftect the fixed Operation & Maintenance costs, which remain on the same level as in the traditional BF-BOF.

As a consequence, the following modelling choices are taken:

- The component of investment cost concerning the Carbon Capture and Storage device will be learning;
- The fixed O&M cost will remain fixed over time, not being affected by learning technologies.

Blast furnace - top gas recycling - basic oxygen furnace with CCS

This technology, as previously said, reuses the top gas exiting the blast furnace (where reduction of the iron oxides take place), which is obviously rich in CO_2, but also of CO and H_2, by removing the component of CO_2 (CCS), and reusing the reducing elements. This leads, besides of the reduction of carbon emissions, to a decrease in consumption of coke oven gas, which indirectly produces a reduction also of the fixed O&M costs, due to the slower degradation of some component of the plants. Obviously, on the other hand, there is an increase in the investment cost due to the presence of the Carbon Capture and Storage device.

Under the modelling point of view, two choices have been taken:

- The system of top-gas recycling, together with the CCS device, are considered as a simple, learning, CCS technology; as a consequence, its contribution inside the investment cost will be affected by learning;

- The reduction in O&M cost is considered as fixed, as it derives from a reduction in use of coke and carbon coke, that is not dependent on the CCS development, but on the content of reductants such as CO and H2.

Direct reduced iron - electric arc furnace with CCS

This technology, exactly as in the case of BF-BOF with CCS, is composed by two traditional sub-technologies, namely the direct reduction of iron and the electric arc furnace, with the addition of an innovative Carbon Capture and Storage device, which is based on a vacuum pressure swing adsorption (VPSA).

Coherently with the choices taken for the BF-BOF with CCS, also in this case:

- The component of investment cost relative to the CCS device has been modeled with technology learning;

- The fixed O&M cost remains unvaried with respect to the reference technology.

Smelting reduction - basic oxygen furnace

This technology is composed by two sub-technologies, namely the smelting reduction, which comprehends the installment of two main devices, the reduction shaft furnace and the melter-gasifier, and the basic oxygen furnace. The former results to be innovative enough to be modeled as learning, while the latter is one of the most traditional sub-technologies.

As a consequences, the modelling choices are:

- The component of investment cost relative to smelting reduction will learn;

- The component of fixed O&M cost relative to smelting reduction is supposed to remain fixed over time.

These choices are explained and justified in the next subsection.

HIsarna - basic oxygen furnace

HIsarna, as previously shown, represents an evolution of smelting reduction process: in fact, if on one hand it also allows the direct use of coal and iron ore as inputs, on the other side it optimizes the process, needing only one unique device where both the Cyclone Converter Furnace and the HIsmelt Smelt Reduction Vessel are present. This allows the technology to reduce sensibly the investment cost, while the fixed O&M costs are lowered only slightly.

The consequent modelling choices are:

- The smelting reduction component of the investment cost will learn exactly as in smelting reduction-BOF process;
- The investment cost reduction with respect to the smelting reduction technology is modelled as fixed (non technology learning), being it related to the absence of a second device for smelting;
- The fixed O&M costs reduction will remain constant because it is due to the reduction in cost of operation and maintenance of already established plants

HIsarna - basic oxygen furnace with CCS

This technology represents an alternative solution to HIsarna - BOF, with the presence of a Carbon Capture and Storage device. As a consequence, it will be modeled in the same way the technology shown just above, with the addition of a learning component in the investment cost, due to the presence of the CCS technology. As a consequence, this technology presents one non-learning sub-technology (basic oxygen furnace) and two learning sub-technologies (smelting reduction - from which a fixed amount of investment cost is removed due to the presence of only one furnace - and CCS technology). It is important to remark that the CCS technology for HIsarna, differently from all the others, is not based on pressure adsorption, but on cryogenic distillation [28].

Ulcored - electric arc furnace with CCS

In this case, the technology presents many similarities with one traditional technology: in fact, it is a direct reduction of iron process, and has an electric arc furnace for steelmaking. However, it also presents the addition, as explained in the technical characterization, of a top gas recycling system, of a pre-heating device and a CCS technology (with a VPSA-based technology). The modelling choice here is to merge these three implementations, and to simplify them as it would be one CCS technology. If on one hand, this system brings with it an increase in the total investment cost, on the other side it reduces the overall fixed O&M cost of the steelmaking technology, for a similar reason to the one explained for the BF-TGR-BOF.

Therefore, the modelling choices are the following:

- The investment cost consists of two components, one non-learning related to DRI-EAF system, and one learning (related to the TGR+CCS+HX system);

- The fixed O&M cost will remain constant and independent on the quantity installed, being its reduction linked to the reduction of degradation of some component more than to technological deveopment.

Hydrogen direct reduction - electric arc furnace

This technology results to be extremely similar to the direct reduction of iron - electric arc furnace, which is a traditional technology and therefore does not learn. The only difference with respect to this technology is the direct use of hydrogen for reduction, and the absence of a steam reformer, which is however compensated by the modifications for the compatibility of pure hydrogen for iron direct reduction [31]. It is important to underline that this technology has hydrogen as an input, so the hydrogen generation technology costs do not have to be included within the steelmaking technology.

Then, the following modelling choices were taken:

- The investment cost of the technology is input exactly at the same level as for DRI-EAF, without learning;

- The fixed O&M cost of the technology is input at the same level as for DRI-EAF without learning.

Green hydrogen direct reduction - electric arc furnace

This technology is identical to the previous one in terms of steelmaking process, so the modelling choices are the same. It is however important to remark that the hydrogen input to this technology comes exclusively from electrolysis, a technology which shows high levels of learning potentials [101]. As a consequence, the hydrogen generation technologies, and in particular electrolysis, has been included within the technology learning analysis, in order to obtain more plausible results. However, the more specific reasons behind the inclusion of electrolysis technology learning in the analysis and on modelling choices are presented in Appendix B.

Ulcolysis - electric arc furnace

This steelmaking process is composed of an ironmaking part based on Ulcolysis sub-process (High temperature molten oxide electrolysis steelmaking), and an electric arc furnace.

The modeling choices, therefore, are straightforward:

- The investment cost of Ulcolysis component is learning, while the EAF component will remain fixed;

- The fixed O&M cost will remain fixed as this technology already allows a sensible reduction with respect to more traditional alternatives, thanks to its extreme simplicity in principle.

Ulcowin - electric arc furnace

Parallelely to Ulcolysis, also Ulcowin presents an innovative ironmaking sub-process whose learning is very accentuated, and a traditional steelmaking part (electric arc furnace).

As a consequence, the choices will be analogous:

- The investment cost of Ulcowin sub-process is learning, while the EAF component is not;
- The fixed O&M cost will remain constant.

Summary on learning components

Summing up what emerged from the last sub-section, the Table 3.4 is obtained.

Technology	Ironmaking base process	Additionally added sub-technologies	Saved technologies	CCS	Steelmaking process
BF-BOF	Blast furnace	-	-	-	BOF
DRI-EAF	Direct reduction	-	-	-	EAF
Scrap-EAF	-	-	-	-	EAF
SR-BOF	Smelting reduction	-	-	-	BOF
DRI-EAF with CCS	Direct reduction	-	-	PSA	EAF
BF-BOF with CCS	Blast furnace	-	-	SEWGS + compression	BOF
BF-TGR-BOF with CCS	Blast furnace	Top-gas recycling	-	VPSA + compession	BOF
HIsarna-BOF	Smelting reduction	CCF	Reduction furnace	-	BOF
HIsarna-BOF with CCS	Smelting reduction	CCF	Reduction furnace	Cryogenic distillation + compression	BOF
Ulcored with CCS	Direct reduction	Top-gas cycle Heat exchanger	Reformer	VPSA + compression	EAF
HDR-EAF	Direct reduction	-	Steam reformer	-	EAF
Green HDR-EAF	Direct reduction	Electrolyzer (External)	Steam reformer	-	EAF
Ulcolysis	Ulcolysis	-	-	-	EAF
Ulcowin	Ulcowin	-	-	-	EAF

Table 3.4. Table of sub-technologies per technology; in red, the learning ones

As it is possible to notice, many sub-technologies show learning potential, in particular, taking into account the coupling between different learning sub-technologies, the following can be mentioned:

- Smelting reduction
- PSA-based CCS technology (in DRI-EAF with CCS application)
- SEWGS-based CCS technology (in BF-BOF with CCS application)
- VPSA-based CCS technology + top gas recycling (in BF-TGR-BOF with CCS application)
- VPSA-based CCS technology + top gas recycling + heat recovery (in Ulcored with CCS application)
- Cryogenic distillation-based CCS technology (in HIsarna-BOF with CCS application)
- Electrolyzer
- Ulcolysis
- Ulcowin

However, many of the technologies mentioned above have enough similarities in the principle/component, that their learning will probably proceed with the same pace.

It is then important to cluster the technologies which present those similarities, because it will be an element that can be considered when characterizing the learning in the analysis.

The above-mentioned sub-technologies are therefore grouped as in Table 3.5.

Substantially, all the PSA-based technologies are grouped together, due to their very similar technological principle [46], comprehending the SEWGS technology (typically used in BF-BOF with CCS [25]), which owns to the same family.

For the same reason, Ulcolysis and Ulcowin are grouped as one unique learning technology; obviously, given the differences between the two processes, this is a very strong assumption, but being the components and the processes involved very similar [26], the assumption results to be acceptable.

In the Appendix B, a more thorough discussion on what are the innovative elements learning in each cluster is performed.

3.2.2 Exogenous technology learning concept

Once having technologically characterized the sector, individuating what are the innovative components/parts which can potentially see beneficial effects from the learning, it is time to decide how to characterize the learning itself.

The technology learning, as explained in the appropriate section above, is usually included in Energy Systems Models (ESMs) endogenously; this means that the learning curves are implemented inside the model, so that the model choices take into account the possibility to invest more on a technology which has high learning potential, because the investment would lead to a reduction of its cost in the upcoming years.

Sub-Technology	Owning to (technology)	Sub-technology cluster
Smelting reduction	SR-BOF HIsarna-BOF HIsarna-BOF with CCS	Smelting reduction
PSA-based CCS	DRI-EAF with CCS	PSA-based CCS
SEWGS-based CCS	BF-BOF with CCS	
VPSA-based CCS + top gas recycling	BF-TGR-BOF with CCS	
VPSA-based CCS + top gas recycling + heat recovery	Ulcored with CCS	
Cryogenic distillation-based CCS	HIsarna-BOF with CCS	Cryogenic-based CCS
Electrolysis	Green HDR-EAF	Electrolysis
Ulcolysis	Ulcolysis	Electrolysis of iron ore
Ulcowin	Ulcowin	

Table 3.5. Grouping of sub-technologies

This aspect can obviously bias the choices of the model, driving it towards investments that can be poorly justifiable in the real world [4]. In addition to this, as explained in the literature review, the implementation of learning curves inside the ESM, make the optimization problem become nonlinear [44], with direct consequences on the computational expense to solve the model [104].

As a consequence, in this analysis, taking into account the example of a relevant paper, which is also performed on the same industrial sector [11], it was decided to implement technology learning exogenously. This means that the learning curve is built outside of the model, accordingly to the result of a first, non-learning simulation, and then, the cost variation over time (output of the exogenous learning curve) are re-input in the model, which will produce new results that will drive the new cost evolution. This produces an iterative procedure, which ends only when the convergence is found between the results of the model of two consecutive iterations. The flow chart of the operation is shown for a better understanding of the reader in Figure 3.9.

The flow chart includes the inputs (LR, I_0, C_0) and the output (I_t), the intermediate elements, and the operations, two of which are exogenous (the implementation of the learning curve and the computation of the difference between values in different iterations) in grey, and one endogenous (the actual run of EUROFustion TIMES Model) in green.

In the following subsections, all the elements present in the flow chart will be discussed, starting from the learning curve and its inputs, moving then to the convergence check and to the operative implementation of the procedure (which are developed in a more through way in the Appendix C.3).

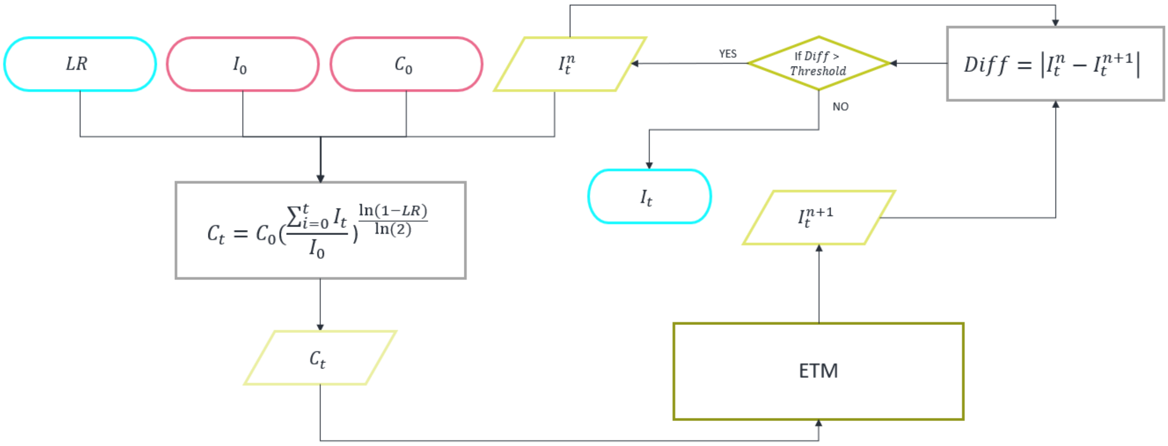

Figure 3.9. Flow chart of the iterative process for exogenous technology learning

3.2.3 Learning Curve characterization

The chosen learning curve, according to the considerations performed in the literature review, is the Wright one; its formulation is reported in Equation 3.1.

$$C_t = C_0(\frac{\sum_{i=0}^{t} I_t}{I_0})^{\frac{\ln(1-LR)}{\ln 2}} \tag{3.1}$$

Every element present in this curve needs to be characterized; this will be performed in the next subsections.

Number of curves

As underlined in the paragraph 3.2.1, the learning of many components and sub-technologies is not independent, and, for this reason, the technologies have been clustered in five different groups. The learning of these clusters can be reflected by five different learning curves, instead of building one learning curve for each innovative sub-technology individuated.

Grouping the sub-technologies practically means that one unique learning curve is being built with technologies that are of the same family, but slightly different; the theoretical justification of such choice will be discussed in the paragraph 3.2.3.

This simplification would have a double advantage: besides reflecting with a higher level of realism the technology learning [104], it would simplify the modelling approach, as the lowest the number of learning curves, the fastest will be the convergence of the iterative procedure.

Initial capital cost (C_0)

The initial capital cost, however, has to be re-scaled to the single sub-technologies, because the learning will affect only that component of the investment cost. As a consequence, a thorough study has been performed on the sources of the paper by Lerede [19], trying to individuate the investment cost components of the different sub technologies. The result is shown in the table 3.6:

Sub-technologies groups	Sub-technology	Investment cost [\$/t_{CS}]
Traditional sub-technologies	BF	416
	BOF	170
	DRI	305
	EAF	244
Smelting reduction	SR	351
CCS-PSA	PSA - DRI-EAF	41.47
	VPSA - Ulcored	45.37
	VPSA - TGR	78.91
	SEWGS - BF-BOF	286.73
CCS-Cryogenic distillation	CD-HIsarna-BOF	46.09
Electrolysis of iron ore	Ulcolysis	6476
	Ulcowin	6696

Table 3.6. Steelmaking sub-technologies with relative investment cost contributions

In Table 3.7, the electrolysis-related initial parameters are reported.

Parameter	Unit measure	Value (referred to 2020)
Investment cost	\$/(GJ/y)	67.16
Fixed O&M cost	\$/(GJ/y)	2.28
Efficiency	-	0.80

Table 3.7. Learning parameters for electrolysis

As anticipated, electrolyzers have been modelled exogenously to the sector, while in the reference paper they were included in the technology [19]: in performing the externalization operation, some key decisions and assumptions have been taken. However, for the seek of brevity and simplicity, they are reported in Appendix C.1.

Initial cumulative capacity (I_0)

The initial cumulative capacity of every technology is a fundamental parameter, as it will guide the behavior of the learning curve; in fact, a technology which has a very low initial installed capacity, will be much more positively affected by an increase in installed capacity, with respect to another technology with the same future installed capacity, but higher initial capacity.

A first point to be remarked is the unit of measurement for the initial installed capacity: it cannot be related to the monetary investments, otherwise, the capacity installed itself would be dependent on the unitary cost of the technology, which is the dependent variable of the learning curve; as a consequence, a different unit of measurement have to be individuated for each technology.

Moreover, a crucial aspect is in the individuation of the final year for the initial installed capacity; in other words, when should one technology's capacity be crystallized over time, and the new capacity will drive the learning curve? In this sense, at least two different approaches can be used, all of which present pros and cons;

- Starting the new installed capacity in the future (with reference to the current year, 2021, or to the last available data), but leaving the introduction year of such technologies unvaried, and by constraining the results of the model until the present year, in order to obtain results that are as close as possible to the real situation;

- Starting the new installed capacity in the future with respect to the last available data, and by imposing the innovative technologies to be introduced in that year, in order to leave their diffusion totally unconstrained;

While the first methodology results to be the closest to the real world situation (only for the sub-sector, because for all the rest of the model, no such constraints would be imposed), it may not be adherent to the reality in the future, when the constraints are not imposed anymore and the model will be free to "jump away" from the current, real-world situation. At the contrary, the second solution, being totally unconstrained, would leave more freedom to the model in finding the most optimal mix of technologies in the sector (which is extremely important in a sensitivity analysis, where differences between different runs have to be highlighted). As a consequence, this second approach has been chosen.

In the table 3.8, for the different learning sub-technologies, the final year of initial installed capacity is indicated, as well as the introduction year in the model.

Moreover, in the table the initial installed capacity has been added; a more thorough discussion on how this last data have been obtained, can be found in the Appendix C.2.

Learning rate (LR)

The estimation of the learning rate has been individuated as the most problematic element in modelling technology learning [104], according to a large number of papers [4]. As a consequence, being the object of this work the analysis of the impact of learning rate taking into account the uncertainty it generates, the possibility to consider different levels of

Sub-technology	Unit chosen for installed capacity	Initial installed capacity	Last considered year for initial installed capacity	Year of introduction in the model
Smelting reduction	Mt_{CS}/y	11.45	2005	2006
CCS techs - PSA	Mt_{CO2}/y	17.65	2024	2025
CCS techs - Cryogenic distillation	Mt_{CO2}/y	0.8	2024	2025
Electrolyzers	GW_e	0.27	2019	2020
Electrolysis of iron ore	t_{CS}/y	18.3	2029	2030

Table 3.8. Modelling choices related to initial cumulative capacities

learning rates, at least for technologies whose future development is still largely uncertain (because of their early stages of development, or because of their unclear potential), must be contemplated.

Therefore, at this point it is important to individuate possible values, or ranges of values, for the learning rates, relying on the existing literature:

- Smelting reduction: according to one of the main reference paper, a plausible value of Learning Rate for technologies whose main improvement to traditional BF-BOF is the direct injection of coal (such as it is for Smelting Reduction) is 6% [11];
- PSA and Cryogenic distillation-based CCS technologies: to the writer's knowledge, no scientific paper has ever estimated values of learning rates for specific CCS technologies; as a consequence, it has to be assumed that all the CCS technologies will learn accordingly to the same learning rate. The value of such learning rate, according to different studies, can be highly oscillant, with a mean value of 10.4% and a standard deviation of 5.4% [66];
- Electrolysis: a similar type of information is found for electrolysis, as a comparative paper [66] found that average value of learning rate for electrolysis technologies is 9.6%, with a standard deviation of 5.5%;
- Electrolysis of iron ore: this very innovative and peculiar technology, being at a very early stage of development does not have any study to assess its cost evolution (and, as a consequence, its learning rate); thus, a strong hypothesis has been performed, that electrolysis of iron ore and electrolysis of water can have the same learning rate, being the type of process quite similar, despite several differences in materials and components.

New cumulative capacity ($\sum_{i=0}^{t}\mathbf{I}_t$)

The new cumulative capacity is obtained as an output from the model as newly installed capacity, for each time step, and summed up to the year of interest to compute the capital cost in the year of interest itself. The technologies owning to the same learning

Learning Sub-Technology	Learning rate - mean value [%]	Learning rate - standard deviation [%]
Smelting reduction	6	-
CCS technologies - PSA	10.4	5.4
CCS technologies - Cryogenic distillation	10.4	5.4
Electrolysis	9.6	5.5
Electrolysis of iron ore	9.6	5.5

Table 3.9. Learning rate values for the different learning technologies

curve (see Table 3.5) will contribute to the newly installed capacity of the entire sub-technology group, taking as a principle the fact that when building the learning curve of a technology, all the different sub-technologies contribute to define its installed capacity [69].

Learning curves

At this point, it is possible to report the different learning curves for the learning sub-technologies.

- Smelting Reduction: Figure 3.10
- PSA-based CCS technologies: Figure 3.11
- Cryogenic distillation-based CCS technologies: Figure 3.12
- Electrolysis: Figure 3.13
- Electrolysis of iron ore: Figure 3.14

The figures show how the initial installed capacity of the different technologies influence their potential cost evolution when installing new capacity: for Smelting Reduction-based technologies (Figure 3.10), if installing some thousands MtCO_2 in capacity, the cost reduction can be in the order of 20%, while for more innovative technologies such as Ulcolysis and Ulcowin (Figure 3.14), it can be from a 50% to over 90% (depending on the level of the Learning Rate). The CCS technologies (Figure 3.11 and 3.12) show interesting potential reduction for the technologies when overcoming the hundreds $\mathrm{Mt}_{C}O2$; finally, in Figure 3.13 it is possible to see how the costs relative to electrolyzers (both investment and fixed O&M) show and interesting potential reduction, while the efficiency increase is obviously less steep.

In order to complete the figure on how the exogenous technology learning has been implemented, a discussion on the convergence criterion and on the operative implementation

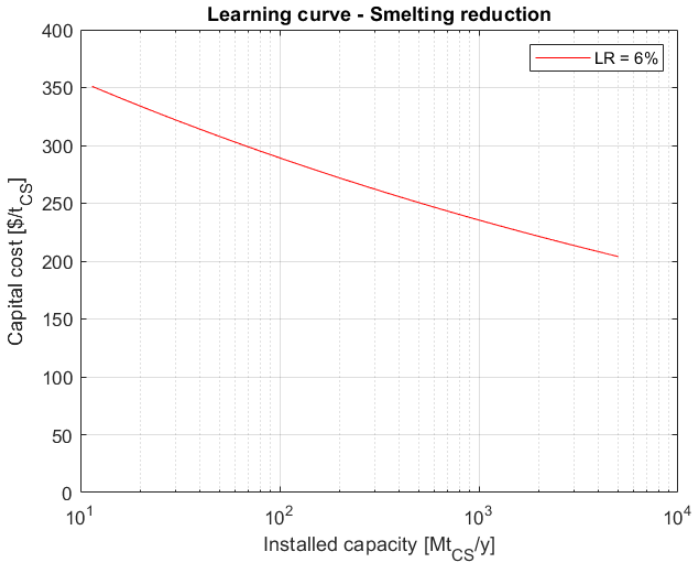

Figure 3.10. Smelting reduction learning curve

is required. Thus, they have been included in the Appendix C.3, respectively in Appendix C.3.1 and Appendix C.3.2, in order to make the description of the primary points of the process as short and clear as possible in the main text.

3.3 Sensitivity analysis details

Having collected all the elements, it is now possible to run the simulations finalized to the analysis: as previously said, the values of the learning rates will be changed, in the framework of two different scenarios, including or not the sector-specific emissions constraints.

The learning rate levels will be three for both the CCS technologies and for the electrolysis-based technologies, while for the smelting reduction, the value of learning rate is fixed, having seen that its penetration in the market is more dependent on the others learning rates rather than its (due to the very large diffusion it has in all scenarios): all the combinations of those will be studied, both with and without the sector-specific emissions constraints. All the variables changing are represented below.

As a result, 18 scenarios will be presented (+ 2 non-learning scenarios, one with and one without sector-specific emissions, with comparative purposes).

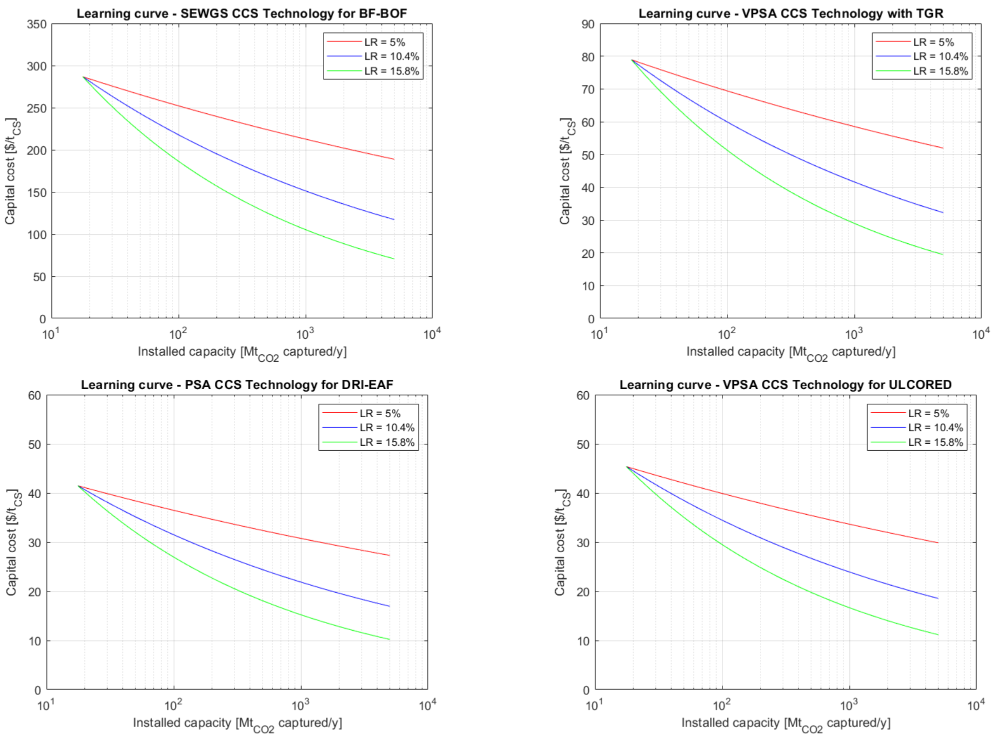

Figure 3.11. PSA-based CCS technologies learning curves

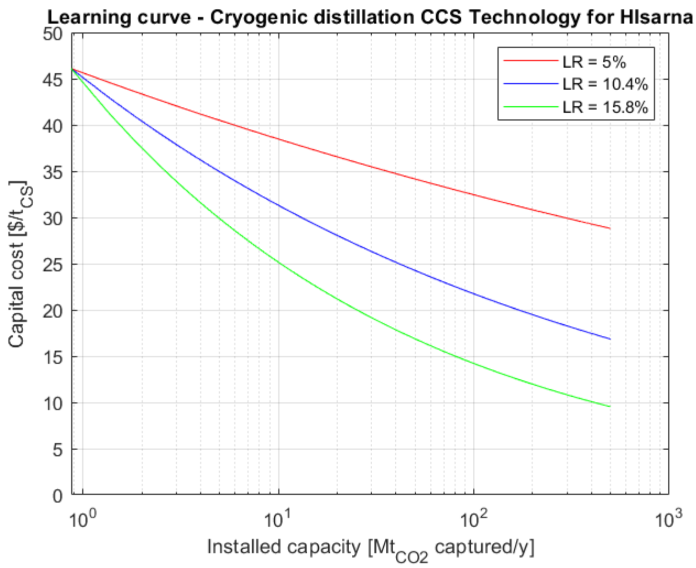

Figure 3.12. Cryogenic distillation CCS learning curve

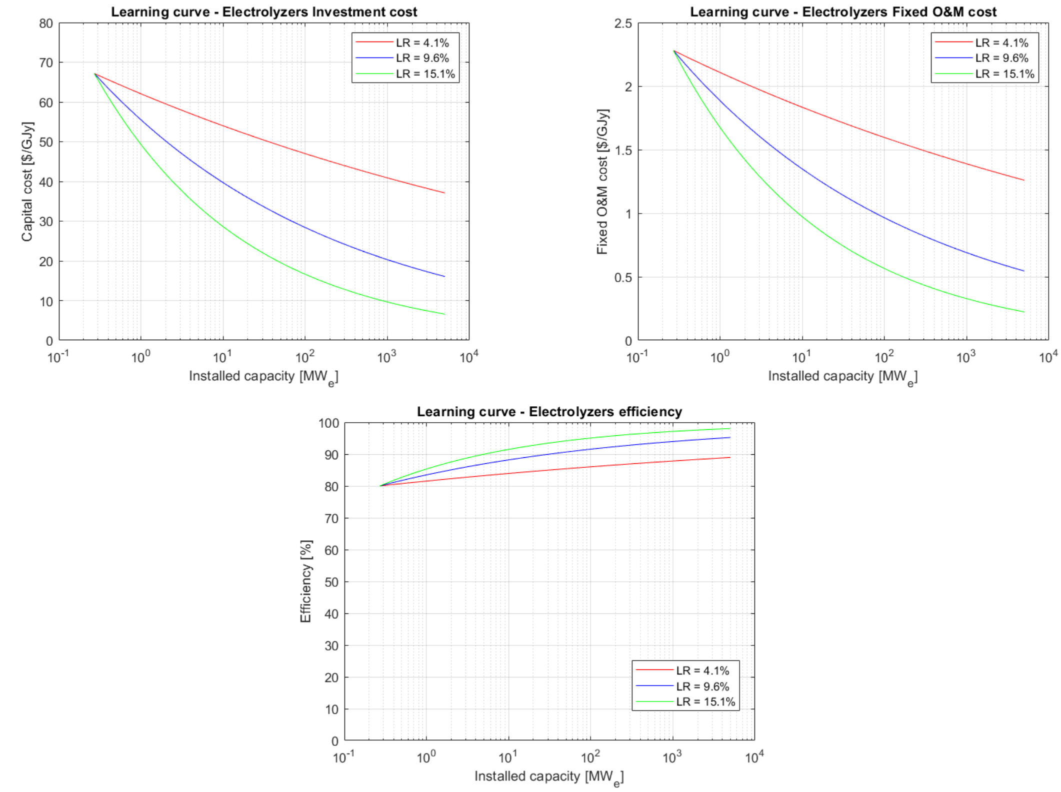

Figure 3.13. Electrolysis: Investment cost, Fixed O&M costs and efficiency

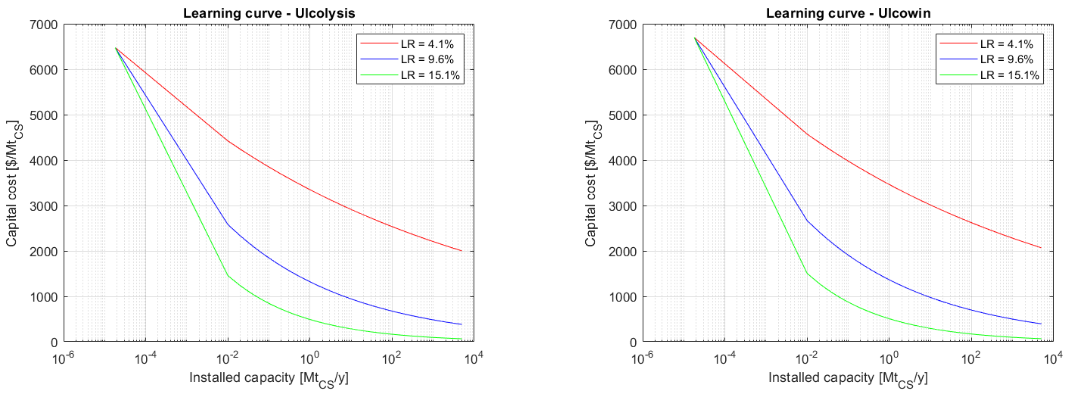

Figure 3.14. Electrolysis of iron ore: Ulcolysis and Ulcowin

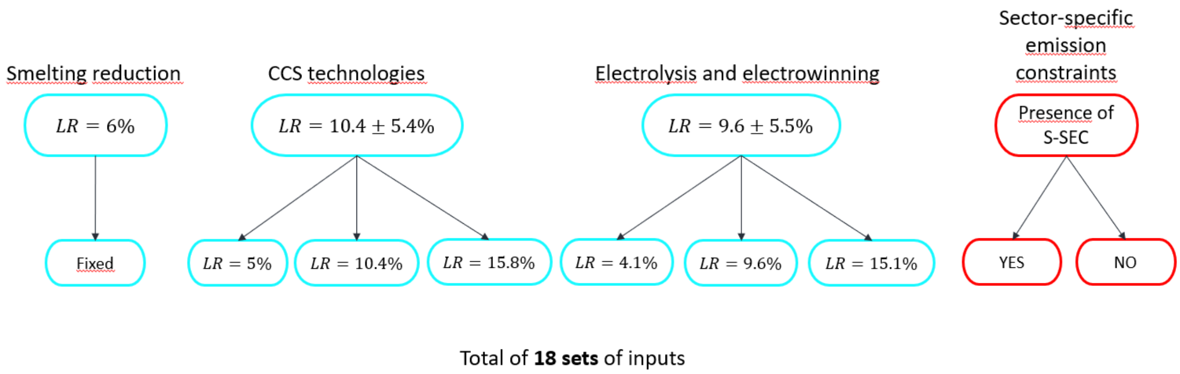

Figure 3.15. Sets of learning rates and sector-specific emissions

Chapter 4

Results

The results were obtained after having run a total amount of 71 simulations. In fact, the convergence of the results, using the iterative procedure, was reached after:

- 3 iterations, in 5 input sets
- 4 iterations, in 9 input sets
- 5 iterations, in 4 input sets

As a consequence, the average number of needed iterations was 3.94 per input set.

This section aims at presenting the results, in the framework of the initial research questions:

Can investments on new, technologically uncertain processes impact the iron and steel sector decarbonization under strict emissions targets? If so, to what extent? And which technologies, considering the effects of investments and their uncertainty, would affect the most the decarbonization?

In order to answer to these questions, a concentric approach will be used. It means that the analysis is starting from a summary view on the global energy system, studying the total power production per source. Subsequently, the focus will be restricted to the iron and steel sector itself, which will be studied in its general future trends, with a focus on the impact of both the technological learning (and the uncertainty it generates) and the emissions constraints; at the end of this sector-specific section, the emissions coming from iron and steel production processes are shown, directly addressing the initial research question. Finally, the most interesting insights from the first two sections will be deepened and discussed in the conclusions, contained in the final chapter.

This approach follows also a consequential rationale: in fact, the iron and steel sector evolution, and consequently its decarbonization, are driven by the economic competition between the different technologies; however, this competition is affected by different factors, such as availability of the fuels to input (which are indirectly addressed in the first, general part of the analysis of results), the capital cost of the technologies, which is directly analyzed in the sector-specific section, and by the emission costs, whose impact is studied via the comparison between scenarios with and without sector-specific emissions constraints.

4.1 Evolution of the global energy system

Although the current analysis is totally centered on the iron and steel sector, the trend of the global energy system evolution is also influencing it: as reported above, for instance, if in the future a given fuel will be more economically convenient, and as a consequence more widespread, steelmaking technologies relying on that fuel will, most likely, be increasingly installed and used.

Therefore, the total power plant capacity per source is being studied, and presented in Figure 4.1, in order to both give an overall idea of the future energy system development (with a particular focus on the electrification process takes place), and, consequently, to link and justify the results to the sector-specific results, which will be presented in section 4.2.

The upcoming decades show, for the whole energy system, a great decarbonization in the power sector, with a decreasing share of fossil fuels used starting from the 2020s: this was highly predictable, having supposed the tightest emission strategy possible (RCP2.6 by IPCC). In order to substitute the fossil fuels, biofuels, hydropower and renewables are used at an increasing rate. Overall, the power production moves from the 5 TW in 2020 to the almost 30 TW installed in the scenario without industry-based emission policy, and to the over 34 TW in the scenario with this tighter policy, by the end of the century (Figure 4.1).

These results, moreover, can already give an idea of what may be the trend in the iron and steel sector: if in the first half of the century, a quite large diffusion of fossil fuels leaves room to fossil fuels-based technologies, in the second half, most likely, electricity-based technologies are expected to have a higher importance.

4.2 Steel production mix evolution

It is expected that the highest impact of the studied phenomena are reflected on the iron and steel sector, which can be studied by analyzing the model outputs concerning the processes and commodities already described in the section 3.1.3.

The best fitting commodity to describe how the iron and steel sector is evolving in the upcoming years is the steel production by process; namely, for every steelmaking process, the yearly production rate is studied. An alternative could have been the installed capacity per process, but, if on one hand it interacts more directly with the capital cost evolution of the technologies (the marginal of the installed capacity, or newly installed capacity, represents the main driver of the learning curves), on the other hand it does not reflect the real evolution of the sector.

In fact, it has been noted that the model sometimes does not completely exploit the availability factor of the installed plants, for many possible reasons; the most common is that, when a new, more economically convenient technology is introduced later in the future, the model prefers to invest on new plants of this technology through which enhance the production, rather than running already existing plants of more obsolete technologies. Obviously, this is not a prevalent phenomenon, but in some circumstances, the installed capacity may show some delay in describing the evolution of the sector.

Moving to the structure of the section, a first sub-section (4.2.1) will describe the general trends within the sector, outlining the premises of the next ones, when the research questions will be answered in two steps: in fact, in subsection 4.2.2 the first research question is addressed, being the impact of the learning showed with all its uncertainty on the sector evolution - with a possible justification connected to the capital cost evolution shown in subsection 4.2.3. In 4.2.4, instead, the influence of the learning levels on the production rates of the different technologies is explicitly shown, focusing on the main point of the second question; finally, the evolution of the emissions, as a consequence of the previous subsections, will be shown in the last one, 4.2.5.

4.2.1 Future trends

One of the focuses in the research questions regards the impact of the technological learning: in other words, the difference between the learning scenarios and the non-learning scenario assesses the importance of learning for the penetration of a technology. In order to understand the general trend of the learning scenarios, which are many and very different, their results were averaged and are reported in the Figure 4.2. The comparison with the non-learning scenario is present, with the latter represented by the dashed lines.

From a first glance, the decarbonization of the sector in the short term immediately appears quite challenging: the model, in fact, covers most of the demand until 2050 with HIsarna-BOF, an innovative but still fossil-based technology, and the remaining shares with traditional, fossil-based technologies, mainly blast furnace and steel from scrap. However, from 2040, small efforts in this sense start to come out: both BF-TGR-BOF and hydrogen direct reduction (in particular, blue hydrogen), take a not negligible portion of the market, 2.5-3% the former and 2-3.5% the latter, depending on the considered scenarios.

However, it is only after 2050 that the two already mentioned technologies start to cover a more relevant portion of the global production: in 2055, around 650 Mt of crude steel (26% of the global demand) are produced using hydrogen direct reduction, while 180 Mt_{CS} (8% of global demand) come from the top-gas recycling with CCS technology applied to the traditional BF-BOF, significantly reducing its emissions.

Their increasing importance in the production share is coupled with the decreasing share of steel coming from fossil based processes, both innovative and traditional. This transition phase, where CCS technologies are used directly (through BF-TGR-BOF) and indirectly (through steam reforming with CCS used to produce the hydrogen addressed to the direct reduction) to decarbonize the sector, ends around 2070, when electricity-based technologies start to cover a significant portion of the sector.

Indeed, from 2070 (or even earlier in some scenarios), both Ulcolysis (process based on the electrolysis of iron ore) and hydrogen direct reduction using hydrogen from electrolysis become more and more important. In this phase, however, the impact of the more strict emissions policies on the industrial sector is visible already in Figure 4.2, as in the scenarios without sector specific emissions constraints, the production via Ulcolysis reaches at most

100 Mt of crude steel per year, while by including the latter, around 1000 Mt_{CS} can be produced with this process.

Also the learning, on a first analysis, results to have an impact on the development of these two last technologies; however, this aspect will be deepened in the next sections.

4.2.2 Uncertainty analysis

As underlined in the research question, another important goal of the paper is to take into account, in the analysis of the impact of the technology learning, the uncertainty that such phenomenon incorporates intrinsically. Therefore, a new element needs to be quantified: the differences in penetration among the different learning scenarios, which indicates how impacting is the level of the learning for the future investment choices.

In designing the graph in Figure 4.3 and 4.4, the technologies have been clustered, into four main categories, in order to have a clearer result in terms both of visual rendering and of delivered message.

- Traditional, non-learning technologies
  1. BF-BOF
  2. DRI-EAF
  3. Scrap-EAF
- Fossil-based, learning technologies
  1. SR-BOF
  2. HIsarna-BOF
- CCS-based technologies
  1. BF-TGR-BOF with CCS
- Hydrogen and electrolysis-based technologies
  1. HDR-EAF
  2. GHDR-EAF
  3. Ulcolysis

The graphs in Figure 4.3 and 4.4 show the different learning scenarios with dashed lines, and the colored areas represent the uncertainty generated by the different learning levels. The non-learning scenario is also present and highlighted with a thicker line, with comparative purpose.

Starting from the scenarios without sector-specific emissions constraints (Figure 4.3, the behavior of the different clusters of technologies is quite defined until 2060, with a very slow increase in production share by hydrogen and electrolysis-based technologies, and by the only CCS technology; however, after 2060, together with a strong increase in share of the former, the dependence on the learning level starts to become relevant:

in 2070, some learning scenarios show hydrogen and electrolysis-based technologies to become the predominant cluster in the market, while other scenarios place them at a level which is only slightly higher than the half of the production from smelting reduction-based processes. Even the latter is characterized by a high dependence on the learning level in the last three decades. However, the learning of these technologies is not subjected to any uncertainty analysis (the learning rates are changed only for CCS and electrolysis-based ones); thus, most probably, it is a consequence of the uncertainty on the production from electrolysis and hydrogen-based technologies, which is also quite large in the last decades of the century.

At the contrary, CCS-based and traditional technologies are only poorly influenced by the level of learning of any technology.

Analyzing the uncertainty internally to the clusters (at the bottom of Figure 4.3), it is possible to see how for the electrolysis and hydrogen-based technologies, it is mainly driven by Ulcolysis: this means, again, that Ulcolysis development is strongly dependent on the learning level of some technology.

For what concerns the scenarios with sector-specific emissions constraints (Figure 4.4) a similar figure can be found, with poor dependence of the sector development from the learning levels until 2055; in this case, however, the predominance of hydrogen and electrolysis-based technologies is much more evident, as takes place in most configurations of learning levels from 2060, and in all of them from 2070. However, in case of low learning level of such technologies, they are partially substituted, especially between 2065 and 2080, by steel from scrap processes, which represent a traditional, yet relatively low-carbon alternative.

Also in this case, the dependence of the CCS-based technologies on the learning levels is very poor.

4.2.3 Costs evolution

In the previous section it was shown how different levels of learning produce substantial differences in terms of share for some technologies (Ulcolysis, but not only), while other technologies have a diffusion that is almost independent from learning (CCS, some traditional technologies). In this section, the goal is to explain these differences. The main driving factor is expected to be the reduction in capital cost driven by the investments performed on each technology, as it represents the main difference between the learning and non-learning scenarios (and among the different learning scenarios).

In Figures 4.5 and 4.6 the four main learning technologies are analyzed in their investment cost evolution over time in the different learning scenarios. The curves are built by combining two curves: the learning curves presented in the appropriate paragraph in Methods part (3.2.3) and the investments performed on each technology over time (computed as described in 3.2.3).

The cost curves highlight strong differences in cost reduction between different technologies. HIsarna, Green HDR and especially Ulcolysis present high potential cost reductions (respectively, around the 30-32%, from 17 to 38% and from 48 to 96% on the total capital cost from 2020 to the end of the century), due to the innovative component covering a large portion of the capital cost. On the other hand, top gas recycling with

CCS component is minor with respect to the total capital cost of BF-TGR-BOF, producing a low cost reduction potential in the technology (around 3-6% on the total capital cost). This is most probably why, while Ulcolysis and Green HDR penetration in the steelmaking market strongly depends on learning, the CCS technologies have almost no substantial benefits from the investments on them. Being based on traditional, already established processes to which additional devices are installed for the carbon capture, they will always be more capitally expensive than traditional technologies. Thus, they may represent a good alternative in the case of tight policies on emissions (e.g. high carbon taxes), but poor electrification of the system, which is rather pushing the development of electrolysis-based technologies (Green HDR and Ulcolysis).

Therefore, as expected, the investment cost reduction (influenced by the new investments on the technology) represents the main driver to the sector evolution differences among the learning scenarios.

4.2.4 Learning rate influence

In the previous subsections, the learning scenarios have been compared in a "monodimensional" way, without putting into explicit correlation the learning rate variations and the results. This subsection, instead, has exactly this purpose, as it targets the final research question, which puts the accent on the individuation of the technologies which can drive in the most effective way the decarbonization under learning conditions.

The analysis will be focused on those technologies which showed the highest levels of uncertainty in subsection 4.2.2, as, for those which did not show relevant uncertainties, an analysis on the learning parameters influencing the results would not provide any significant insight. For a similar reason, only the results from the second half of the century are shown: however, the similarity of the results in the first half of the century will be more thoroughly discussed in section **??**. Starting from the scenarios without sector-specific emissions constraints, the main technologies of interest are Ulcolysis and HIsarna-BOF, according to Figure 4.3.

The graphs in Figure 4.7 and 4.8 are built as 3D graphs with the two variable learning rates (for CCS and electrolysis-based technologies) on the x and y axis, and the yearly production rate per source on the z axis, in three different milestone years (2050, 2070 and 2095), with a comparison with the non-learning scenario (dashed line). Two graphs are produced, one for the scenarios without sector-specific emissions constraints, and one with.

The 3D graph in Figure 4.7 shows the strong dependence that both technologies production have with the learning rate of Electrolysis technologies, while the LR of CCS technologies has a very minor influence on the results. This means that the uncertainty correlated to the improvement of electrolysis-based technologies can determine huge differences for the penetration of Ulcolysis and HIsarna-BOF in the market: in fact, scenarios with high learning levels foresee a penetration of Ulcolysis in the market equivalent to the 9% in 2070 (200 Mt_{CS}/y) and 25% in 2095 (550 Mt_{CS}/y), which consequently reduces the penetration of HIsarna, while scenarios with low learning predict a nearly zero penetration of the former, and an unvaried production of the latter with respect to non-learning scenario.

On the other hand, the uncertainty correlated to the development of CCS technologies does not produce almost any difference in the evolution of both technologies.

Moving to the case with sector-specific emissions constraints, instead, the technologies of interest were individuated in Ulcolysis and steel from scrap, according to the Figure 4.4.

Moving to the analysis of the results in Figure 4.8, some similarities, as well as some differences with Figure 4.7, can be underlined.

Starting from the latter, in the scenarios with sector-specific emissions constraints, the penetration of Ulcolysis in the second half of the century is never as low as in the previous group of scenarios: this because the technology, independently on its capital cost, results to be vital for the sector decarbonization if tightening the carbon emissions policies strategies. Indeed, even in the non-learning scenarios, the technology covers around 10% of global production in 2070, and around 45% in 2095.

However, also in this case the main figure is represented by the positive impact that the learning rate of electrolysis-based technologies has on the steel production of Ulcolysis (around +100% in the high learning scenarios with respect to the low-learning ones in 2070) and the negative effect it has on steel from scrap processes (-30% in the same year, comparing the same scenarios).

Also in this case, the influence of the learning rate of CCS technologies is very poor: this result was expected, because, as it does not influence the penetration in the market of the CCS technologies themselves, the other technologies will not be affected.

4.2.5 Sector emissions evolution

If in the previous subsections the research question was treated with a view to the technologies to invest in, implicitly dealing with the impact that they may have on final emissions, this subsection has the role of speaking explicitly about the impacts on emissions in the sector.

Again, the graphs for analyzing the correlation between emissions and learning are built as 3D surface graphs, with the same characteristics as the ones shown before with the production rates. In the graph in Figure 4.9, the sector emissions are reported on the z axis, in four different milestone years (2035, 2050, 2070 and 2095).

In 2019, according to IEA, the global emissions from the iron and steel sector amounted to 2.6 Gt_{CO2}; at the same time, the emissions in the very short term are projected to grow due to the increase in demand in the next decades, especially in China [1].

These elements are perfectly reflected in the results shown in Figure 4.9. In fact, in 2035, a peak of 2.8 Gt_{CO2} of emissions is expected in all the scenarios, independently on the strategies taken under the policy and technological development point of view. This is due to the fact that industrial sector, and specifically iron and steel sector, are extremely hard to decarbonize, as it will be shown in subsection **??**.

2050, however, will represent a turning point for the development of the sector: in fact, the impact of a tighter strategy on emissions policy for the industrial sector, would lead to a reduction of the emissions of a 10%, while not applying such policy would make emissions stagnate on levels similar to 2020 (Figure 4.9).

If until 2050 the impact of technological development of innovative technologies remains quite secondary with respect to the role of emissions policy, in the second half of the century this trend changes disruptively. Indeed, from 2070 the emissions result to be extremely variable depending on the level of learning of technologies, in particular of electrolysis-based ones.

In fact, scenarios in which a high level of learning is assumed for electrolysis-based technologies finds a reduction of emissions of a 43% with respect to the current levels, while only a 31% would be obtained with low learning. However, if the technological development of such technologies is coupled with an emissions strategy aimed at containing industrial sector emission, the results become even more relevant: the iron and steel sector emissions would be reduced of a 75% in case of high level of learning, and of a 47% in case of low learning.

At the end of the century, the lowest levels of emissions are obtained, being the emissions constraints at their tightest level: if not formulating a sector-specific emissions strategy, the emissions slightly overcomes the 1 Gt_{CO2}/y (62% in reduction with respect to 2020) in case of high learning level, while in case of low learning, the emissions remain on similar values as in 2070 (-33% of 2020 emissions). Instead, in presence of sector-specific emission strategies, the emissions variate from 0.45 Gt_{CO2}/y (-83%) to 0.6 Gt_{CO2}/y (-77%).

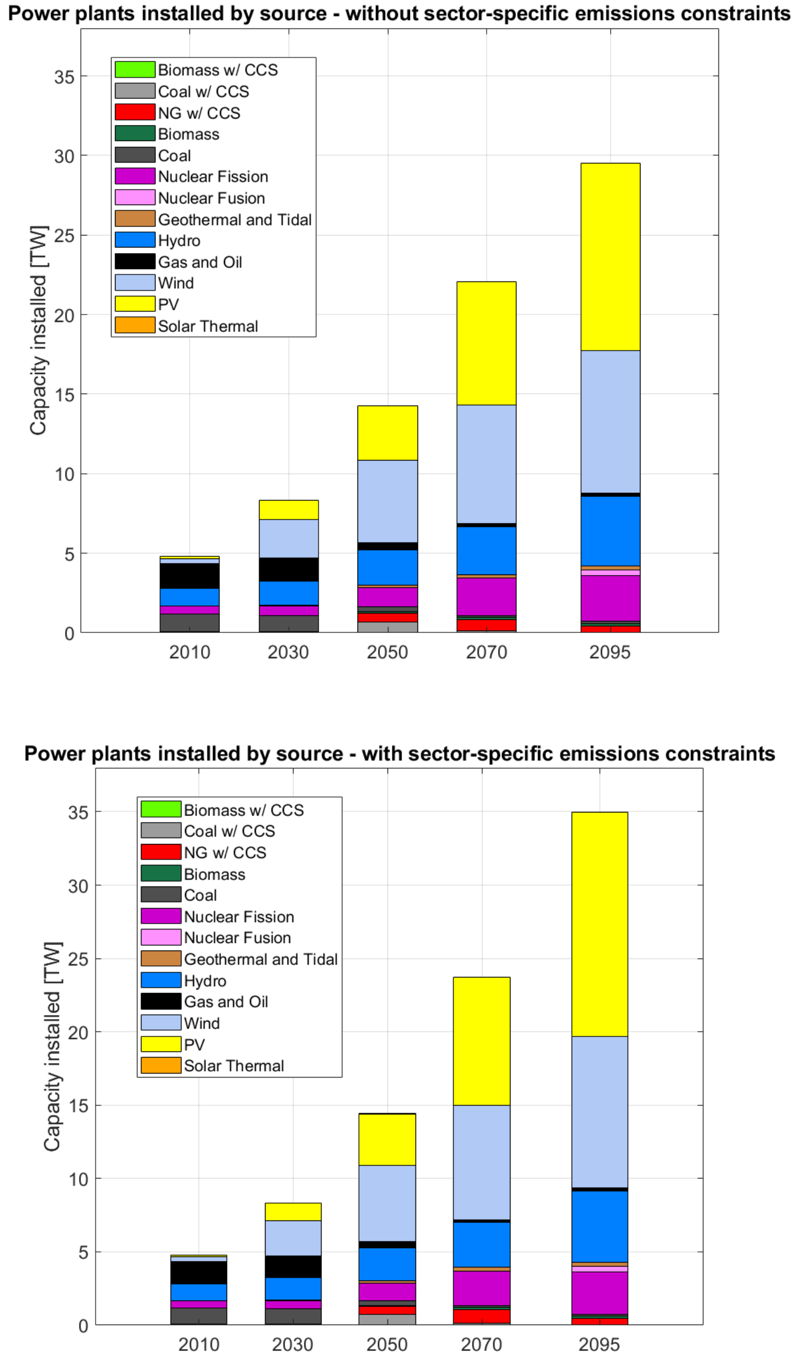

Figure 4.1. Power plants capacity installed per source in five milestone years

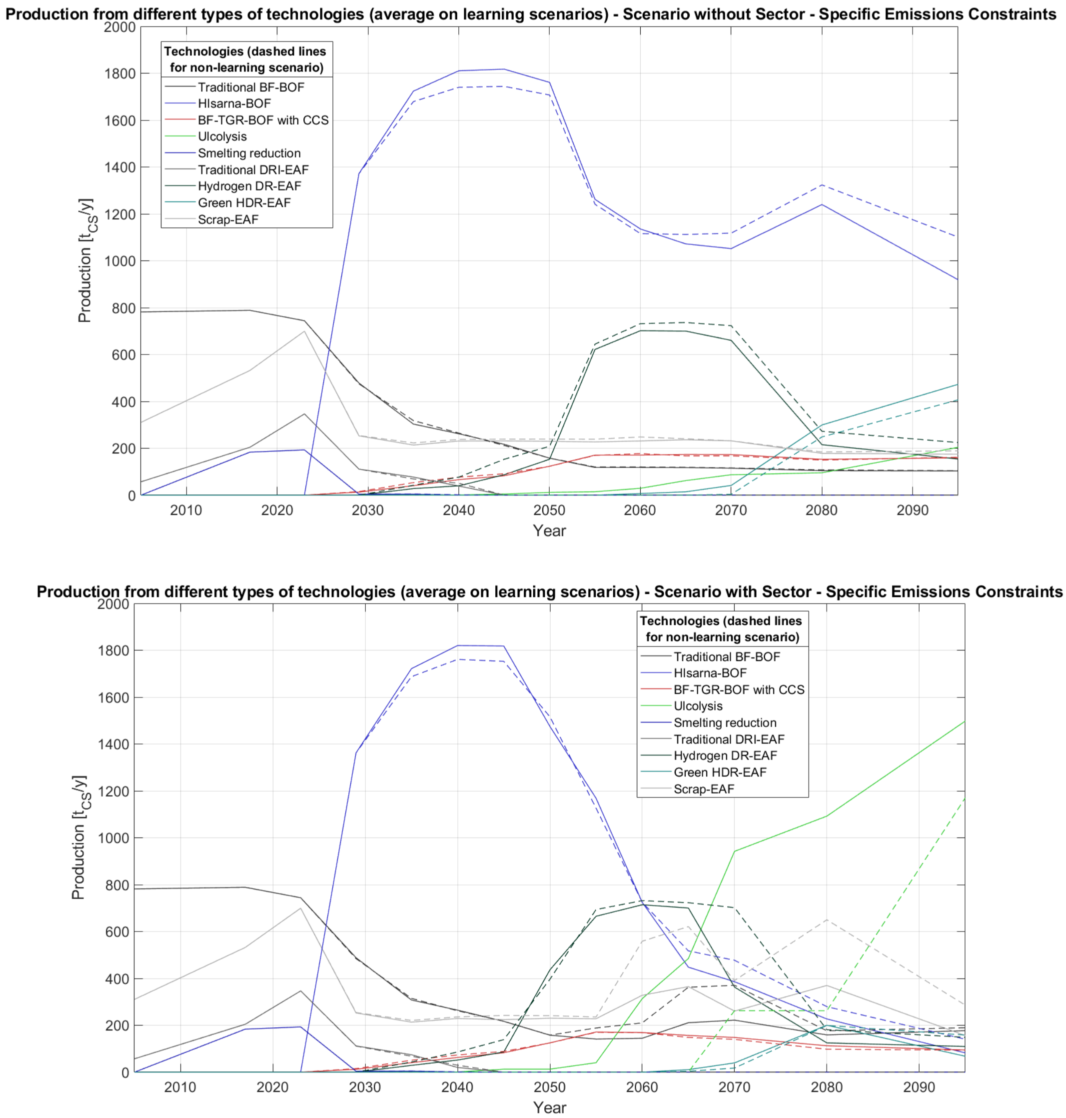

Figure 4.2. Steel production mix, general trends

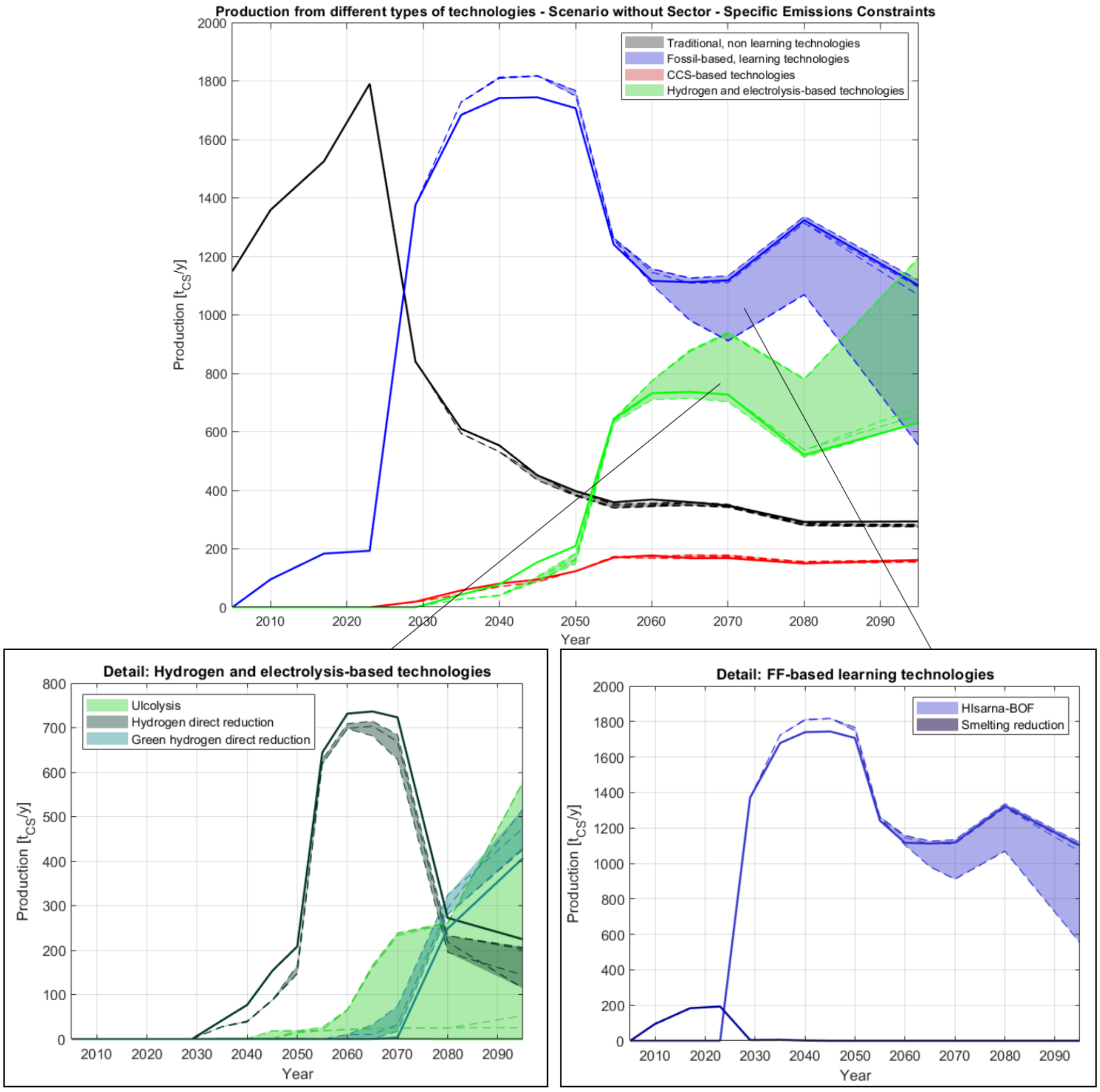

Figure 4.3. Steel production uncertainties without emissions constraints

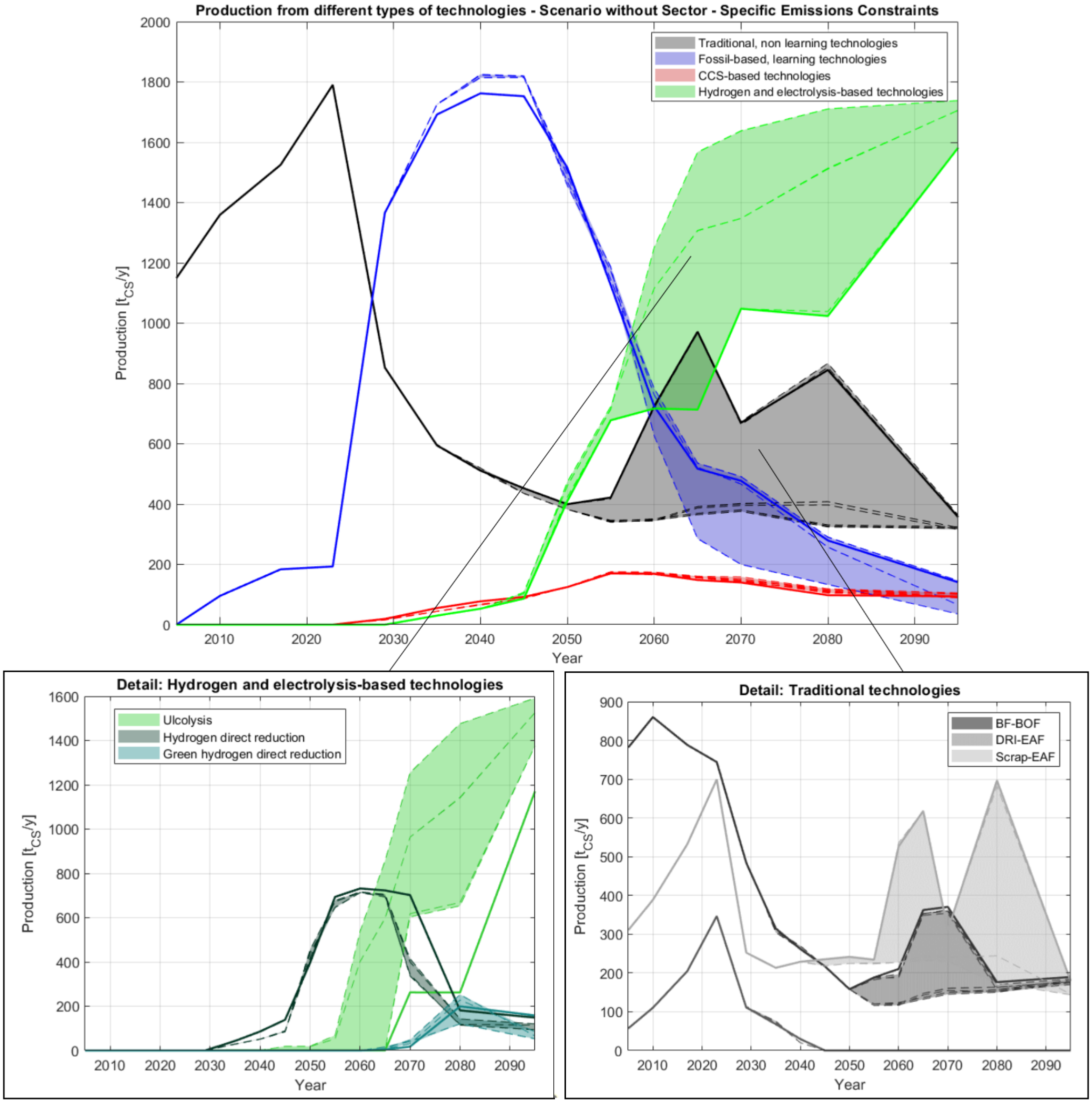

Figure 4.4. Steel production uncertainties with emissions constraints

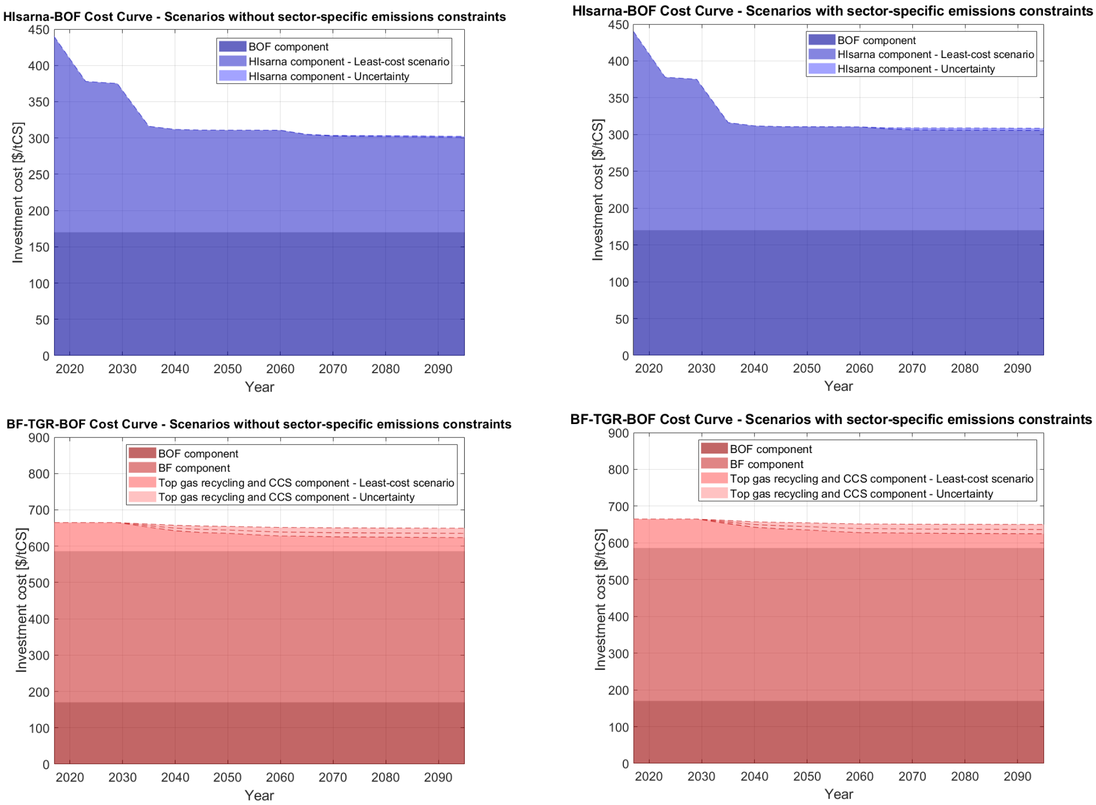

Figure 4.5. Cost curves of HIsarna-BOF and BF-TGR-BOF with CCS, in the two scenario types

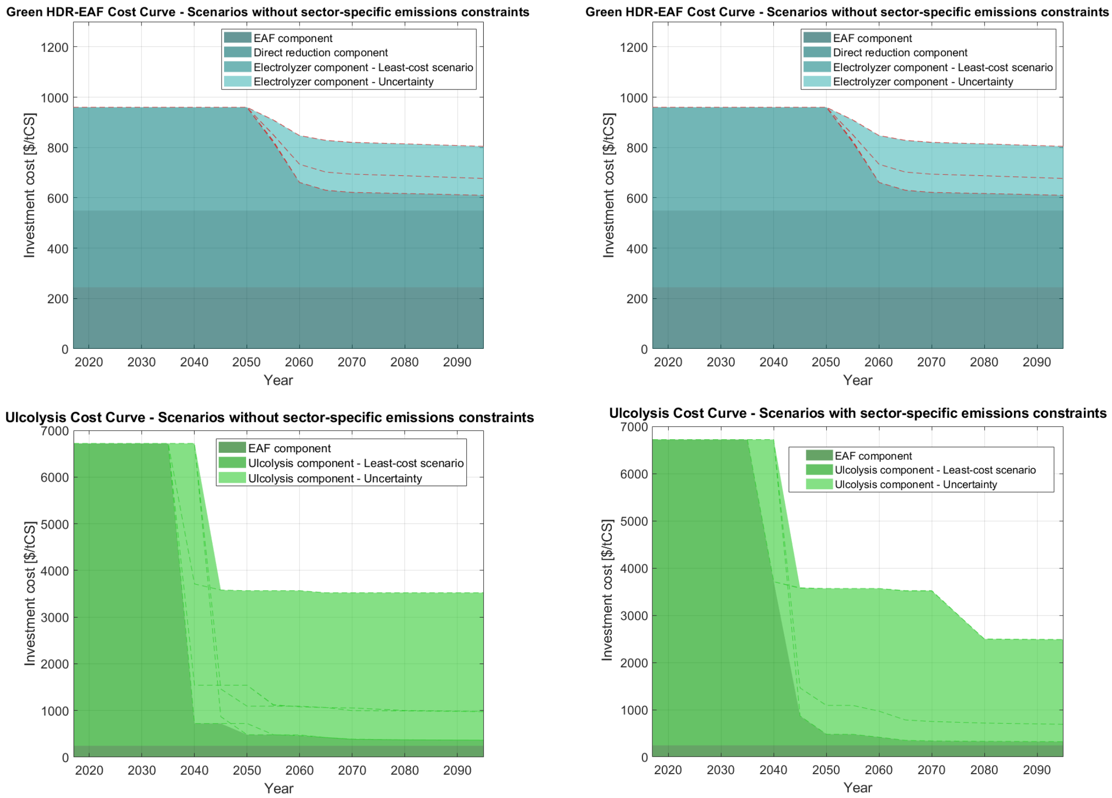

Figure 4.6. Cost curves of HDR-EAF and Ulcolysis, in the two scenario types

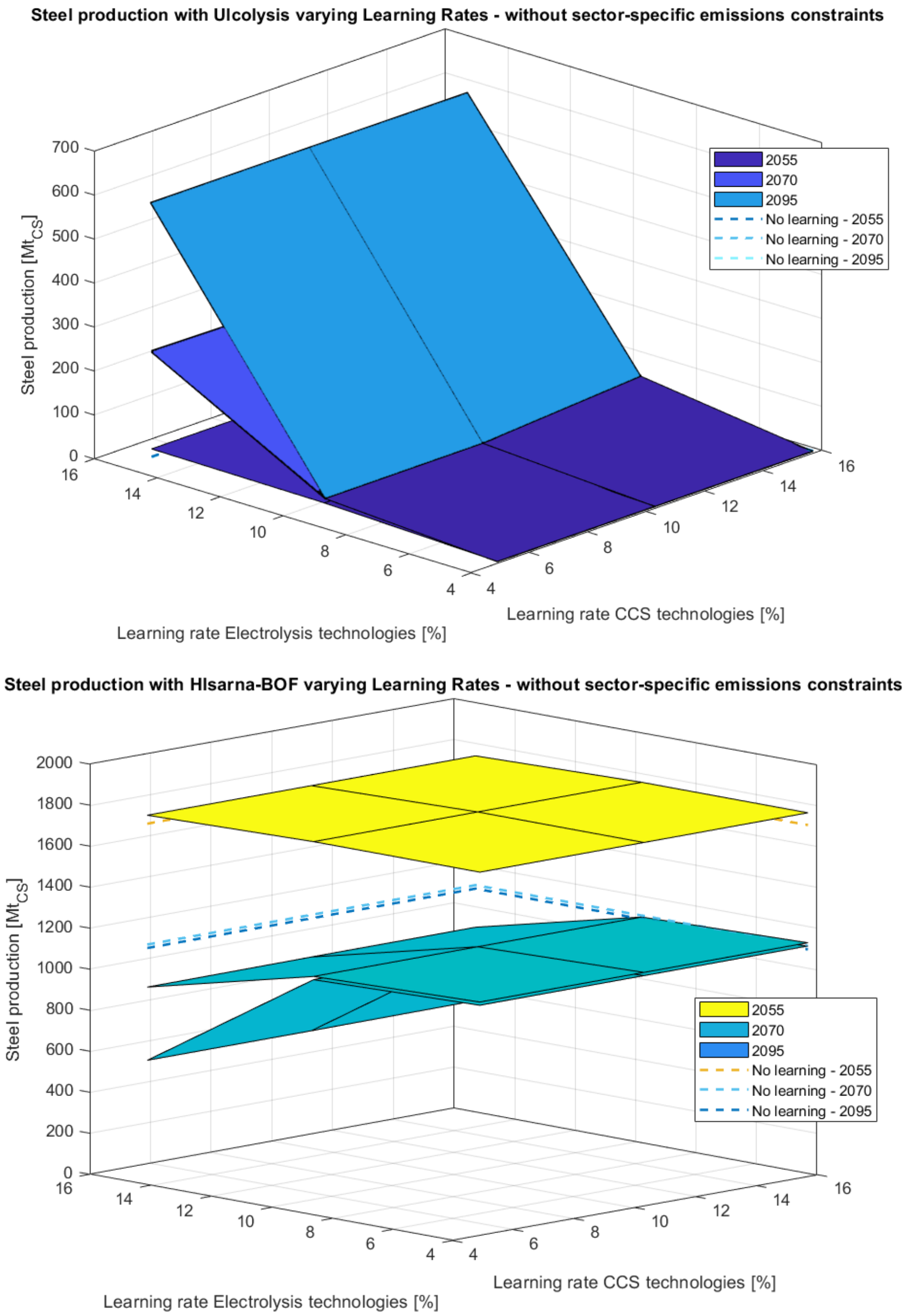

Figure 4.7. Production rates for Ulcolysis and HIsarna-BOF varying the LRs

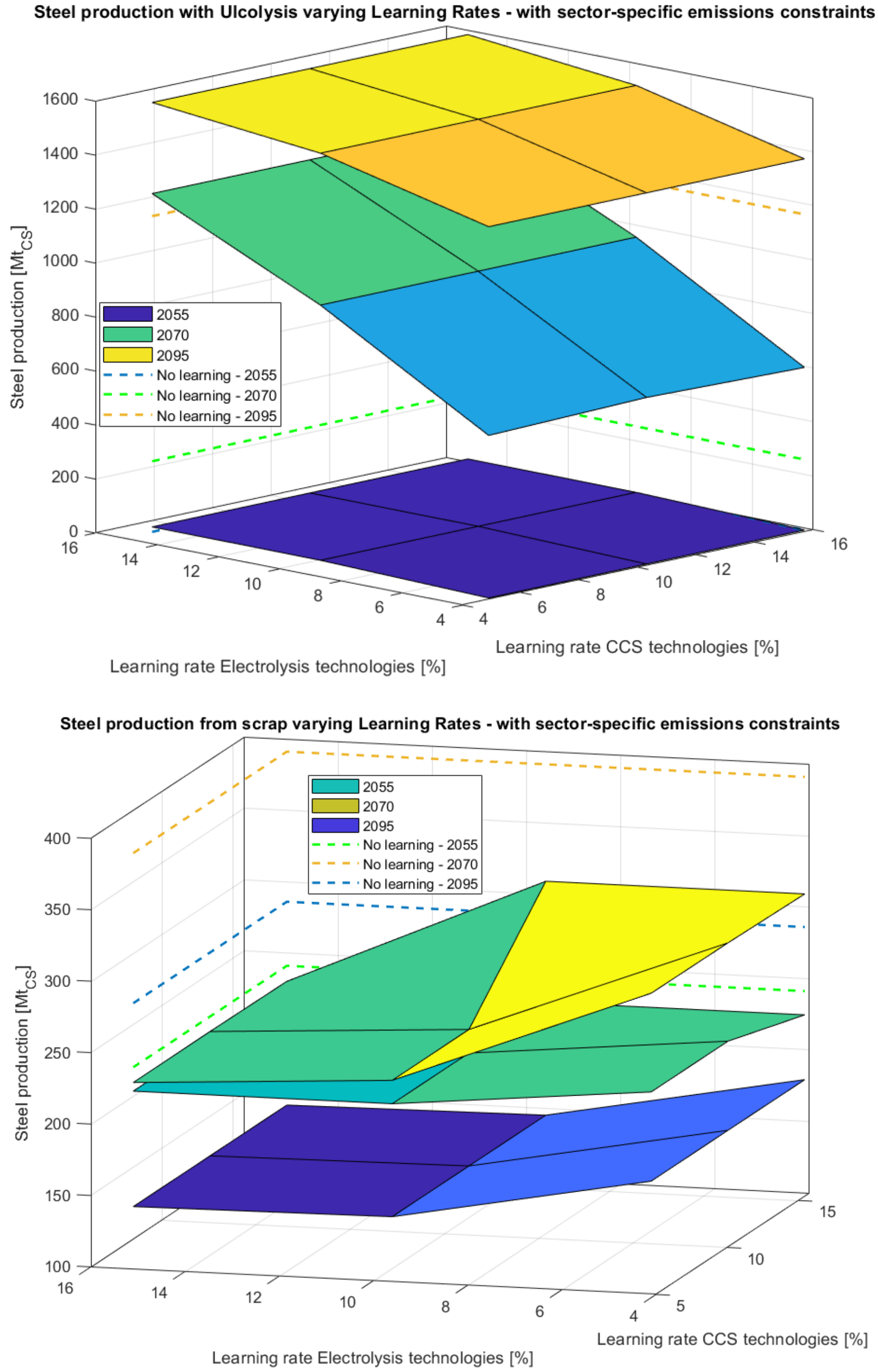

Figure 4.8. Production rates for Ulcolysis and Steel from scrap varying the LRs

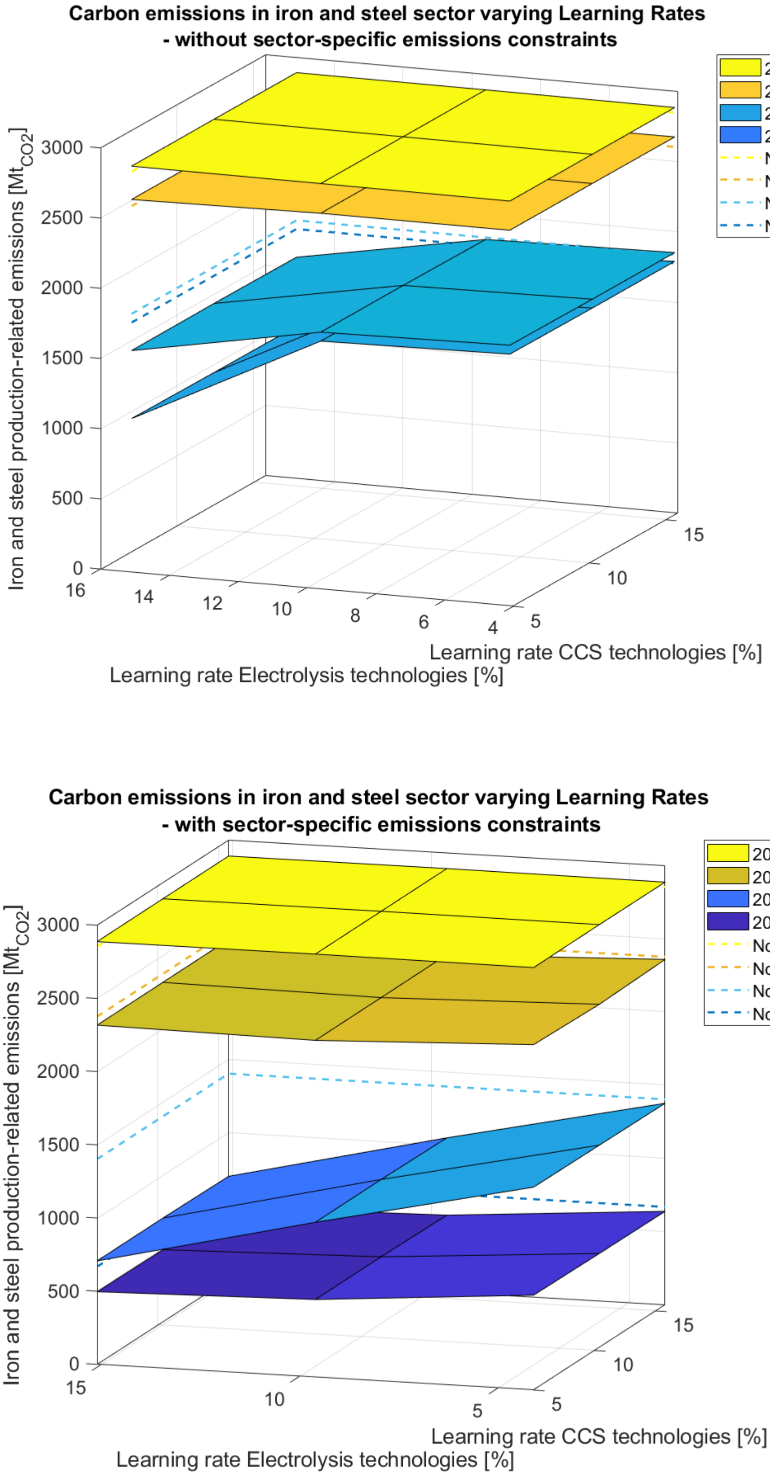

Figure 4.9. Sector emissions without and with sector-specific emissions constraints

Chapter 5

Conclusions and future perspectives

The purpose of the current work was to understand if the iron and steel sector decarbonization could be affected by the investments on innovative technologies, taking into account the uncertainty that characterizes the correlation between the investments on a given technology and its performance improvement. In addition, the most promising technologies in this sense were expected to be individuated, in order to deliver a more meaningful message to policy-makers.

After having chosen an appropriate energy system model to solve the problem (EURO-Fusion TIMES Model) and a learning model (curve correlating investments on a technology and its performance evolution over time, in particular the one theorized by Wright), the latter was applied on the iron and steel sector of the former, after having characterized it.

The results showed that the iron and steel sector decarbonization can be positively influenced by the improvement of innovative, carbon-free technologies depending on the investments performed on them, but only in the long-term. In fact, until 2050, at least the 70% of the global production will be provided through fossil fuels-based processes. This figure is coherent with the results obtained by IEA for 2050 projections in the latest Technology Roadmap [1], and is due to several different reasons: first of all, the electrification of the energy system becomes predominant in the second part of the century (in 2050, the use of fossil fuels is still higher than the electricity in the final demand). A second factor regards the higher investment cost for electricity and hydrogen-based technologies in the iron and steel sector with respect to the other ones: as an example, electrolyzers become a commercially-widespread solution around 2045, but the output hydrogen is rather used in other industrial processes, such as ammonia production, while its use is introduced for the production of iron and steel only two decades later. This brings as a consequence that emissions in the iron and steel sector can reduce, by 2050, of a maximum 10-11%, while in the industrial sector emissions reduce of almost a half with respect to the current values. Finally, 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.

In this framework, having ascertained that the influence of the technological improvement of the less carbon intensive processes is rather limited by 2050, it is clear that only ad-hoc policies could help the decarbonization of the sector in the short term. For example, a solution to be evaluated could be the introduction of an appropriate emission trading scheme designed specifically for the steel sector. Alternatively, by exploiting the presence of CCS alternatives to all technologies based on fossil fuels, it could be necessary to include this type of technology on all new plants installed. Although both solutions are rather impactful and difficult to accept by a sector whose market is extremely elastic, being its decarbonization quite difficult for the reasons explained above, there are few alternatives given the current state of the market and the limited time available.

After 2050, instead, the production shifts towards less carbon-intensive solutions, such as electrolysis of iron ore and green hydrogen direct reduction, but depending on the assumed level of learning and on the presence or not of sector-specific emissions strategies. In fact, the decarbonization of the sector is driven by two main factors, namely the capital cost reduction of the innovative, less carbon-intensive processes and the rising cost of fossil-based alternatives due to the emission costs. As a consequence, in order to maximize the decrease of sector emissions, a proper industry-specific emission strategy must be designed, as well as the technological improvement of electrolysis-based technologies must be maximized. In fact, due to their higher cost reduction potential, these technologies present a strong dependence on the level of learning. Instead, the influence of the technology learning level of CCS technologies, whose potential cost reduction is much lower, is almost irrelevant. These figures are also coherent with the pathway designed by ULCOS project, which defined electrolysis-based technologies as key ones in the long term, while CCS technologies result to be more useful in the transition period [7]. In fact, a low influence of learning on the spreading of CCS technologies does not indicate that they may not play a role in the decarbonization of the sector.

A further development to this work may be represented by a policy-oriented analysis of the decarbonization of the sector, in order to understand what strategies could help in such purpose, especially in the short and medium term, when the impact of technology development is reduced. In particular, it may be interesting to focus on the CCS technologies, which covered only a marginal role in this analysis, but which could be extremely useful in the short term.

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Appendix A

Regions in EUROFusion TIMES Model

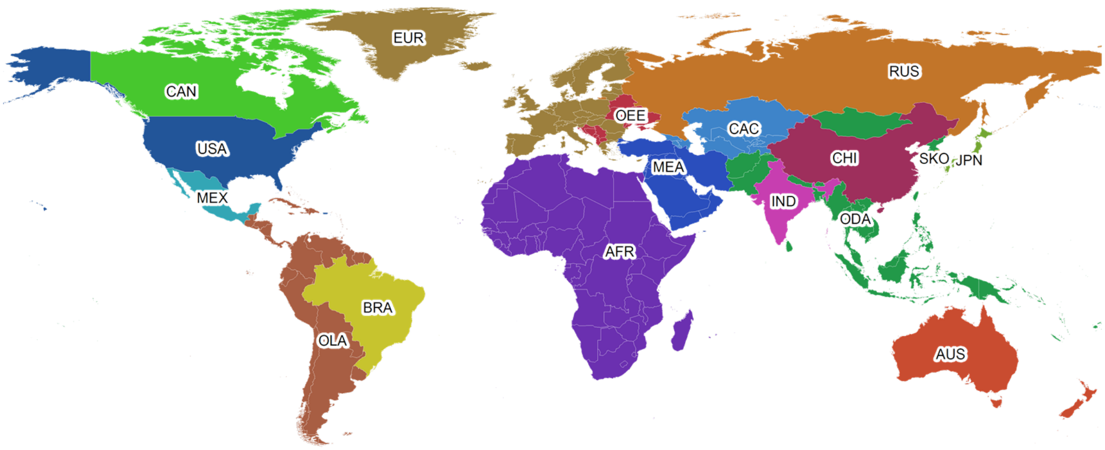

Figure A.1. Macro regions in ETM [6]

Abbreviation	**Region**
AFR	Africa
AUS	Australia and New Zealand
BRA	Brazil
CAC	Central Asia Countries
CAN	Canada
CHI	China
EUR	Western Europe
IND	India
JPN	Japan
MEA	Middle−East Asia
MEX	Mexico
ODA	Other Developing Asia countries
OEE	Other Eastern Europe
OLA	Other Latin America
RUS	Russia
SKO	Korean Peninsula
USA	United States of America

Table A.1. List of macro-regions in ETM [6]

Appendix B

Innovative aspects of learning sub-technologies

This appendix has the aim to show why the learning is assumed to be possible for the groups of sub-technologies individuated in Table 3.5; in other words, what technological improvements would guide their potential cost reduction.

B.1 Smelting reduction

Despite it is a technology that is already mature, with several large-scale plants installed worldwide, it has several points that need to be improved in order to increase its cost-effectiveness, starting from some lack of theoretical knowledge on the process, to more practical aspects. [47]

In fact, the stratification of the slag inside the melting-gasifier is poorly known, and it would be extremely important to understand how the different layers interact between themselves and with the operation conditions. By understanding fully the process, a more optimized design of the melting-gasifier could be realized, decreasing the investment cost (computed per ton of output) of this type of plants. [47]

Other problems observed in COREX plants concerns the air vent, which usually 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.[47] [48]

Finally, further scale-up would furtherly reduce the costs, even if MtCS/y-sized plants already exist worldwide.

B.2 PSA-based CCS technologies

The pressure swing adsorption-based carbon capture and storage technologies represent, as previously explained in the technical characterization, an innovative alternative to already-established CCS technologies, as the amine-based ones. In fact, they bring some evident advantages, such as the lower energy consumption, a lower environmental impact of the sorbent used, and less amount of sorbent itself used for the process [59]. By comparing PSA-based CCS and relative amine-based counterparts, however, it is possible to notice that the former show lower electrical efficiencies and CO_2 recovery [46]. This last problems show potential solutions which could enhance its technological attractiveness: by rising the input temperatures, the gas cleanup could be performed with less energy losses, rising the overall efficiency [46]; in substance, an evolution of PSA-based process towards the same direction as SEWGS-based ones, would push their penetration in the CCS market. This is another reason why, PSA-, VPSA-, and SEWGS-based processes have been coupled.

B.3 Cryogenic distillation-based CCS technologies

As previously said, cryogenic distillation presents problems mainly in terms of high energy expenses for the cooling of CO_2 to condensation temperatures. However, alternative strategies can be applied to reduce the consumption of energy, such as cyclic distillation, heat-integrated distillation column, reactive distillation and thermally coupled columns. All 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 [60]. In addition to operative expenses savings, the scale-up would bring significant reductions to the overall investment cost of the CCS system.

B.4 Electrolysis

The electrolysis is the technology that, differently from the others, show a very high learning potential in different parameters, as a consequence a further distinction has been performed in this sense:

B.4.1 Electrolysis investment cost

According to different studies [49] [50] [51], the investment cost of a PEM electrolyzer shows potential reductions in the following components:

Flow fields and separators

- They covered almost 30% of cost
- Separators designed according to the minimization of entropy generation (using CFD simulations)
- For this reason, they are subjected to a continuous design improvement, which (around 40% reduction in cost from 2009 to 2015, with an enhanced production of hydrogen up to 15%); in this period, several improvements also under the material point of view have been performed (new manufacturing process, nitride coating), with also lower exposure to hydrogen over the lifetime, that ensures a longer lifetime

- Now it represents still the highest percentage of the total cost

Membrane electrode assembly

- It covered roughly 25% of the cost
- Price is highly driven by noble metals (in particular, PGM – platinum group metal – covers more than 50% of material cost); in more recent application, they are trying to stop using PGM, with a very sensible reduction in cost (and raw materials cost volatility)
- Catalysts play a very central role, as two of their characteristics should be enhanced: on one side, the OER activity should be improved, together with the process to enhance electronic structure, on the other hand, the conductivity should be improved as well; the aim of both these improvements is to increase the current density, which represent a vital source for cost reduction. Moreover, non-carbon supports should be individuated, manufacturing scale-up would drive to higher reductions in cost.
- The labor cost is also very high for manufacturing the electrodes, and can be lowered only through higher automation and quality control methods
- Membrane: 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

Labor

It covers a bit more than 20% of the total cost; it can be decreased through higher levels of automation

B.4.2 Electrolysis fixed O&M cost

Coherently with the research performed for the investment cost, in this section the fixed O&M cost decrease over time will be justified by analyzing the different factors that can be improved.

- Automation: a large part of fixed O&M costs in large-scale plants is represented by the labor, and in an increasingly automation-centered scenario, this component can be sensibly deceased;
- Characterization of degradation modes: part of fixed O&M costs in PEM electrolysis plants is supposed to be devolved in continuous activities of testing and maintenance, that is partially due to the poor scientific knowledge available about degradation modes and failure paths of such plants. [52] Improving the knowledge under this point of view could drive the fixed O&M costs to very low levels compared to the current ones;

- Durability of materials: various sources [52] [53] 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 [52] 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, differently from what had been done in steelmaking technologies, that do not present such cost reduction potentials.

B.4.3 Electrolysis efficiency

For what concerns the efficiency of the process, it is dependent by a large series of interdependent factors, that can be singularly improved, or whose configuration can be optimized to rise the efficiency.

First of all, when talking about the energy efficiency for electrolysis processes with temperature close to the ambient, it can be computed as "the ratio of the theoretical energy (H) to decompose water under equilibrium conditions (no current) to the real energy used (H + energy losses) to electrolyze water at a given current intensity" [54].

Mazloomi [53] individuated the following objects of study to increase the efficiency:

- Electrode: besides being one of the most important factors influencing the investment cost of an electrolyzer, electrodes can influence the increase in efficiency, by changing the material of the electrode, or the size and alignment, or the space between those (which should be minimized);

- Electrolyte: despite it is not largely affecting the total cost of the electrolyzer, the electrolyte is instead vital for determining the efficiency, and in particular its electrical resistance and quality are very important; by changing the electrolyte, Taner [55] obtained a sensible increase in the overall efficiency of a PEM electrolyzer;

- Separator material: the separator is responsible for a large part of power losses, being an obstacle to the free movement of electrons and ions, and being its electrical resistance much higher than the one of the electrolyte; however, several researches are focusing both on the material itself to reduce this double problematics, and on the pressure and temperature conditions to minimize the losses.

And, dependently on the choices above, some working parameters can be optimized, with the aim of maximizing the efficiency:

- Temperature: PEM electrolyzers work at 50-80°C; an increase of the temperature is usually beneficial for the efficiency, as the splitting reaction potential of water decreases, together with surface reaction and ionic conductivity of the solution, on the other side, the higher temperatures lower the durability of materials and their stress resistance;

- Pressure: it has a direct effect on the power losses due to voltage drops, that are lower when the electrolyte is compressed; however, newer researches are showing how, by compressing the inlet water, the a even higher gain in terms of efficiency increase can be noticed, both in the electrolysis phase (5%) and in hydrogen compression phase (50%) [53];

- Applied voltage waveform: applying a simple DC power supply lowers in a significant way 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 and contemporarily minimize the reduction of efficiency [52]). However, the majority of publications in this field agree with the fact that a sensible increase of efficiency is still expected: that is why, in this case, the increase of efficiency is modeled as part of the technology learning.

B.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 presents a high technology learning potential. In particular, the following points represent the major fields of potential improvement:

- Cell design: the cell designs performed until now based on three elements, namely the uniform distribution of current density, the steadiness of the process inside the cell and the low transfer resistance [56]; this goal is achieved in a study by Arcelor-Mittal [56], which however underlines how the design is strictly dependent to other problematic aspects, which, once optimized, could drive further modification in the cell design

- Input product: one recent study [57] compares different efficiencies of the process depending on the input product, between hematite, iron ore and iron-rich Bayer process residues; the result is that hematite and iron ore show better results in terms of electrolysis, however, further studies could assess that more precise concentrations of minerals inside the ore could further enhance the reactions;

- Electrolyte: in some experiments [58], one problem resulted to be the cell voltage (set to the minimum threshold for iron ore electrolysis), which, exceeding the thermodynamic threshold of decomposition of constituents of the electrolyte, did not allow to reach the expected theoretical results; as a consequence, some research has to be performed in this sense;

- Scale-up: all the current researches are set to build small scale plants, in the order of few kg_{CS}/day, while when increasing the size, further development to the process could be automatically implemented.

Appendix C

Technology learning methodologies

In this appendix, three different problems in modelling the technology learning are assessed: the approach used to externalize electrolysis, in order to study its development as a standalone process, the computation of the initial installed capacities for the different clusters of technologies presented in Table 3.5, and the operative details of the technology learning implementation.

C.1 Externalization of electrolysis from iron and steel sector

This subsection deals with the externalization of the electrolysis, from the iron and steel sector to the appropriate technology in the Hydrogen module.

C.1.1 Investment cost

The problem here is that data on electrolysis technology already existed both internally and externally to the sector. A key aspect, at this point, will regard how to deal with the conversion between the cost represented for the electrolyzers outside the iron and steel sector, and the cost inside it. For the first, in fact, the cost is expressed as \$/GJ (obtained as \$/kg$_{H2}$ divided by the specific energy of hydrogen – 120 MJ/kg), while for the latter it is expressed in \$/t$_{CS}$. At this point, the possible conversion could come by looking at the energy input to the HDR process (6.12 GJ/t$_{CS}$). It is possible to see how the cost looks to be coherent among the two: if we convert the cost of electrolyzers alone inside the model (78.15 \$/GJ in 2015) to the ironmaking process, we obtain a cost per tonne of crude steel equal to 479 \$, which is slightly higher than 411 \$/tCS (modeled inside the iron and steel sector by Lerede [19], but already referring to 2020, so the lower price can be explained in this way). In Figure C.1 it is possible to see how the prices previously input in the model are coherent with the price from literature within the iron and steel sector.

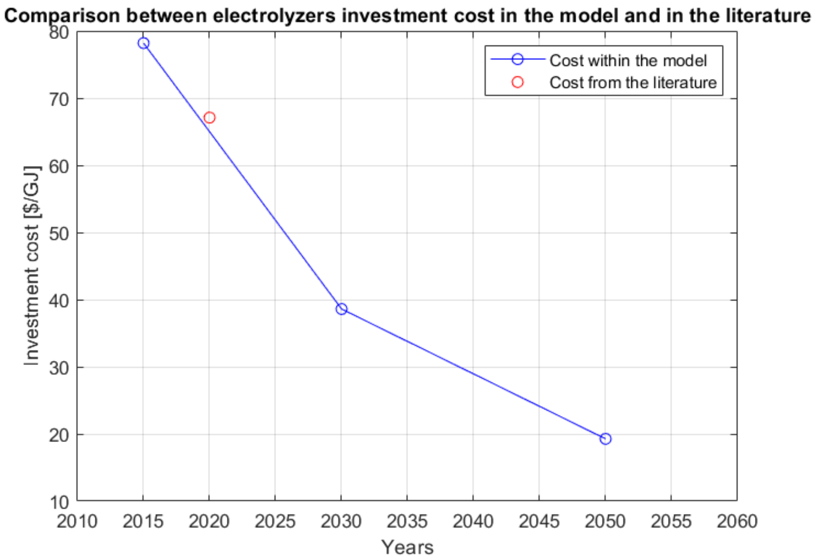

Figure C.1. Electrolyzers investment costs from model and literature

As a consequence, it was decided to start with the base year cost (2015) as in the model, and then to implement the technology learning starting from the year 2020 (this is a necessary approach in order to model the technology learning which has already taken place from 2015 to 2020).

C.1.2 Fixed O&M costs

In addition to the investment cost, for the electrolyzers also the fixed O&M costs have to be modeled. For what concerns the yearly fixed O&M costs, a similar reasoning to the investment cost has to be performed, and a coherent cost was also found here (Figure C.2)

A similar decision to the one for the investment cost is therefore taken for the fixed O&M costs evolution.

C.1.3 Efficiency

Finally, concerning electrolysis efficiency, it is modelled with a starting value of 80% in 2020, as proved in different papers [70] [71]. Obviously, the learning curve for efficiency has to be modelled in different ways; the most diffused one is to use the same curve as for capital costs, but with the residual to 100%, as shown in the formula below:

$$\varepsilon_t = 1 - (1 - \varepsilon)(\frac{\sum_{i=0}^{t} I_t}{I_0})^{\frac{ln(1-LR)}{ln(2)}} \tag{C.1}$$

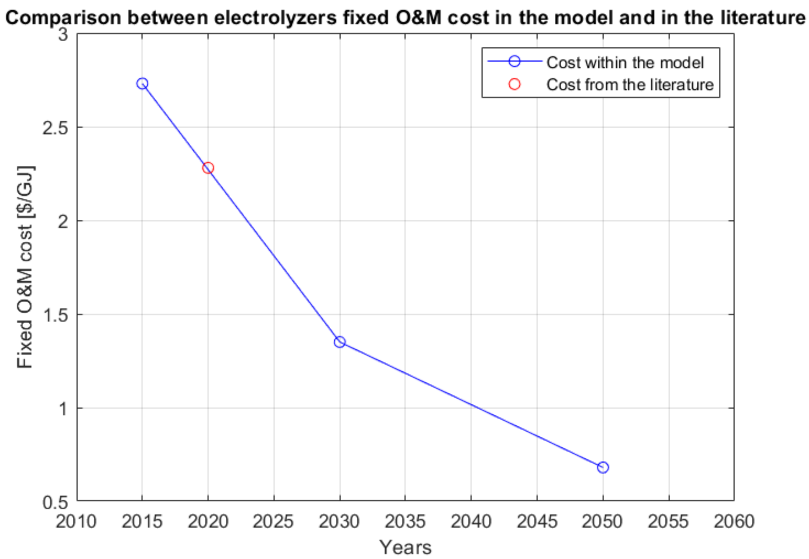

Figure C.2. Electrolyzers fixed O&M costs from model and literature

C.2 Initial installed capacity computation

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

C.2.1 Smelting reduction

For this technology, we evaluate the Corex© and Finex© investments, and from this we are going to evaluate the production of steel via these technologies; finally, a total capacity of around 11.45 Mt_{CS}/y [65] can be assessed, divided as follows:

- Corex:
  - 2 x C-2000 plants by JSW, India
  - 2 x C-2000 plants by Essar, India
  - 1 x C-2000 plant by ArcelorMittal, South Africa
  - 2 x C-3000 plant by Baosteel, China
  - 1 x C-2000 plant by Posco, Korea
- Finex:
  - Demo plant by Posco, Korea
  - 1 x F-1.5M by Posco, Korea
  - 1 x F-2.0M by Posco, Korea
- HIsarna: it is not included because not yet established (only a demo plant is planned to be built in next years)

C.2.2 CCS technology (physical adsorption)

For this technology, we are evaluating all the CCS-based plants in the world, looking which of them has this type of technology [61]. At the moment, the only CCS-based iron and steel plant which is active (no other plants are planned until 2025, year of start for all the CCS technologies within the model) is the Abu Dhabi CCS1 (DRI-EAF with CCS); for all the other technologies, we are looking also at other types of plants:

- 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, we can think 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

C.2.3 CCS technologies (cryogenic distillation)

In this case, the initial capacity has been computed accordingly to the data found in different papers reviewing the capacity installed of innovative CCS technologies [61] [64]:

- There is one planned plant by Tata steel for the integration of HIsarna with CCS to be built by 2022 (and within 2025 it is possible to suppose the building of the first demo plant, producing 0.5-1.0 Mt_{CS}/y);
- For what concerns other applications of the same cryogenics-based technology, we can find in China, Yulin, there is a 50.000 t_{CO2}/y capture facility

C.2.4 Electrolyzers

In this case, it was chosen as an introduction year of the technology 2020, as the most recent data for the cumulative capacity are dated 2019; according to IEA [63], in fact, the total installed capacity of PEM electrolyzers accounted 270 MW_e, equivalent to 0.27 GW_e

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

For this technology, we are taking into account the pilot plant which will be built within 2022, having no information about subsequent plants (and, in addition to this, it will probably be delayed, as the project is being seriously endangered by the current Covid crisis); it will produce roughly 50 kgFE/day = 18.3 tFe/y [36]

C.3 Exogenous learning technology: operative details

In this subsection, concerning operative details in the implementation of exogenous technology learning, two problems are assessed: the first regards the design of the convergence conditions for the iterative procedure, and the second one is describing in practice the implementation of the procedure.

C.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 overcomes certain burdens, another iteration is started, while in the opposite case the iterative procedure is stopped and the results analyzed.

Obviously, the results should be as similar as possible to the ones of the prior iteration in every time step; as a consequence, the check is performed on the results of every time step. In particular, the modular difference between two subsequent iteration is computed as in Equations C.2 and C.3.

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

$$RelErr_t = \frac{\sqrt{\sum_{i=1}^{num_{technologies}} (I_{t,i}^{n+1} - I_{t,i}^{n})^2}}{\sqrt{\sum_{i=1}^{num_{technologies}} (I_{t,i}^{n+1})^2}} \tag{C.3}$$

Where i indicates the technologies, and n the iteration number. The first check regards the relative error, which should be lower than a 5%; however, being in some time steps the newly installed capacity small with respect to the existing one, a check on the relative error would 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 of one order of magnitude) could be negligible. As a consequence, a double check system was designed: if the relative error check produces a negative result, then 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.

To sum up, the convergence condition is described in Figures C.3 and C.4.

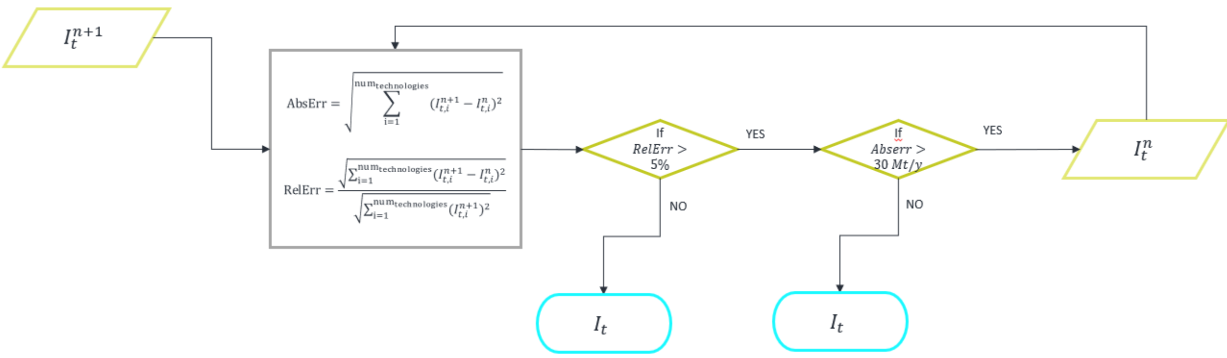

Figure C.3. Convergence criterion for steelmaking technologies

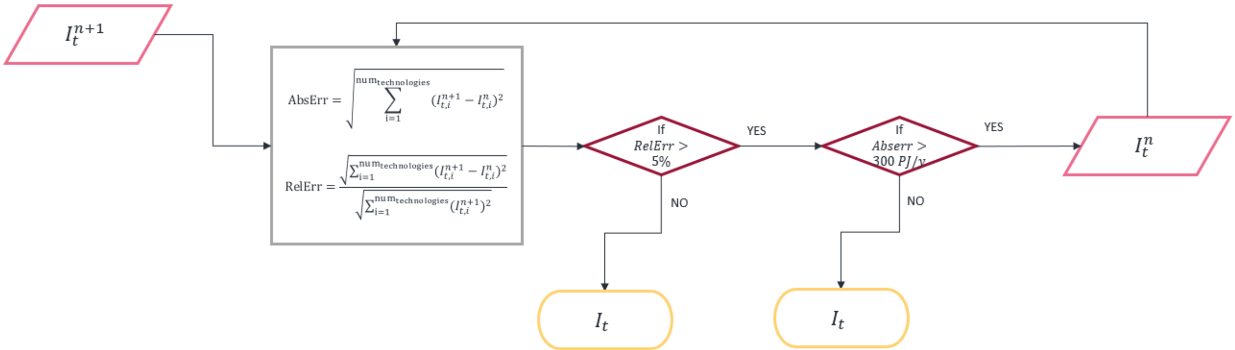

Figure C.4. Convergence criterion for electrolysis technologies

C.3.2 Operative implementation

The operative implementation of the described iterative procedure has been performed in the following way: obviously, the central point is represented by the EUROFusion TIMES Model, to which the learning curves are input by using two Scenario files, one concerning the steelmaking technologies, and one concerning the electrolysis technology. The model presents an input interface (VEDA-FE) and an output interface called VEDA-BE.

1. The procedure starts with the first run, where both scenario files are input with constant costs over time (no learning). They are imported in VEDA-FE, enabled in the co-called Case Manager (where the scenario files for the run are chosen), and the model is run;

2. The output of the run are imported in VEDA-BE;

3. The output data concerning the newly installed capacity (VAR_NCAP in VEDA-BE) are copy-pasted in an Excel file

4. The already mentioned Excel file takes the data of the newly installed capacity (time step per time step), and inputs those to the learning curves; on this point, a more technology-specific discussion is needed:

   - Smelting reduction: the newly installed capacity of Smelting Reduction, HIsarna-BOF and HIsarna-BOF with CCS are summed and input in the learning curve, without any further processing (the unit of measurements of the newly installed capacity in VEDA-BE is the same as the one of the installed capacity in the learning curve);
   - 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$_{CS}$, converted by using the capture rate of the different CCS technologies into Mt$_{CO2 captured}$/y, and summed: the result is input in the learning curve;

- 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} captured/y, and input in the learning curve;
- Electrolysis: the newly installed capacity of electrolyzers, in PJ/y, is converted into MW_e, and input into the learning curve;
- Electrolysis of iron ore: newly installed capacities of Ulcolysis and Ulcowin are summed and directly input (without any conversion) in the learning curve

5. The Scenario files, which are appropriately built to be input to VEDA-FE and are, with an link, connected to the already mentioned Excel paper, are updated with the outputs of the learning curves (namely, the updated unit capital costs);

6. The updated scenario files are syncronized and the model is run again;

7. The output data, imported in VEDA-BE and re-copied in the already-mentioned Excel file, are automatically checked inside the file itself, which compares the result of the current iteration with the ones of the previous one, giving as a result the relative and absolute error; if they respect the convergence condition, the procedure is stopped and the data in VEDA-BE are analyzed, otherwise, the procedure will go on, restarting from the point 4 of this list.