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Industrial Deep Decarbonization: Modeling Approaches and Data Challenges

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Abstract

Industrial energy consumption represents almost 40 percent of current global total final consumption and is still dominated by fossil fuels. In this paper, we present key decarbonization options—namely fuel switching and electrification, carbon efficiency, material efficiency, carbon capture and storage, and circular economy practices—and analyze their potential for decarbonization in six main energy-intensive industrial sectors: steel, cement, chemicals, light manufacturing, aluminum, and pulp and paper. We then develop a framework to distinguish among the different modelling approaches to industrial energy demand and emissions, with specific focus on the data challenges that constrain modelling and the difficulties of modelling innovation and technology diffusion. We present the most widely used models of industrial energy demand and emissions and classify them along three key dimensions: the analytical approach underlying each model, the methodology used to generate decarbonization pathways, and the granularity with which different industrial sectors be represented. By highlighting the strengths and weaknesses of available tools for industrial emission modelling, we point to necessary future model development efforts that would greatly improve the ability to develop deep decarbonization pathways for industry.

Contents

1. Introduction

Increasing carbon efficiency and switching to carbon-neutral technologies for industrial production are imperative to achieve deep greenhouse gas (GHG) emissions reductions and to address climate change, as well as to ease concerns regarding energy security and higher energy prices. Energy consumption by the industrial sector represents almost 40 percent of current global total final consumption and is still dominated by fossil fuels, in particular coal. In 2021, industry was the second-largest emitting sector, after power generation, and was directly responsible for emitting 9.4 gigatonnes (Gt) of CO_2. This estimate, which is equivalent to a quarter of global emissions, does not include indirect emissions from electricity used for industrial processes (IEA 2022c). Industrial energy and carbon intensities vary significantly across sectors as well as within sectors across different countries, with six sectors emerging as particularly energy- and emissions-intensive (see Section 2).

The aim of this paper is to describe the most common approaches to the modeling of industrial emissions, with a particular focus on the ability of available models to depict the different mitigation options relevant for energy-intensive industries. These options range from increasing energy efficiency to developing and deploying novel negative-, zero-, or low-emissions technologies. Importantly, producing quantitative forecasts of industrial energy demand and emissions is strongly dependent on the availability of past data for model calibration. Furthermore, different modeling approaches and methods are characterized by the capacity to provide more or less detailed scenarios in terms of geographic, sectoral, and technological detail. Understanding the strengths and weaknesses of available approaches and tools for industrial energy and emissions modeling provides the basis for developing and interpreting results that can be used to inform energy- and climate-related policymaking.

We also describe the most promising deep decarbonization options in each sector and discuss whether and how these options are represented in industrial energy models. It is important to recognize that deep emissions reductions cannot be achieved by pursuing a single decarbonization strategy alone; rather, these reductions are more likely to be achieved through a combination of many mitigation options, as well as investment in and support for different technologies and subtechnologies. Conversely, ignoring some of these options and promoting only select ones reduces the likelihood of achieving deep decarbonization targets. Therefore, our assessment of the relevance of various mitigation options for industrial deep decarbonization should not be interpreted as suggesting that one option should be chosen over the others.

The paper is organized as follows. Section 2 identifies and describes the energy-intensive sectors that account for the majority of industrial energy demand and emissions, the focus of this paper. Section 3 reviews the available strategies through which industrial energy emissions can be reduced. Section 4 illustrates more detailed and specific technological options in each of the key energy-intensive sectors. Section 5 provides an overview of the data available to measure industrial energy demand and emissions, which are critical inputs for model development and calibration. It also discusses the difficulty of obtaining data to model several of the decarbonization approaches that are relevant in industrial sectors for deep decarbonization, due to limited data coverage and detail. Section 6 presents a framework to distinguish among the different modeling approaches to industrial energy demand and emissions, while Section 7 summarizes common approaches to modeling innovation and technology diffusion. Section 8 looks at the key models that have been used in the literature to this end, and Section 9 concludes.

2. Energy-Intensive Industry Sectors

While all industrial sectors rely on fossil fuels for their production activities, energy intensity varies significantly across them. The most energy-intensive sectors worldwide are steel, cement, chemicals, light manufacturing (as defined in Section 2.4), aluminum, and pulp and paper. Historically, these sectors accounted for about half of all industrial sectors' delivered energy use (EIA 2016). The aim of this section is to justify our focus on a limited number of carbon-intensive sectors by describing their contribution to economic growth (output), energy demand, and CO_2 emissions. To this end, we rely on the IPCC Sixth Assessment Report (IPCC 2022) for steel, cement, and chemicals and IEA reports (IEA 2022a,d,e) for light manufacturing, aluminum, and pulp and paper. It is important to note that in providing this overview, we take a global perspective and largely abstract from national specificities and intersectoral heterogeneity.

2.1. Steel

Crude steel production rose globally by 41 percent between 2008 and 2020. Worldwide, around 40 percent of steel is used in buildings, 20 percent in industrial equipment, 18 percent in consumption goods, 13 percent in infrastructure, and 10 percent in vehicles. Emissions associated with steel production[1], primarily from the use of coke ovens and blast furnaces, are estimated at 3.7 to 4.1 gigatonnes of CO_2 equivalent ($GtCO_2e$), accounting for 20 percent of all worldwide direct industrial emissions in 2019 (IPCC 2022).

1 Percentages sum up to 101 percent. This is due to rounding in the original source of the data.

2.2. Cement

Since the mid-20th century, cement output has grown faster than world population , indicating an increase in the use of cement for infrastructure and buildings. In 2019, direct emissions from cement manufacturing were estimated at between 2.1 and 2.5 $GtCO_2e$, or 14 to 17 percent of total worldwide direct industrial GHG emissions, despite major advances in energy efficiency in this sector over the past two decades. Typically, about 40 percent of these direct emissions result from the combustion of fuels to produce the high temperatures needed in the manufacturing process, and the remaining 60 percent occur during the decomposition of calcium carbonate (IPCC 2022).

2.3. Chemicals

Chemical products include plastic, rubber, fertilizers, solvents, and other substances such as food additives and pharmaceuticals. In 2019, the chemical sector's emissions were estimated at 1.1 to 1.7 $GtCO_2e$, or 10 percent of total worldwide direct industrial emissions. Processes used to produce chemicals such as ammonia (used in the production of nitrogen fertilizers), methanol (used in the production of adhesives, resins, and fuels), and olefins and chlorine (essential components of plastics emissions) are very energy-intensive (IPCC 2022).

2.4. Light Manufacturing

In 2019, light manufacturing accounted for 17 percent of total industrial emissions. Between 2010 and 2020, overall output from these industries increased, although emissions fell by around 2.3 percent over the same period (IEA 2022d). According to the IEA definition, light manufacturing includes a diversified set of industries: food production (14 percent of light manufacturing emissions), timber (1 percent), machinery (8 percent), vehicles (2 percent), textiles (3 percent) and other consumer goods (55 percent), construction (9 percent), and mining (8 percent).

2.5. Aluminum

In 2021, aluminum, a crucial input in several critical energy transition technologies, accounted for approximately 3 percent of the world's direct industrial CO_2 emissions. Over the past 10 years, the global aluminum industry's direct emissions have been rising gradually as a result of rising production. Because of slight improvements in emissions intensity over time and leveling output in 2019, emissions decreased for the first time in 10 years, but this trend subsequently reversed. The aluminum manufacturing process uses significant amounts of electricity, and the source of electricity is important in determining its overall emissions profile. In 2021, direct emissions from the sector were 275 megatonnes (Mt), but overall emissions including indirect emissions from power consumption were substantially larger, at 1.1 Gt of CO_2 (IEA 2022a).

2.6. Pulp and Paper

In 2021, pulp and paper production reached 190 Mt of CO_2 emissions, which is a historic high and accounts for nearly 2 percent of total industrial emissions. Paper output is expected to expand until 2030, and therefore improvements in the industry's emissions intensity are required to reduce future emissions from pulp and paper. Future paper output is expected to rise slightly as a result of an increase in packaging and sanitary paper goods, particularly in developing economies, which more than compensates for the decline in printing-related paper production (IEA 2022e).

3. Available Approaches for Industry Decarbonization

While industrial processes across and within sectors differ greatly, five high-level strategies can be identified to reduce industrial energy emissions: (1) fuel switching, including alternative feedstocks, and electrification of industrial production; (2) carbon efficiency improvements through more efficient or digital technologies (energy efficiency) or through zero-carbon technologies; (3) improvements in material efficiency, including through radically novel processes and business models; (4) deployment of carbon capture and storage technologies; and (5) circular economy practices based on the reduce, repair, refurbish, reuse, and recycle paradigm. Some of these strategies are more in line with deep decarbonization targets, while others represent more marginal improvements. In this section, we provide a broad definition of each of these approaches. In Section 4, we discuss the extent to which each approach is relevant for each sector and provide concrete and promising examples of specific technologies in each energy-intensive sector.

3.1. Fuel Switching and Electrification

One way to reduce energy emissions is through fuel switching and electrification, which represent a move from a carbon-intensive energy carrier to one that has low or zero associated emissions. **Fuel switching** entails a shift away from coal, refined oil products, and natural gas toward sustainable energy sources such as biofuel, solar heating, geothermal, sustainable hydrogen or ammonia, nuclear, or net-zero synthesized hydrocarbon fuels. The ability of fuel switching to achieve drastic emissions reductions depends on the nature of the chosen fuel as well as on the specific industrial sector under consideration.

For instance, biofuels—namely, fuels from biogenic sources—are available in a variety of forms, some of which have properties similar to those of fossil fuels and the same uses. While biomethane, biomethanol, and bioethanol are available today at costs generally comparable with those of fossil fuels (IPCC 2022), the extent to which their use will lead to deep decarbonization is questioned in the literature: while their carbon cycle goes into and out of the atmosphere, they may not in fact be GHG-neutral because of the way they are produced, which involves changes in land use, soil carbon depletion, and fertilizers (Hepburn et al. 2019). However, most biofuel, chemical, and biogas manufacturing techniques create considerable side flows of concentrated CO_2, which can be easily absorbed when combined with carbon capture and storage and carbon capture and utilization (e.g., bioenergy with carbon capture and storage, or BECCS) and might represent a source of negative emissions (IPCC 2022).

Yet the use of biogenic carbon to achieve deep decarbonization across all sectors is challenging. Capturing carbon during a production process and using it as a feedstock would require large amounts of hydrogen to transform the CO_2 into a variety of chemicals through a reaction process (IPCC 2022). Furthermore, the sustainable supply of biomass faces significant challenges, including the availability of land for bioenergy crops, water use needs by bioenergy crops, the necessity to adapt bioenergy crops to a changing climate, and the ability to transport and store large quantities of crops. All these challenges currently are not fully managed, nor are they likely to be in the near future (Harris et al. 2018: Bui et al. 2023).

Switching to solar energy, which has no associated GHG emissions, is more in line with deep decarbonization targets. Direct solar heating in industry, for instance, has an acknowledged potential, particularly in countries with high solar irradiance and industries with modest heat demands, such as food and beverage production, textiles, and pulp and paper (IPCC 2022). Major barriers to adoption for these technologies are location and application specificity, the need for energy storage technologies to compensate for intermittency (Asiaban et al. 2021), high capital costs, and the absence of standardized mass production for equipment.

Direct electrification is a switch from direct fuel use toward electricity and represents an important option to achieving industrial carbon neutrality (IPCC 2022). Electricity is a versatile energy carrier that can be produced from a variety of primary sources, with significant potential for process improvements in terms of end-use efficiency (Eyre 2021), quality and process controllability, digitizability, and the absence of direct local air pollutants. The emissions reductions that can be achieved through electrification vary depending on the specific sector or subsector. For instance, they are higher in manufacturing, which uses fossil fuels as energy carriers, but lower in the chemical sector, which uses fossil fuels as feedstocks and not to generate energy or heat. Furthermore, the potential for emissions reductions depends on whether the electricity is produced using low-GHG-intensity primary sources (wind, solar, hydro, advanced geothermal nuclear, fossil fuels with capture and storage) (IPCC 2022). Roelofsen et al. (2020) estimate that almost half of the fuel consumed for energy can be electrified with technology that is already available.

As discussed in Section 4, important progress is being made in all industrial sectors; however, electrification is most easily achieved in light manufacturing sectors. For sectors with large needs of high-temperature heat (e.g., primary steel production), significant technological barriers still have to be overcome. Direct induction and infrared heating are options for higher temperature requirements, whereas steam boilers, curing, drying, and small-scale process heating are easily electrifiable from a technical point of view. Of course, electrification is economically attractive only if electricity prices are comparable to those of fossil fuel (IPCC 2022). Because of a variety of factors, electricity and fossil fuel prices vary by country, yet the EU average electricity price per kilowatt hour (kWh) has been consistently lower than that of gas since 2008 by a factor of three to five (Eurostat 2022).

3.2. Energy Efficiency Improvements in Production Process

Increasing the energy efficiency of production processes is a second approach to reducing GHG emissions from the industrial sector. **Energy efficiency** improvements not resulting from fuel switching are an important, yet incremental, mitigation strategy, as they often do not entail radical technological changes. Energy efficiency can be achieved through two channels: advances in energy-saving best available technologies (BATs) and shifting industrial plants' specific energy consumption to a more efficient technology, ideally a BAT (IPCC 2022). While improving energy efficiency in industrial processes has a high emissions reduction potential, energy efficiency alone will not lead to deep decarbonization in industrial sectors. For instance, combustion produces approximately 10 percent of global GHG emissions due to high-temperature heat in basic material manufacturing processes (Sandalow et al. 2019), yet until recently, efforts and investments to reduce carbon emissions in heat generation were relatively limited; consequently, technological approaches for decarbonizing industrial heat production are still far from maturity (ICEF 2020). There is still high potential for the use of non-high-temperature waste heat, particularly if coupled with high-temperature heat pumps to increase the temperature of the waste heat to the needed level (Nandhini et al. 2022).

Another key method to improve energy efficiency is through **digitalization**. The development of technology including sensors, communications, analytics, digital twins, machine learning, virtual reality, and computing technologies enables future advances in process control and optimization. Smart energy solutions with real-time tracking enable the optimization of new technologies, energy demand responsiveness, and energy supply-and-demand balance, including pricing, product quality control, and forecasting and reducing unproductive time for humans and robots (IPCC 2022). Significant investments in digital solutions are being carried out in most industrial sectors, also as a result of public commitment to promote the transition toward

Industry 4.0 (see, e.g., EU 2020; ABI Research 2022; Verdolini 2023).[2] Yet the potential for digital technologies to reduce emissions through increased efficiency is higher in non-energy-intensive sectors and generally limited in energy-intensive sectors (IPCC 2022). Importantly, quantitative evidence is scarce regarding the impact of digital technologies on industrial energy demand and associated emissions. As a result, it is hard to inform models regarding the potential enabling role of digital technologies. Moreover, appropriate governance of digitalization will be required to ensure that the benefits of digital technologies are used “deliberate[ly] for the good” (Creutzig et al. 2022).

3.3. Material Efficiency

Material efficiency, the supply of goods and services with less material, is increasingly recognized as a critical strategy to lowering GHG emissions in the industry (IEA 2019). Yet, similarly to energy efficiency, material efficiency is not sufficient to achieve the deep decarbonization of industry. Options for improving material efficiency exist at every stage of a material’s or product’s life cycle, such as by designing lightweight products, optimizing to preserve end-of-life service while reducing material use, and developing circular principles. The precise open physical mapping of current material supply chains allows material efficiency measures to be tracked down to where emissions are emitted, and these alternatives may be comparable to decarbonization and conventional energy efficiency techniques (IPCC 2022). Many material efficiency actions, such as designing lightweight items, result in direct GHG emissions savings in the short term; others also have long-term emissions reduction effects. For example, developing a product that can be reused or has a longer lifespan reduces emissions both today and in the future. While material efficiency is generally not well represented in climate-energy-economy models, the International Energy Agency developed a scenario in 2015 that projects a 17 percent decrease in industrial energy demand in 2040 (IEA 2015) due to increased material efficiency.

3.4. Carbon Capture and Storage Technologies

Carbon capture and storage (CCS) and **carbon capture and utilization** (CCU) represent potential options to achieve deep decarbonization, but these technologies have not yet been proven at a commercial level, and there are concerns about the long-term storage of carbon. For instance, the most developed method for long-term CO_2 storage in subsurface pore space is sequestration in sedimentary formations. Major potential hazards from CO_2 storage in subterranean pore space include leakage from wellbores or nonsealed cracks in the caprock, building of pressure in the reservoir that might result in caprock hydraulic fracturing, and pollution of drinking water. Induced seismicity may result from the injection of CO_2 into subterranean reservoirs. Most studies believe that produced earthquakes carry a modest risk of causing fault displacements and compromising reservoir security, but others contend that even small- to moderate-magnitude earthquakes can damage the seal and undermine the integrity of sequestration reservoirs (Kelemen et al. 2019).

2 Industry 4.0 refers to rapid improvements in industrial systems and product design, production, and maintenance as a results of what the literature has defined as the fourth industrial revolution (hence the 4.0), mostly promoted by the widespread diffusion of digital technologies (European Parliament 2015).

CCS and CCU use similar capture technologies to collect concentrated flows of CO_2 from smokestacks; the main difference between the two is what occurs to the CO_2 after it is captured. CCS involves the recovery and storage of CO_2 from combustion, gases, and ambient air to the geosphere for thousands of years (IPCC 2022). CCU involves the capture of carbon from one process and its reuse for another, lowering emissions from the first process, yet potentially, but not inevitably, releasing carbon to the environment in subsequent operations (Tanzer and Ramirez 2019). The net potential impact of these technologies on carbon emissions is a source of debate in the literature. Their contribution to deep decarbonization scenarios depends on the initial source of carbon, fossil fuel or biomass, as well as the period of storage or usage, which can range from days to millennia (IPCC 2022). According to recent analysis, CCS can technically achieve near-zero CO_2 emissions in applications where the CO_2 can be captured during the production process, with highly variable partially negative emissions over the life cycle if the origin is biogenic fuels. Brandl et al. (2021), for instance, argue that capture rates up to 98 percent are technically feasible and result in negligible increase to the overall system costs. However, achieving net zero would require the indirect capture of residual emissions by complementary carbon dioxide removal technologies, such as afforestation, BECCS, or direct air capture with carbon storage (DACCS).[3] A recent modeling analysis concludes that the contribution of CCS to emissions reductions is high in the sectors of steel, cement, and refineries, as well as the power sector to a lesser extent. The emission reduction potential of CCS varies however across different countries of the world and depending on the socio-economic pathway modelled. (Turgut et al. 2021).

3.5. Circular Economy Approaches

Finally, industrial energy emissions can be lowered through circular economy (CE) approaches to the provision of goods and services. This would entail strategies to **reduce**, **repair**, **refurbish**, **reuse**, and **recycle**. CE practices can contribute significantly to emissions reductions, though alone they are not sufficient to achieve deep decarbonization targets in industrial sectors. Circularity entails closing material and energy flow loops in the provision of goods and services by implementing policies and procedures for more efficient energy, materials, and usage while generating the least possible amount of waste to the environment (IPCC 2022). This may be done through, for

3 While not a mitigation option, direct air capture (DAC) could be used to offset both fuel and process emissions at industrial plants. DAC refers to chemical processes that separate CO_2 from the ambient air. The required energy to capture CO_2 increases as the concentration of CO2 falls, so the energy requirement to remove a single ton of CO_2 from the atmosphere is quite high. (The concentration of CO_2 in the air is about 400 parts per million [ppm], compared with about 120,000 ppm in flues at coal-fired power plants.) The costs of DAC depend on the source of the energy, and estimated costs vary from $100 to over $1000 per ton (NASEM 2019). To date, investment in DAC facilities has been limited because of the highly uncertain future of this technology, which is for several reasons: DAC is generally considered to be among the more expensive carbon dioxide removal (CDR) pathways; most CDR pathways offer benefits besides CO_2 removal, whereas DAC provides no cobenefits; and DAC requires large amounts of energy per ton of CO_2 removed. More recently, funding and incentives have targeted the further technological development of this mitigation option, including in the United States and the European Union.

instance, the production of durable items that can easily be fixed and whose parts can be reused, refurbished, and recycled, as opposed to a linear production mode (Wiebe et al. 2019). Given that CE encourages reduction, reusing, and recycling, a considerable proportion of energy- and GHG-intensive raw material demand and associated processing may be eliminated, resulting in considerable carbon emissions reductions. The extent to which circularity practices will result in lower energy demand (and associated emissions) has yet to be determined. In the case of recycling scrap metal, the resulting material is often of lower quality, with properties that differ from the raw metal, because the scrap metal is often made up of a variety of materials that are hard to separate. This is referred to as downcycling. Conversely, recycling and upcycling may be achieved, but at the cost of high energy use (IEA 2020).

Circularity can be implemented at three levels: micro (inside a single firm), meso (involving three or more enterprises), and macro (cross-sectoral collaboration). Each level necessitates its own set of instruments and strategies, such as incentives and tax policies (macro level) and eco-design laws (micro-level) (IPCC 2022). At the micro level, more organizations, particularly multinational corporations, are implementing CE practices as a result of their advantages (D'Amato et al. 2019). Industrial parks, from a meso-level perspective, minimize infrastructure costs by clustering industrial operations in specified regions and are often established around big corporations. At this level, typical CE techniques and strategies include sustainable supply chains and industrial symbiosis, a collaboration among different industrial actors to optimize the use of resources and reduce waste generation (IPCC 2022). The primary advantage of industrial symbiosis is the reduction of both virgin materials and final waste, as well as avoided delivery costs from exchanges among firms, which could boost the competitiveness of small and medium-size enterprises. The macro-level approach aims to exploit the potential CE synergies that exist outside the confines of a single industrial park, expanding symbiosis to entire urban settings through the utilization of waste from municipalities as alternative energy sources (Sun et al. 2017).

4. Demand Reduction and Energy Efficiency Potentials of Energy-Intensive Sectors

This section discusses specific options for decarbonization in each of the six energy-intensive sectors, providing details on which specific technologies and practices could be adopted to achieve emissions reductions by promoting fuel switching and electrification, increasing energy and material efficiency, deploying CCS and CCU, or implementing circular economy approaches. Table 1 provides a visual summary of this section, highlighting the relative importance of each strategy in each of the sectors. As clarified earlier, this section takes a global perspective and largely abstracts from national specificities and heterogeneity within sectors.

4.1. Steel

Steel production may be classified into two categories: primary production from iron ore and secondary production from steel scrap. The blast furnace to basic oxygen furnace (BF-BOF) route is the most used primary production route worldwide, while the electric arc furnace (EAF) is the preferable procedure for secondary production through melting and alloying recycled steel waste, as it requires less energy and generates fewer emissions (IPCC 2022). An alternative but less common way to produce steel is using direct reduced iron (DRI) to reduce iron ore—thus replacing BFs—which is generally followed by an EAF (IPCC 2022). In 2019, approximately 73 percent of worldwide crude steel output was produced using BF-BOF technologies, while 26 percent was produced using the EAF method. Of the latter, about 5.6 percent is derived from DRI (World Steel Association 2021). Importantly, production processes vary geographically; for instance, the majority of US steel production is done through EAFs.

Table 1. Summary of Relevance of Different Mitigation Options by Sector

	Fuel switching and electrification	Energy efficiency	Material efficiency	CCS/CCU/DAC	Circular economy
Steel	High	Medium	High	Medium	High
Cement and concrete	Low	Low	High	Medium	Low
Chemicals	High	Low	Medium	High	Medium
Light manufacturing	High	High			
Aluminum and non-ferrous metals	High	Low	Medium	Low	Medium
Pulp and paper	High	High	Low	Medium	Low

There are several approaches to significantly reduce GHG emissions in the steel sector (IPCC 2022). First, potential **energy efficiency** improvements of primary steel production—that is, BF-BOF approaches—are estimated at 15 percent (IPCC 2022). Second, **circular practices**, promoting secondary rather than primary production, are another effective way to reduce emissions. This option, however, strongly depends on the accessibility of domestic and foreign scrap supplies and necessitates meticulous sorting and scrap management, particularly to get rid of copper contamination (Daehn et al. 2017). One important technology in circular practices is the electrowinning process, a low-temperature electrolysis method for extracting solid-state elemental iron from iron ore. The iron is then put into an EAF to produce liquid crude steel, which may also be mixed with scrap steel (Junjie 2018).

Third, **fuel switching and electrification**, using carbon-free energy and feedstock sources as input, or **carbon capture and storage** technologies (IPCC 2022) could potentially reduce an estimated 80 percent of current emissions from primary steel production with today's dominant technology, BF-BOF. The extent to which BF-BOFs can be retrofitted for capture is currently a matter of debate in the literature. Fan and Friedmann (2021) , who consider near-term options to rapidly reduce GHG emissions in steel production by examining technical options in terms of cost, viability, readiness, and ability to scale, argue that it would be challenging to retrofit BF-BOFs beyond 50 percent capture; conversely, Hughes and Zoelle (2021), who perform a sensitivity analysis on the cost of capital for iron and steel retrofit, assume that retrofitting can achieve up to 99 percent capture. Note that BF-BOFs must have their furnaces relined every 15 to 25 years (IPCC 2022); this costs from 80 to 100 percent more than building a new facility. For this reason, it is more economically viable to construct a new facility that is built for 90+ percent capture than to retrofit.

DRI with CCS using syngas based on methane can also be used to reduce emissions in the steel industry. Currently, the majority of DRI plants employ syngas of H2 and CO based on methane as a fuel and a reductant. Furthermore, hydrogen-based DRI (H-DRI) is being developed on the widely used DRI technique but using only hydrogen. Iron ore reduction is frequently followed by an EAF for smelting. This steel manufacturing method may be practically CO2 neutral if hydrogen is created using carbon-free sources (Vogl et al. 2018). Molten oxide electrolysis (MOE) is another method for extracting metal from its oxide source. The benefits of liquid metal production are the ease with which the manufactured metal may be collected and the capability to operate continuously. The use of electricity for metal extraction includes using renewable energy and the decoupling of metal production from CO2 emissions. As a result, if suitable for industrial scales of production, this technology will be of significant interest to the steel industry (Wiencke et al. 2019).

Fourth, emissions in the steel sector can be dramatically reduced by increasing **material efficiency** (i.e., less steel usage per vehicle) as well as through **circularity** practices and demand-side options that would lower the demand for steel manufacturing or increase the intensity of product use (i.e., car sharing). In particular, the IEA estimates that stringent measures targeting material efficiency could realistically lower the demand for steel by 40 percent by 2060 (IEA 2019).

4.2. Cement and Concrete

Available analyses suggest that the cement industry has limited mitigation options, yet some exist. One strategy is based on **material efficiency**; making stronger concrete via improved mixing, aggregate size, and dispersion is one of the easiest and most efficient methods to minimize cement and concrete emissions. Because cement is low cost, corrosion- and water-resistant, and easy to work with, architects, engineers, and contractors frequently overbuild with it. Buildings and infrastructure can be intentionally planned to limit the use of cement to its necessary applications and substitute other materials for nonessential uses. This might cut the use of cement by 20–30 percent (IPCC 2022). Indeed, while fuel switching and electrification do not appear to be viable options to minimize or reduce the CO2 emissions specifically associated with the typical Portland A cement manufacturing process (IPCC 2022), available assessments indicate that some countries have high clinker-to-cement ratios, with the United States having the highest. Decreasing these ratios would reduce emissions (Pascale et al. 2021; IEA 2022b; CTCN 2016).

Second, **fuel switching and electrification** have the potential to lower emissions in specific phases of the production process. For instance, the use of bioenergy solids, liquids, or gases (IEA 2018), hydrogen, or electricity for producing the high-temperature heat needed at the calciner can also minimize the energy-related emissions of cement manufacture. Because of their different qualities of quick and slow combustion, co-burning hydrogen and bioenergy may be beneficial in this respect.

Third, given limited other mitigation options, **carbon capture and storage** technology is frequently cited as a potentially significant component of an ambitious mitigation approach in the cement industry. CCS technology can capture only the process emissions or both the energy and process CO_2 emissions. Several CCS techniques may be used, including post-combustion technologies like membrane-assisted CO_2 liquefaction and amine scrubbing, oxy-combustion in an atmosphere with little to zero nitrogen to generate a concentrated CO2 stream for capture and disposal, and calcium looping (Dean et al. 2011).

Fourth, **switching to different materials and production processes** may be required to achieve deep decarbonization in this sector in the long run if material efficiency, improved mixing and aggregate sizing, and CCS with extra bioenergy are not viable in some places or at all to reach near-zero emissions. Among the successful strategies to reduce CO_2 emissions in the global cement industry is the use of supplementary cementitious materials (SCMs) (Ayati et al. 2022), including from industrial and agricultural wastes, to replace part of the clinker in cement (Singh 2022). However, implementing this option at a large scale will be challenging due to the limited supplies of conventional SCMs, unless new types of SCMs become available (Scrivener et al. 2018). Limestone calcined clay cement (LC3), which is made by blending clinker, calcined clay, limestone, and gypsum, has been gaining considerable attention and investments as an important alternative to Portland cement because it reduces CO_2 by up to 40 percent, uses low-grade raw materials, and requires a lower calcination temperature for clay. It is cost-effective and does not require major modification in cement plants. In addition, alkali-activated materials and geopolymers, aluminate cements, magnesia-based cements, and gypsum-based materials represent promising alternative binders that can be produced with lower carbon footprints (Peng and Unluer 2023). Indeed, some of these alternative solutions to limestone-based ordinary Portland cement have been tested and used regionally and have given rise to partial savings (IPCC 2022), but they remain harder to implement as compared to accessing limestone resources (Material Economics 2019).

4.3. Chemicals

A key characteristic of the chemical sector is the heterogeneity of its products, each of which has its own production process, distinct set of technologies, and mitigation options, making it challenging to model decarbonization in this sector. This is particularly true for some of the chemical production processes for which no technological options currently exist that allow production of certain chemicals to be decoupled from the use of a carbon source (IPCC 2022). The processes that consume the most energy in this sector are those for the production of high-value chemicals (such as ethylene or propylene, typically precursors to plastics), fertilizers, methanol, and some halogens such as chlorine (Worrell et al. 2000).

Yet the literature suggests that the chemical sector offers several major mitigation options. There are several potential routes to lower emissions in the chemical sector. First, this sector has one of the highest potentials for **electrification**, suggesting the prospect of a rapid decrease in associated emissions (Madeddu et al. 2020). Indeed, despite the industry's consistent improvements in energy efficiency over the last few decades, the demand for heat and steam in the manufacturing of basic chemicals is responsible for a large share of emissions (Bazzanella and Ausfelder 2017). Most of this energy is now provided by fossil fuels; these in theory can be replaced with bioenergy, hydrogen, or electricity with minimal or no carbon emissions (IPCC 2022).

Second, **fuel switching** can also significantly lower emissions; this is particularly the case for ammonia manufacturing, which accounts for around 30 percent of all CO_2 emissions in the sector (IPCC 2022). Nitrogen and hydrogen are combined to make ammonia through a catalytic process, with hydrogen most frequently produced through natural gas reforming (Material Economics 2019) or, in some areas, coal gasification, which has significantly higher related CO2 emissions. Future low-carbon alternatives for ammonia production include methane pyrolysis, which converts methane into hydrogen and solid carbon (Material Economics 2019), hydrogen produced by electrolysis using low- or zero-carbon energy sources, and natural gas reforming with CCS. Compared with conventional processes, electrifying ammonia would result in a reduction in the overall amount of primary energy used, although innovative synthesis procedures still have a substantial opportunity for efficiency improvement (IPCC 2022). Switching to synthetic feedstock also plays a crucial role in those chemical production processes for which no carbon-free options exist. For instance, a possible strategy is synergistic combination of low-GHG hydrogen and carbon obtained by direct air capture or from point sources for further valorization (Kätelhön et al. 2019). To replace the steam cracker (IPCC 2022) or a Fischer-Tropsch process that may manufacture synthetic hydrocarbons, low-carbon methanol can be produced and used in make to order/make to assemble processes to convert methanol to olefins and aromatics (IPCC 2022). Another strategy involves employing biomass resources (Isikgor and Becer 2015) or existing residual streams to process carbon from renewable sources in defined biotechnological processes at the beginning of a product's life cycle (IPCC 2022).

Third, the literature identifies a large number of **new technologies relevant for mitigation** in the chemical sector that have expected deployment dates ranging from now to 2025. However, their potential contribution to achieve deep decarbonization varies. Among those with the highest potential in this respect are various carbon capture methods and electrolytic hydrogen generation (IPCC 2022); conversely, methane pyrolysis, electrified steam cracking, and biomass-based ethanol-to-ethylene and lignin-to-BTX (benzene, toluene, and xylenes) pathways are considered medium in importance. While macro-level calculations demonstrate that large-scale usage of carbon circulation through CCU as a main approach is feasible in the chemicals industry, it would be highly energy-intensive, and the climatic effect would be heavily dependent on the source of CO_2 and procedure for absorbing it (Kätelhön et al. 2019). CCS plays a particularly important role in those production processes for organic compounds that will continue to require a carbon source as an input (IPCC 2022). Yet the large-scale deployment of carbon dioxide removal technologies would require a complete reshaping of the chemical sector, with some industries dedicated to the production of sorbents, necessary to operate the technology. Sorbent production is currently only a by-product of processes in the chemical sector. Upscaling it would imply an increase in energy demand from the chemical sector, as these processes are very energy intensive (Realmonte et al. 2019).

Fourth, **circularity practices** are also relevant in the chemical sector. For instance, the pyrolysis of used plastics can produce both gas and naphtha pyrolysis oil, a portion of which might replace conventional naphtha as an energy source in the steam cracker (Honus et al. 2018). Catalytic cracking, hydrocracking, and polymer selective chemolysis are additional methods for chemical recycling (Ragaert et al. 2017). Achieving near-zero emissions may require combining chemical recycling with CCS to reduce carbon losses and process emissions. Finally, achieving deep emissions reductions requires demand-side strategies such as efficient end use, material efficiency, and reducing demand growth, in addition to recycling whenever possible to minimize the requirement for primary production (IPCC 2022).

4.4. Light Manufacturing

As previously discussed, light manufacturing comprises a diversified set of industries, each of which has specific production processes and technologies and, consequently, mitigation options. Process heat for applications such as drying consumes the most energy in the light manufacturing industry, and approximately 90 percent of the fossil fuels employed by the sector are used to generate process heat, whereas electricity is predominantly used to power motor-driven systems (IEA 2022d). As a result, **fuel switching and electrification** represent an important mitigation option, with high relevance for the achievement of deep decarbonization. For instance, current fossil-based approaches for heating and drying may be replaced by low- or zero-GHG electricity via direct resistance, high-temperature heat pumps, mechanical vapor recompression, induction, infrared, or other electrothermal processes. Direct solar heating is feasible for low-temperature requirements (100°C), while concentrated solar heating is a viable option for greater temperatures. Heat pumps on the market can provide 100°C–150°C, although temperatures of up to 280°C are possible. Where high temperatures (>1000°C) are necessary, plasma torches powered by electricity can be employed, as well as hydrogen or biogenic or synthetic combustible hydrocarbons. **Energy efficiency** also plays an important role, particularly aimed at using waste heat, which can be transferred from plant to plant at progressively lower temperatures or distributed as low-grade steam or hot water, then increased as needed via heat pumps and direct heating (IPCC 2022). These geographic clusters also could allow for reduced infrastructure costs for hydrogen generation and storage, as well as CO_2 collection, transportation, and disposal (IEA 2022d). Material efficiency, CCS, and circular economy practices are not discussed for this sector due to its heterogeneity.

4.5. Aluminum and Nonferrous Metals

Primary aluminum is often produced in two stages, generally performed in the same location. In the first stage, the Bayer hydrometallurgical method is employed to separate aluminum oxide from bauxite ore; this requires temperatures of up to 200°C when sodium hydroxide is used to extract the aluminum oxide and up to 1000°C for kilning (IPCC 2022). In the second stage, the aluminum oxide is then electrolytically separated into oxygen and elemental aluminum using the Hall-Héroult method. This is by far the most energy-intensive phase of the aluminum production process.

In both stages, **electrification** has the potential to significantly lower emissions if the electricity is from low- or zero-carbon sources. Electrification also has high emissions mitigation potential in the production process of other nonferrous metals, such as nickel, zinc, copper, magnesium, and titanium, which generate lower total emissions (IPCC 2022). This is the case, for instance, for ore extraction technologies using low-carbon electricity rather than pyrometallurgy, which requires heat to melt and extract ore once it has been smashed. Other important mitigation options for nonferrous metals include higher **material efficiency** and **circularity practices** aimed at the recycling of existing stock. In the case of nonferrous metals, many of these decarbonization options are available and have been used on occasion in the past, but they have not been widely used because they are costlier than traditional techniques and, with low fossil fuel prices, are not economically attractive (IPCC 2022).

4.6. Pulp and Paper

Pulp mills, integrated pulp and paper mills, and paper mills that use virgin pulpwood and other fiber sources, wastes and coproducts from wood product manufacture, and recycled paper as feedstock are all part of the pulp and paper industry (IPCC 2022). In chemical pulping operations, pulp mills often have access to bioenergy, which can supply most or all of their heat and electricity requirements. Mechanical pulping is mainly powered by electricity; hence decarbonization is dependent on grid emissions variables. Excluding the lime kiln in kraft pulp mills, temperature requirements are normally less than or equal to 150°C–200°C, mostly for heating and drying via steam. This indicates that this industry may be easily decarbonized by improvements in **energy efficiency** as well as **fuel switching and electrification**, including the use of high-temperature heat pumps. Electrification of pulp mills might, in the long run, make bioresidues now used for energy accessible as a carbon source for chemicals. The pulp and paper sector has the capability, resources, and knowledge to undertake these changes. Inertia in deploying low- or zero-carbon production options and technologies is primarily induced by equipment turnover rates and relative fuel and electricity prices. Pulp mills have been highlighted as prospective candidates for postcombustion carbon capture and storage, which may enable some net negative emissions (IPCC 2022).

5. Data on Industrial Energy Demand and Emissions

The availability, granularity. and comparability of industry-level data on energy demand and emissions across different countries constrain the ability to set up and calibrate models to explore possible pathways of industrial energy emissions reductions. That is to say, there currently is no detailed and comprehensive data source from which modelers can obtain information on energy demand and associated emissions by fuel type or by technology in the different industrial sectors in different countries over time. Several main challenges are present in this respect, and they often compound one another. These challenges are discussed in this section and can be observed in the detailed description of available databases, including data on industrial energy demand, presented in Appendix A. Note that these data-related challenges are additional to any difficulty linked with the modeling of diverse mitigation options across different sectors and different countries with the sufficient level of detail necessary to generate industry-level decarbonization pathways (discussed in the next section).

5.1. Lack of A Common Detailed Statistics Classification

There is currently no common detailed statistical classification of industrial sectors that is used worldwide to collect energy and emissions statistics. **As a result, it is extremely challenging to collect data from different national statistical offices and compare them.** The three most widely used approaches to classify industrial activities are the International Standard Industrial Classification of All Economic Activities (ISIC), the North American Industry Classification System (NAICS), and the Statistical Classification of Economic Activities in the European Community (NACE) (see Appendix B for details). These classifications are used by different countries and international institutions to gather specific data on industrial energy demand. While NAICS is used by the United States and Canada, NACE is the official classification of the EU, and ISIC is often used by international organizations such as the IEA.

5.2. Lack of Comprehensive Data on Energy Demand of Different Energy Carriers

Information on energy demand at the sectoral level exists for the major world economies but is rarely accompanied by details regarding different energy carriers. **This constrains the ability to explore the role of fuel switching in reducing energy emissions at the sectoral level.** For instance, the World Input-Output Database (WIOD; Timmer et al. 2015) November 2016 release consists of a series of databases covering 28 EU countries and 15 other major countries in the world for 2000–2014. The database provides energy and environmental accounts at the sectoral level but does not include details on the types of fuels used (e.g., different types of coal versus gas).

5.3. Lack of Detailed Sectorial Information on Energy Demand at the Level of Different Products

When detailed information is available at the energy carrier level, information on sectoral use or allocation is often lacking or dated. In the rare cases where this information is available, it cannot be broken down across the different products produced in a given sector. **This constrains the ability to model sectoral specificities and thus to produce sectoral scenarios to deep decarbonization.** For instance, the World Energy Balances database (IEA 2022f) contains detailed country-level statistics on all energy carriers but no sectoral breakdown.

5.4. Limited Geographic and Time Coverage of Detailed Databases

Databases exist that provide detailed information regarding energy demand by energy carriers at the sectoral level, but their coverage is not comprehensive in time or space. **This limits the ability to model different sectors across different countries—or to simply account for sectoral dynamics in foreign countries through calibration**. This is particularly problematic in several energy-intensive sectors that are not concentrated geographically and whose dynamics are not necessarily driven by specific countries.

5.5. Difficulty in Linking Data on Emissions and Fuel Inputs

Detailed databases providing information on GHG emissions exist, some of which include sectoral detail, but emissions data cannot easily be linked to data on fuel inputs. **This means that overall emissions reduction pathways at the sectoral level may be modeled, but the drivers of emissions reductions at the sectoral level cannot be easily calibrated and studied.** For instance, one would have to make assumptions as to whether emissions reductions come from fuel switching or from broader technological change dynamics. The IEA Air Emission Accounts provide data on 16 pollutants for up to 88 industrial sectors or subsectors for 40 countries (no data for the United States are available), but they do not include information on the energy carriers associated with the levels of emissions. A few privately owned databases on emissions by sector and country exist, but their reliability is often not clear, as they do not provide information on the specific energy inputs or details on how they are compiled.

5.6. Difficulty in Predicting Costs and Performance of Radically Novel Technologies

It is challenging to predict the cost and performance of radically novel technologies, as well as the speed of their diffusion once they have reached the market. **This makes it hard to inform models regarding the prospects of technologies such as CCU, CCS, and other radically novel technologies, including promising technology options such as molten oxide electrolysis, new cement chemistries, or electric kilns.** In this respect, several contributions have used expert elicitation methods to generate probabilistic forecasts of energy technology costs starting from the 1970s, focusing on nuclear and, more recently, on a set of low-carbon technologies including CCS (Verdolini et al. 2018). Yet recent contributions in the literature have shown that expert estimates of future technology costs tend to be pessimistic, with realized cost decreases surpassing expectations for all those technologies for which we have both observed and expert elicitation data (Meng et al. 2021; Wiser et al. 2021). Nevertheless, the generality of these results for radically novel technologies such as CCU and CCS cannot be taken for granted. Furthermore, projections of future energy technology costs generated based on learning curves often fail to capture the true trajectory of subsequently realized technology costs for radically novel energy technologies (Meng et al. 2021).

5.7. Lack of Comprehensive Data on Material and Energy Flows

A lack of detailed data on material and energy flows **limits the ability to model circularity strategies and associated emissions reduction potentials**. Researchers studying industrial metabolism have been developing methodological approaches to the modeling of circular practices relevant in the context of the provision of goods and services, but much work remains to properly integrate material efficiency measures into conventional climate change models. Efforts are being made to endogenize material efficiency methods within climate change modeling, assess the synergy effects and trade-offs between energy efficiency and material efficiency initiatives, and collect data for calculating the emissions saved from actual material efficiency actions. This necessitates analysts working in multidisciplinary teams and engaging with stakeholders throughout the whole material supply chain. A fruitful avenue of future research being pursued by several large-scale projects is the linking of models focused on material flows with models for the integrated assessment of energy, the economy, and carbon emissions, with a sufficient level of detail for industrial sectors (Haberl et al. 2019).

All known databases on industrial energy use and demand or emissions are plagued by at least one of these limitations (see Appendix A). Taken together, these limitations also imply that it is not possible to describe precisely and comprehensively all mitigation options available in the different sectors. For instance, scarcity of data on material greatly limits the ability to model some mitigation options, such as circularity.

Overall, the inability to precisely track over time and space how different energy technologies use different fuels with different carbon contents illustrates the trade-offs in modeling industrial energy demand. Modelers can focus on a single sector in a single country and, depending on the country of interest, potentially rely on detailed fuel and emissions data, or they can focus on modeling several sectors in one or more countries, without access to details on technological options or types of fuel.

6. Approaches for Industrial Energy Demand Modeling

The literature includes several approaches to modeling climate mitigation, based on the specific purposes for which they were conceived. Although the criteria for classifying the modeling approaches may vary, three key dimensions emerge as particularly useful in this respect (Lopion et al. 2018): the analytical approach underlying each model, the methodology used to generate decarbonization pathways, and the granularity with which different economic sectors, including industry, can be represented. In each of these dimensions, modelers can choose among different approaches, each of which has pros and cons. Importantly, within large-scale, complex models, such as integrated assessment models of the economy, energy, and climate feedbacks, different approaches may be adopted in different modules or parts of the model. Therefore, the three dimensions discussed here should be understood as broad guiding principles by which to classify models and understand their founding principles and not a strict classification method.

6.1. Analytical Approach: Bottom-up and Top-down Models

Models adopt either a bottom-up or a top-down analytical approach. Accordingly, the energy system would be described from either an engineering or an economic angle. Bottom-up models integrate a high level of technical information within the energy system modeling, as they give highly precise images of energy demand and supply technologies, quantifying the demand of energy and mass of each technology component (Herbst et al. 2012). Their key strength is the characterization of the interlinks between technology components based on the mutual dependencies of energy and mass flows. This feature enables them to provide in-depth analyses of sectoral strategies; however, it also determines their partial equilibrium nature, as bottom-up models ignore relationships between sectors. Disadvantages of bottom-up modeling are related to data requirements and the exclusion of intersectoral feedbacks. Modelers are largely reliant on data availability and trustworthiness to model technology diffusion, investments, and operational costs. The main criticism of bottom-up modeling concerns the failure to account for program costs, the feedback of energy policy, and the lack of macro-effects of the assumed technology shift on general economic activity, structural changes, employment, and pricing (Herbst et al. 2012).

Top-down models describe technologies as a set of techniques by which inputs such as capital, labor, and energy can be transferred into useful outputs; therefore, they give an aggregated description of the energy system but lack detailed technological variability (IPCC 2022). They have a high level of endogenous modeling of social and economic behavioral relationships, such as those among welfare, economic growth, and employment. This type of modeling enables a full understanding of energy policy effects on the economy of a region or country (Herbst et al. 2012). A drawback is that because of their inadequate technological detail, they may be unable to provide an accurate picture of technical advances, nonmonetary hurdles to energy efficiency, or regulations for certain technologies. Top-down models are not suitable to portray credible technology prospects, especially as discontinuity would apply in the long run, when intrasectoral structural change would occur as a result of technological development and saturation (Herbst et al. 2012). Moreover, because top-down modeling approaches are based on the theory of efficiently allocating markets, they tend to underestimate the complex nature of barriers and their nonmonetary forms, such as a lack of knowledge, insufficient decision routines, or group-specific preferences of technology producers or wholesalers. Four key top-down approaches are input-output models, computable general equilibrium (CGE) models, econometric models, and system dynamics models.

Because of their inherent differences, these two approaches are useful in answering radically different questions. Bottom-up models are often used when there is a specific interest in producing decarbonization pathways for specific sectors, for which assumptions are made (and imposed on the model) regarding all other, more aggregate drivers of emissions. Top-down models are necessary if the focus of the analysis is modeling feedback loops between climate policies and welfare, employment, and economic growth. Finally, because of the complementarity between bottom-up and top-down models, hybrid approaches have been used where the macroeconomy interacts with an energy system module.

6.2. Methodology: Simulation and Optimization Approaches

Models can adopt either a simulation or an optimization approach to generate decarbonization pathways; often, both approaches can be used in different parts of the same model. Simulation allows for reproducing a system via interpreting the principles of its operations. These models represent the key behaviors and characteristics of a given process (in our case, industrial energy demand), while the simulation allows the model to represent how the process evolves under different conditions over time. Simulation can be static, if it describes the current system as a snapshot, or dynamic, if the current output is affected by evolution from previous periods. Simulation models can shed light on the endogenous relationships between variables to reproduce real-world systems, and although this may happen in a simplified fashion, they can also be rather complex. Typical applications of simulation models are exploratory analyses, where the modeler starts with realistic values for inputs and modifies them within reasonable ranges to determine what happens with the outputs. By tweaking the initial conditions, the behavior of the simulated system changes and can be observed. A class of simulation models explores multiagent approaches, interpreting the decisionmaking processes of key energy system players, which are suited to interpret market imperfections and consumer and firm heterogeneity (Hansen et al. 2019).

Optimization is used to determine optimal system design or optimal choices. Unlike simulation models, optimization models provide the best solution for a given answer. They consist of three elements: the objective function, decision variables, and the constraints. Successful optimization depends on properly identifying the constraints placed on various parameters—for example, the maximum level of energy from a given energy source or emissions from a given source.

Depending on the description of the energy system in a given model, optimization and simulation models can be demanding in terms of computing power and time and can implement sensitivity analyses to explore robustness of results at different levels of complexity. The distinction between optimization and simulation seems particularly relevant for the modeling of mitigation options that are novel and disruptive and affect the timing of when new technologies may enter the market. Optimization models apply typically intertemporal approaches, which means that availability and costs of all the technologies in the future are known from the start of the modeling. Simulation models are typically coupled with limited foresight, which means that information on technologies is limited at a certain time in the simulation. This is critical for modeling radically novel technologies, such as radical deep decarbonization strategies, where simulation models display more inertia toward novel technology diffusion than optimization models, which show an earlier market uptake. The introduction of novel technologies is, however, linked to the level of technological detail of an energy system, as well as to a complex set of parameters governing the technology capacity and growth in the market.

6.3. Granularity of Sectoral Modeling

Finally, models differ with respect to the detail and granularity with which they depict the energy sector, its energy and emissions. Models can depict a single industrial sector, aggregating all production activities (typical of top-down models) or specifying a few key sectors of interest while lumping all other economic activities in the "other" category, or they can be very detailed and include a large number of sectors and subsectors (typical of bottom-up models). Several trade-offs are associated with the choice of aggregate versus detailed representation. The more sectorally detailed a model, the better it can depict differences among the various mitigation options within and across sectors. This can be achieved only if very detailed data are available to feed the mode and usually leads to long computing times to achieve a solution.

The variation of models along these three dimensions has important implications for modeling industrial energy demand and emissions. Bottom-up, sectorally-detailed models are more likely to allow the study of the choices among the different sector-specific mitigation options described in Section 4. Yet they often abstract from general equilibrium effects and are based on strong assumptions regarding the development of macro-level variables and indicators. This limits the ability to model circularity practices that go beyond a specific sector or geography and understanding of the global implications of choosing different mitigation options in different sectors or countries. The opposite is true for top-down aggregated models.

Given these trade-offs, over time a larger number of models have adopted a hybrid approach, including features of both top-down and bottom-up models. Sometimes models also combine optimization and simulation in different modules or portray certain aspects of the economy at an aggregated level while they detail specific sectors of interest. Integrated assessment models (IAMs), for instance, often use a hybrid approach for energy demand and emissions.

An IAM is a specific type of model that combines data gathered from two or even more disciplines into a single framework i.e., the economy, the energy system, and the environment. Researchers in physical, biological, earth, economic, and social sciences have typically produced elements of these models autonomously. The need to study interdisciplinary interactions among these components, as in the case of climate change, has led to the development of cohesive and consistent frameworks that include several components to assess the status and implications of environmental change more accurately, as well as possible solutions (Bosetti 2021). Some energy-intensive industries, such as iron and steel or cement, are included individually in most top-down IAMs, but few sector-specific technologies are expressly included. Instead, advances in energy efficiency in the industry sector and its subsectors are frequently dictated by exogenous assumptions or are a function of energy costs. Similarly, fuel switching is mostly caused by changes in relative fuel prices, which are affected by CO2 price trends (Pauliuk et al. 2017). Fuel switching can be regulated in IAMs that include specific technologies based on the features of those technologies, but in IAMs that lack technological detail, more generic limits of fuel switching in the industry sector are integrated.

Most IAMs employ aggregated, top-down industrial sector models that are calibrated from long-term historical data, such as the introduction of new technologies or fuels. As a result, these models can implicitly reflect real-world constraints in the entire sector that bottom-up approaches may not completely explore. These constraints may result from factors such as infrastructure building delays or market participants' insufficient understanding of new technology. Furthermore, because IAMs model the climate system, these models can mainly account for the effects of climate change on the growth and structure of economies (Pauliuk et al. 2017). However, top-down models are often limited in their portrayal of specific technologies and processes in the industry sector, especially of technology-driven structural change. This lack of technological information restricts the models' utility in analyzing technology- and sector-specific mitigation methods and policies. Top-down models also feature a highly aggregated depiction of industrial energy demand, making it difficult to evaluate demand-side mitigation techniques such as recycling, product-service efficiency, and demand reduction choices (Pauliuk et al. 2017).

7. The Modeling of Innovation and Technological Change and Relevant Policies

This section provides a brief overview of the different approaches to portray technological change in low-carbon emissions technologies, including radically novel technologies, relevant for industrial sectors. As noted in the previous section, the different methodologies to model innovation may coexist in a given model. Another related key point regards the ability of models to mimic how specific policies and policy instruments affect the different phases of the innovation process.

Innovation comprises stages ranging from basic R&D to prototyping, demonstration, and larger-scale market diffusion. How a model does or does not account for all these different stages affects the speed and depth of emissions reductions (Blanco et al. 2022).

In most models, a novel technology enters the market when its costs decrease and become equal to, or lower than, the costs of the dominant technology (van Sluisveld et al. 2020). Technology cost decrease can be calibrated using historical data or relying on expert estimates. The former relies on the learning curve approach: it assumes that costs decrease either as a function of R&D investment (learning-by-researching) or as a function of cumulative production or time (Nagy et al. 2013). Learning curve model parameters are derived from historical data and then used to project future cost decreases. The latter approach, which relies on expert estimates regarding the trajectory of future costs, has been used for radically novel technologies, for which historical data are not available (Verdolini et al. 2018). This was the case for the cost of nuclear power in the 1970s and the cost of CCS and other radically novel technologies more recently. Recent evidence has shown that both learning curve and expert-based approaches underestimate the cost reductions in several low-carbon technologies, with expert-based methods emerging as particularly pessimistic. Yet these results may not necessarily extend to more radical technologies. Moreover, no alternative approach exists in terms of informing the modeling of innovation (Meng et al. 2021).

Another important distinction between models is whether innovation is modeled exogenously or endogenously. In the former, technology costs are assumed to vary over time at some fixed rate, which can be derived from either historical data or expert estimates or by relying on marginal abatement cost curves derived elsewhere. In the latter, technology cost decreases are calibrated to historical values, but costs are a choice variable in the model, and agents can decide how much to invest in it (Krey et al. 2019; Mercure et al. 2016). For example, technology cost reductions can be assumed to follow a predefined (historically observed) pattern or can be modeled as a function of R&D investment, which can be chosen (as opposed to being imposed) in the model. Modeling innovation exogenously rather than endogenously generally underestimates future cost reductions; for instance, it ignores policy-induced carbon-saving technological change or spillovers. In any case, assumptions regarding the speed of innovation and technological change can be tested through sensitivity analysis (Blanco et al. 2022).

Finally, most models rely on the assumption that when the cost of a new technology becomes competitive, the technology will naturally diffuse through the economy following a certain pattern, such as an S-shaped diffusion pattern (Hall 2006). This often results in an overestimation of the diffusion potential of many novel technologies, because diffusion is driven solely by cost in the models, and no consideration is given to other key barriers that may slow down deployment. These include noncost, nontechnological barriers or enablers regarding behaviors, society and institutions (e.g., path dependence or the coevolution of technology clusters over time), the risk aversion of users and capital markets, personal preferences and perceptions in a world of heterogeneous agents, network or infrastructure externalities, and a lack of supportive institutional frameworks (Iyer et al. 2015; Baker et al. 2015; Marangoni and Tavoni 2014; van Sluisveld et al. 2020; Napp et al. 2017; Biresselioglu et al. 2020). Ignoring these barriers generally leads to an overestimation of technology diffusion in such models. To address these issues, models can impose ad hoc restrictions on certain technologies, such as a ceiling to penetration. In addition, these barriers can be accounted for through scenario narratives, such as those in the Shared Socioeconomic Pathways (Riahi et al. 2017), in which assumptions about technology adoption span a plausible range of values. The literature also indicates that models tend to underestimate cost reduction potentials but to overestimate penetration rates. Careful calibration and sensitivity analysis are necessary to test the robustness of model results regarding technology innovation and diffusion (Blanco et al. 2022).

Given the key role that policies play in the innovation process, it is paramount to understand how they can be modeled and accounted for. A large number of contributions have explored how different policy instruments influence the availability of novel technologies, cost decreases over time, and technology diffusion in the market. Policy instruments are traditionally categorized as supply-side policies, which target technology innovation directly in the form of R&D investments or subsidies for research, and demand-side policies, which include both command-and-control policies such as emissions limits and market-based policies such as taxes or permits (IPCC 2022). A general result emerging from this literature is that low-emissions innovation and technology diffusion can be effectively supported through policy packages tailored to national contexts and technological characteristics. Yet low-emissions innovation can jointly achieve environmental, social, and economic benefits only if environmental policies are part of a broader, comprehensive and tailored policy package that addresses potential negative impacts and strengthens governance of the innovation system (Penasco et al. 2021; IPCC 2022).

No available models are able to account for such complex policy instruments. First and foremost, models portraying innovation and technology diffusion exogenously can account for the impact of different policy instruments on cost and diffusion dynamics only through sensitivity analysis. Second, even models that represent innovation as an endogenous process include only a limited set of policy instruments: taxes or markets for permits, emissions limits, and emissions standards. The potential role of instruments such as public procurement, public-private partnership, voluntary industry standards, or the nuances of policy design that affect the effectiveness of the policy instrument cannot be studied in depth, and these instruments are thus overlooked or implicitly assumed. Finally, a number of nonenvironmental policies, such as those targeting inflation or the ease of accessing capital, can influence innovation. These often are not appropriately accounted for in models of industrial energy demand.

8. Specific Models for Industry Energy Demand and Emissions

This section gives an overview of the most widely known models used to forecast industrial energy demand. Details are provided in Appendix C, where we classify each model based on the three criteria discussed in the previous section (top-down or bottom-up, simulation or optimization, and level of granularity of the industry module), describe the mechanisms through which the specific model represents industry energy demand and the main assumptions made, and note an application in the literature. Given the nature of this paper, we exclude models in which the entire industrial sector is portrayed as a single sector. The models analyzed for this paper and presented in Appendix C are as follows:

1. World Energy Model, International Energy Agency
2. National Energy Modeling System, US Energy Information Administration
3. Global Change Assessment Model, Pacific Northwest National Laboratory
4. Regional Model of Investment and Development, Potsdam Institute for Climate Impact Research
5. Modular Energy System Simulation Environment, Imperial College London
6. The Integrated MARKAL-EFOM System, Imperial College London, Grantham Institute
7. IMAGE, PBL Netherlands Environmental Assessment Agency
8. Material Economics Modelling Framework, Material Economics
9. Energy-Environment-Economy Global Macro-Economic, Cambridge Econometrics
10. Industrial Sector Energy Efficiency Model for Iron and Steel, Lawrence Berkeley National Laboratory
11. Universal Industrial Sectors Integrated Solutions, US Environmental Protection Agency
12. Hybrid Technological Economic Platform, CENSE and College of William and Mary
13. FORECAST, Fraunhofer Institute for Systems and Innovation Research

A main result of this analysis relates to the granularity with which radical technologies are modeled. Many of the energy system models and the integrated assessment model described in Appendix C are not detailed enough to model separately some of the specific key mitigation options described in Section 4—such as the electrowinning process or molten oxide electrolysis—in different energy-intensive sectors. Many provide only high-level details on the process of innovation and its direction. This is also true in the case of detailed sectoral models, which generally are not technology- or subtechnology-specific. Moreover, these models do not describe circularity practices, such as the difference between conventional and new types of SCMs, mostly because they do not model material flows but rather model the cost of a given technology or its energy demand and efficiency. Importantly, efforts are currently underway to integrate the modeling of GHG emissions with the modeling of material flows, yet this process has proven to be challenging, and no model is currently available that incorporates simultaneously attention to GHG emissions and the material side of the economy.

9. Conclusions

The aim of this paper is to improve the understanding of challenges linked with the modeling of emissions and energy demand in key energy-intensive industrial sectors, with a particular focus on the role that new low-carbon technologies can play in achieving deep mitigation targets. With the aim of highlighting the sectoral peculiarities of various emissions reduction strategies, we first discuss the relevance of different emissions reduction approaches—fuel switching and electrification, carbon efficiency, material efficiency, carbon capture and storage, and circular economy practices—for six high-energy-demand sectors: steel, cement, chemicals, light manufacturing, aluminum, and pulp and paper. To highlight the limitations of modeling industrial energy demand and associated emissions, we then detail the data limitations that constrain model calibration and describe the methodologies that characterize the most well-known integrated assessment models of industrial energy demand.

Three key insights emerge from this analysis. First and foremost, models need to be further developed to appropriately capture industrial decarbonization options and the effects of policies. None of the widely used industrial energy and emissions models have the capacity to portray the adoption and diffusion of granular technological options for emissions reduction in energy-intensive sectors. No model can portray heterogeneous innovation and technology adoption dynamics due to firm characteristics (e.g., size or access to capital). Most available models, including those with relatively high sectoral detail, are not technology- or sub-technology-specific and rely on only a high-level representation of the innovation process. Moreover, available IAMs do not track material flows and consequently cannot describe circularity practices and their relevance for mitigation. While efforts in this respect are underway, much work remains ahead for the research community. In this respect, the soft or hard linking of available models with other technology-specific more detailed models, including agent-based models emerges as an important research avenue for the future.

Data availability also represents a key barrier for model development. Data collection efforts are inadequate and need to be scaled up. However, marked firm heterogeneity both within and across sectors is a main barrier in this respect. Given the lack of a coordinated, state-driven effort to gather statistics on industrial energy demand and use, researchers have difficulty obtaining the necessary data. When entrepreneurs are willing to share, data are often limited and lack panel dimension or cannot be compared across countries and sectors because of a lack of precise collection standards.
This situation could be partly resolved if policymakers create a framework aimed at facilitating the sharing of data regarding the environmental performance of small and medium-size enterprises or entrust national statistical offices with this task. This would allow researchers to rely on data whose consistency has been certified by numerous studies, and data harmonization would require less time than when performing the same operations multiple times on the same dataset.

Last but not least, while a portfolio of different options is available in all industrial sectors to reduce energy demand, existing technologies are not sufficient to achieve deep decarbonization goals across industrial sectors. Nor is it possible to achieve these goals by relying on only one technological option. Thus R&D on relevant decarbonization technologies needs to be sped up to ensure the further development of additional low-carbon industrial technologies in all energy-intensive sectors and make available other decarbonization solutions that are not in use yet.

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Appendix A. Available Datasets to Track Industrial Energy Demand and Emissions, and Their Limitations

Table A.1. GTAP 11 and GTAP-E

Characteristic	Definition
Content	GTAP 11 describes global bilateral trade patterns, international transport margins, and protection matrices that link individual countries or regions. For each country or region, the database presents values of production as well as intermediate and final consumption of commodities and services in millions of US$. GTAP-E provides carbon dioxide (CO_2) emissions data, distinguished by fuel and user.
Spatial coverage	Both GTAP 11 and GTAP-E cover 141 countries and 19 aggregate regions of the world for each reference year.
Temporal coverage	Both GTAP 11 and GTAP-E provide a time series of snapshots of the global economy for each of five reference years: 2004, 2007, 2011, 2014, and 2017.
Industrial sectors	Both GTAP 11 and GTAP-E represent 65 products and services.
Industry classification	Both GTAP 11 and GTAP-E sectors are derivable from the International Standard Industry Classification (ISIC).
Strengths	For GTAP 11 high spatial coverage; for GTAP-E both high spatial coverage and distinction of CO2 emissions by fuels and by user.
Weaknesses	GTAP uses a sector classification derivable from the ISIC classification. The result is a product/service classification and not an industry sector classification. [Section 5.1] Data are dated and presented as a snapshot for five years. [Section 5.4]

Source: Aguiar et al. (2023)

Table A.2. GTAP 10 Database Sectors

#	Code	Sector
1	pdr	Paddy rice
2	wht	Wheat
3	gro	Cereal grains nec
4	v_f	Vegetables, fruit, nuts
5	osd	Oil seeds
6	c_b	Sugar cane, sugar beet
7	pfb	Plant-based fibers
8	ocr	Crops nec
9	ctl	Bovine cattle, sheep and goats, horses
10	oap	Animal products nec
11	rmk	Raw milk
12	wol	Wool, silk-worm cocoons
13	frs	Forestry
14	fsh	Fishing
15	coa	Coal
16	oil	Oil
17	gas	Gas
18	oxt	Other extraction (formerly omn); minerals nec
19	cmt	Bovine meat products
20	omt	Meat products nec
21	vol	Vegetable oils and fats
22	mil	Dairy products
23	pcr	Processed rice
24	sgr	Sugar
25	ofd	Food products nec
26	b_t	Beverages and tobacco products
27	tex	Textiles
28	wap	Wearing apparel
29	lea	Leather products
30	lum	Wood products

#	Code	Sector
30	lum	Wood products
31	ppp	Paper products, publishing
32	p_c	Petroleum, coal products
33	chm	Chemical products
34	bph	Basic pharmaceutical products
35	rpp	Rubber and plastic products
36	nmm	Mineral products nec
37	i_s	Ferrous metals
38	nfm	Metals nec
39	fmp	Metal products
40	ele	Computer, electronic and optical products
41	eeq	Electrical equipment
42	ome	Machinery and equipment nec
43	mvh	Motor vehicles and parts
44	otn	Transport equipment nec
45	omf	Manufactures nec
46	ely	Electricity
47	gdt	Gas manufacture, distribution
48	wtr	Water
49	cns	Construction
50	trd	Trade
51	afs	Accommodation, food and service activities
52	otp	Transport nec
53	wtp	Water transport
54	atp	Air transport
55	whs	Warehousing and support activities
56	cmn	Communication
57	ofi	Financial services nec
58	ins	Insurance (formerly isr)
59	rsa	Real estate activities
60	obs	Business services nec
61	ros	Recreational and other services
62	osg	Public Administration and defense
63	edu	Education
64	hht	Human health and social work activities
65	dwe	Dwellings

Table A.3. EDGAR V7.0

Characteristic	Description
Content	Provides emissions of the three main greenhouse gases (CO_2, CH_4, N_2O) and fluorinated gases in kilotons (Kt) per sector and country.
Spatial coverage	210 countries.
Temporal coverage	Time series for 1970–2021.
Industrial sectors	26 sectors.
Industry classification	EDGAR sector classification, derivable from the IPCC Guidelines sector classification.
Strengths	High spatial and temporal coverage; data on three main GHGs.
Weaknesses	EDGAR uses a sector classification derivable from 2006 IPCC Guidelines sector classification [Section 5.1] No data on energy demand. [Section 5.2] Energy carrier is identified only by bio/fossil. [Section 5.3]. No data on material and energy flows. [Section 5.7]

Table A.4. EDGAR Database Sectors

#	Code	Sector
1	AGS	Agricultural soils
2	AWB	Agricultural waste burning
3	CHE	Chemical processes
4	ENE	Power industry
5	ENF	Enteric fermentation
6	FFF	Fossil fuel fires
7	IDE	Indirect emissions from NO_x and NH_3
8	IND	Combustion for manufacturing
9	IRO	Iron and steel production
10	MNM	Manure management
11	N2O	Indirect N_2O emissions from agriculture
12	PRO_COAL	Fuel exploitation COAL
13	PRO_GAS	Fuel exploitation GAS
14	PRO_OIL	Fuel exploitation OIL
15	PRU_SOL	Solvents and products use
16	RCO	Energy for buildings
17	REF_TRF	Oil refineries and transformation industry
18	SWD_INC	Solid waste incineration
19	SWD_LDF	Solid waste landfills
20	TNR_Aviation_CDS	Aviation climbing & descent
21	TNR_Aviation_CRS	Aviation cruise
22	TNR_Aviation_LTO	Aviation landing & takeoff
23	TNR_Other	Railways, pipelines, off-road transport
24	TNR_Ship	Shipping
25	TRO	Road transportation
26	WWT	Waste water handling

Table A.5. World Input-Output Database (WIOD) 2016

Characteristic	Description	Environmental accounts
Content	World input-output tables (WIOTs) in current prices, denoted in millions of US$. A WIOT provides a comprehensive summary of all transactions in the global economy between industries and final users across countries.	Gross energy use (TJ), emissions-relevant energy use (TJ), and CO2 (kt).
Spatial coverage	43 countries	41 countries
Temporal coverage	Time series for 2000–2014	Time series for 2000–2016
Industrial sectors	58 sectors	64 sectors
Industry classification	ISIC Rev. 4*	NACE Rev. 2
Strengths	High temporal coverage; presents both emissions and energy use; twelve energy carriers for gross energy use; emissions-relevant energy use.	
Weaknesses*	Data are dated; the time series ended in 2014. [Section 5.4] There is no information about fuel inputs related to CO_2 emissions. [Section 5.5]	

*The first and second levels (sections and divisions) of ISIC Rev. 4 (UN 2008) are the same as those of NACE Rev. 2 (Eurostat 2008). NACE Rev. 2 divides the third and fourth levels (groups and classes) of ISIC Rev. 4 in accordance with European standards. However, NACE Rev. 2 groups and classes can always be combined with the ISIC Rev. 4 groups and classes from which they were derived. The additional divisions in NACE Rev. 2 over ISIC Rev. 4 are intended to create a categorization that is better adapted to the economic systems of Europe.

Table A.6. NACE Rev. 2

#	Code	NACE Rev. 2
1	vA01	Crop and animal production; hunting and related service activities
2	vA02	Forestry and logging
3	vA03	Fishing and aquaculture
4	vB	Mining and quarrying
5	vC10_12	Manufacture of food products, beverages, and tobacco products
6	vC13_15	Manufacture of textiles, wearing apparel, and leather products
7	vC16	Manufacture of wood and of wood and cork products, except furniture; manufacture of articles of straw and plaiting materials
8	vC17	Manufacture of paper and paper products
9	vC18	Printing and reproduction of recorded media
10	vC19	Manufacture of coke and refined petroleum products
11	vC20	Manufacture of chemicals and chemical products
12	vC21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
13	vC22	Manufacture of rubber and plastic products
14	vC23	Manufacture of other nonmetallic mineral products
15	vC24	Manufacture of basic metals
16	vC25	Manufacture of fabricated metal products, except machinery and equipment
17	vC26	Manufacture of computer, electronic and optical products
18	vC27	Manufacture of electrical equipment
19	vC28	Manufacture of machinery and equipment nec
20	vC29	Manufacture of motor vehicles, trailers and semi-trailers
21	vC30	Manufacture of other transport equipment
22	vC31_32	Manufacture of furniture; other manufacturing
23	vC33	Repair and installation of machinery and equipment
24	vD35	Electricity, gas, steam, and air-conditioning supply
25	vE36	Water collection, treatment, and supply
26	vE37_39	Sewerage; waste collection, treatment, and disposal activities; materials recovery; remediation activities; and other waste management services
27	vF	Construction
28	vG45	Wholesale and retail trade and repair of motor vehicles and motorcycles
29	vG46	Wholesale trade, except of motor vehicles and motorcycles

#	Code	NACE Rev. 2
30	vG47	Retail trade, except of motor vehicles and motorcycles
31	vH49	Land transport and transport via pipelines
32	vH50	Water transport
33	vH51	Air transport
34	vH52	Warehousing and support activities for transportation
35	vH53	Postal and courier activities
36	vI	Accommodation and food service activities
37	vJ58	Publishing activities
38	vJ59_60	Motion picture, video, and television program production; sound recording and music publishing activities; programming and broadcasting activities
39	vJ61	Telecommunications
40	vJ62_63	Computer programming, consultancy, and related activities; information service activities
41	vK64	Financial service activities, except insurance and pension funding
42	vK65	Insurance, reinsurance, and pension funding, except compulsory social security
43	vK66	Activities auxiliary to financial services and insurance activities
44	vL68	Real estate activities
45	vM69_70	Legal and accounting activities; activities of head offices; management consultancy activities
46	vM71	Architectural and engineering activities; technical testing and analysis
47	vM72	Scientific research and development
48	vM73	Advertising and market research
49	vM74_75	Other professional, scientific and technical activities; veterinary activities
50	vN	Administrative and support service activities
51	vO84	Public administration and defense; compulsory social security
52	vP85	Education
53	vQ	Human health and social work activities
54	vR_S	Other service activities
55	vT	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
56	vU	Activities of extraterritorial organizations and bodies
57	vTOTII_new	Total industrial activities
58	vCONS_h_new	Final consumption expenditure by households

Table A.7. Eora26

Characteristic	Description
Content	Global multiregion input-output table (MRIO) documenting intersectoral transfers, environmental indicators covering GHGs emissions, labor inputs, air pollution, energy use, water requirements, land occupation, N and P emissions, and primary inputs to agriculture.
Spatial coverage	190 countries.
Temporal coverage	Time series for 1990–2021.
Industrial sectors	26 sectors.
Industry classification	The Eora26 sector classification is based on common sector classifications, but no concordance matrix to or from other classifications is available.
Strengths	High spatial and temporal resolutions; high number of environmental indicators.
Weaknesses	Eora26 classification is not derivable from other standard classifications. [Section 5.1] No data on energy carriers for energy use. [Section 5.2] No data on energy carriers for GHG emissions. [Section 5.5]

Table A.8. Eora26 Classifications

#	Classification
1	Agriculture
2	Fishing
3	Mining and quarrying
4	Food and beverages
5	Textiles and wearing apparel
6	Wood and paper
7	Petroleum, chemical, and nonmetallic mineral products
8	Metal products
9	Electrical and machinery
10	Transport equipment
11	Other manufacturing
12	Recycling
13	Electricity, gas, and water
14	Construction
15	Maintenance and repair
16	Wholesale trade
17	Retail trade
18	Hotels and restraurants
19	Transport
20	Post and telecommunications
21	Financial intermediation and business activities
22	Public administration
23	Education, health, and other services
24	Private households
25	Others
26	Re-export and re-import

Appendix B. Classification of Industrial Sectors

To understand the different approaches to industrial modeling, it is necessary to understand industry classifications and the availability of sector-level data on energy demand and emissions. Table B.1 summarizes the characteristics of the different classification methods.

Table B.1. Available Classifications of Industrial Sectors

Structure	Code	ISIC Rev. 4	NACE Rev. 2
Section	Letter-based	21 sections	21 sections
Division	2-digit	88 divisions	88 divisions
Group	3-digit	238 groups	272 groups
Class	4-digit	419 classes	615 classes
Structure	**Code**	**NAICS (OMB 2022)**	
Sector	2-digit	20 sectors	
Subsector	3-digit	99 subsectors	
Industry group*	4-digit	311 industry groups	
NAICS industry	5-digit	709 NAICS industries	
National industry	6-digit	1,057 national industries	

*Represents the lowest level of compatibility among the United States, Canada, and Mexico.

B.1. The International Standard Industrial Classification of All Economic Activities (ISIC)

ISIC is the United Nations' system for classifying economic activities based on a collection of ideas, definitions, guiding principles, and classification criteria that have been universally accepted (UN 2008). It provides a thorough framework for collecting and reporting economic data intended for use in economic analysis, decisionmaking, and policymaking. ISIC classifies productive activities into four levels of distinct hierarchical categories to make data collection, display, and analysis at specific economic levels easier and more uniform worldwide. **Sections** are the highest level of classification, with all forms of productive activity divided into major categories designated by letters. These are subdivided into ever more specific categories designated by numbers: two-digit **divisions**, three-digit **groups**, and four-digit **classes**. The criteria used to define the categories are based on "the inputs of goods, services, and factors of production, the process and technology of production, the characteristics of outputs, and the use to which the outputs are put" (UN 2008).

The ISIC categories have been used to organize economic activities that meet these requirements. The economic activities' process and technology have been prioritized for defining specific ISIC classes at the most granular level of categorization, especially in the categories related to services. Data may be used to investigate specific industries or industrial groups and evaluate the economy by disaggregating the data into various degrees of detail. Numerous factors, including the intended use of the classification, the accessibility of data, and the amount of aggregation considered influence the criteria used to define the categories at every level. Similarities between manufacturing processes are always considered when classifying activities at the sector level at high level of detail; undoubtedly, the more aggregate the sector, the more heterogenous are the processes bundled in the classification.

B.2. The North American Industry Classification System (NAICS)

NAICS is a system for classifying organizations based on their economic activities. Its goals are to make it easier to gather, tabulate, display, and analyze data on businesses, as well as to improve uniformity and consistency in the analysis and presentation of statistical data about the USA, Canadian, and Mexican economy. By working together on NAICS, the Instituto Nacional de Estadística y Geografía of Mexico, Statistics Canada, and the US Office of Management and Budget have created a uniform framework that makes the industry statistics provided by the three nations comparable. NAICS is used by federal statistics organizations and policy analysts to gather and disseminate data by industry, and state agencies, academia and researchers, the business community, and the general public also make extensive use of the system.

NAICS is a hierarchical system in which enterprises are categorized from the broadest to the most granular levels and is the first industrial categorization system created using a single aggregation basis. It reflects recent technological advances as well as the increase and diversity of services. NAICS (2017) classification is highly comparable to the most current version of ISIC. Four principles influence NAICS development: (1) NAICS has a product-oriented framework, grouping together manufacturing units that employ the same or comparable production processes. (2) The system focuses on building production-oriented categories for new and emerging sectors, the service sector in general, and industries involved in high technology production. (3) Time-series consistency is preserved to the highest degree possible. (4) The system seeks two-digit compliance with the ISIC classification.

B.3. The Statistical Classification of Economic Activities in the European Community (NACE)

NACE is the European Union's accepted system of categorizing productive economic activity, in which a code is assigned to a statistical unit for each activity. The acronym NACE (Nomenclature statistique des Activités économiques dans la Communauté Européenne) comes from the French name for the system and refers to the multiple statistical categories of economic activities in the European Union since 1970. NACE provides a framework for gathering and displaying a wide range of statistical data based on economic activities. An economic activity is defined by the input of resources, the manufacturing process, and the output of goods. When resources such as labor, capital goods, manufacturing processes, or intermediary items are combined to create certain commodities or services, that is considered an economic activity. An activity might be a single, straightforward process, or it might consist of a variety of smaller activities that are each classified in a distinct category. NACE originated from ISIC but is more detailed. ISIC and NACE include identical elements at the highest levels, with NACE being more granular at lower levels. NACE consists of a hierarchical structure as defined by the NACE regulations, introductory instructions, and explanatory notes (Eurostat 2008).

Statistics based on NACE are comparable at the European and global levels, and the usage of this classification system was made mandatory in the EU by member states, the European Commission, and the European Statistical System. To guarantee worldwide comparability, the criteria and rules defined for the use of NACE inside the EU are the same as those for ISIC. Statistics collected by the EU member states regarding economic activity categorization must be produced by NACE or a national categorization derived from it (Eurostat 2008). The NACE regulations permit member states to use a national version of the system for domestic reasons. Such national versions must comply with NACE's hierarchical structure. Many member states have created their own versions, generally by adding a fifth digit to represent national needs.

Appendix C. Model Summaries

Table C.1. World Energy Model (WEM)

Type	Simulation
Approach	Hybrid
Spatial resolution	Global (26 regions)
Temporal resolution	Yearly to 2050
Industry sectors	Nonferrous metals (aluminum) Iron and steel Chemical and petrochemical Nonmetallic minerals (cement) Pulp and paper Other industry

The International Energy Agency's WEM is a large-scale simulation model that is updated annually; it has been developed over many years and focuses on energy use in 26 regions until 2050 (IEA 2021). For each region, it includes three main modules: final energy consumption (covering residential, services, agriculture, industry, transportation, and nonenergy use), energy transformation, and other transformation. The model's outputs include energy flows by fuel, investment requirements and costs, CO2 emissions, and end-user pricing. WEM's industrial sector is divided into six subsectors: nonferrous metals (including aluminum), iron and steel, chemicals and petrochemicals, nonmetallic minerals (including cement), pulp and paper, and other industries (transport equipment, machinery, mining and quarrying, food and tobacco, wood and wood products, construction, textile and leather, and nonspecified). Energy consumption in the industrial sector is driven by the manufacture of goods in the energy-demanding industries and by value added in the nonspecified industry sectors.

In each subsector, energy consumption is computed as the product of production forecasts and manufacturing process energy intensity. The energy intensity of new capacity is dependent on the use of energy-efficient technology and the level of energy costs, while the energy use per unit of production for existing infrastructure is rather stable. Each production method for aluminum, iron, steel, five primary product categories in chemicals and petrochemicals, cement, pulp and paper, and cross-cutting technologies in non-energy-demanding industries offers chances for technological efficiency. Energy-efficient technologies are adopted based on their prospective penetration rate and payback time frame, both of which vary depending on the circumstance. In addition to single-equipment efficiency, the industry sector model also includes choices for system optimization and process improvements. The WEM industrial model may reflect material efficiency techniques in addition to energy efficiency technology and measures, offering further energy savings. Energy-intensive industries often have more restricted opportunities to improve energy efficiency than less energy-intensive industries because energy costs contribute significantly to production costs. This strategy's use is restricted to the material and energy needs of the corresponding industrial sectors. WEM does not examine the effects on energy use upstream, during mining or material transportation, or the impact on consumption downstream, nor does it include the possible energy savings from substitute materials.

WEM is used only to produce the IEA's World Energy Outlook (WEO) and, to the best of our knowledge, is not available for use outside of the agency. For the WEO, WEM uses a scenario approach to look at potential changes in the energy sector based on the model. Four scenarios—the Announced Pledges, Net Zero Emissions by 2050, Stated Policies, and Sustainable Development Scenarios—were simulated in depth for the World Energy Outlook 2021. The scenarios include the most recent energy data, policy statements, investment patterns, and technological advances and are based on modeling and analysis. When examining figure developments, the WEO scenarios take into consideration the complete range of existing national conditions, resources, technology, and prospective policy options. WEM enables the assessment of the impact of certain policies and initiatives on energy consumption, production, trade, investment requirements, supply prices, and emissions. Policies and measures are derived by the WEO policy database and include initiatives addressing renewable energy, energy efficiency, and climate change.

Table C.2. National Energy Modeling System (NEMS)

Type	Optimization/simulation Partial equilibrium	**Industry sectors**	Food Paper Chemicals Glass Cement and lime Iron and steel Aluminum
Approach	Hybrid		
Spatial resolution	Regional/national (United States)		
Temporal resolution	Yearly to 2050		

NEMS is a computer-based energy-economy modeling system for the United States developed by the US Energy Information Administration (EIA 2019). NEMS forecasts energy production, imports, conversion, consumption, and pricing based on assumptions about macroeconomic and financial aspects, global energy markets, resource availability and costs, behavioral and technical choice criteria, cost and performance characteristics of energy technologies, and demography. Thus, it provides a standardized framework to describe the interactions of the US energy infrastructure and its reaction to a wide range of different assumptions, regulations, and policy initiatives, as well as to measure the effect of new energy initiatives and regulations. The forecast time frame is around 30 years. NEMS can be used to assess the energy, economic, environmental, and security effects of existing and proposed government laws and regulations pertaining to energy production and use on the US energy system and the potential impact of advanced and innovative energy production, conversion, and consumption technologies. In addition, NEMS can assess the effect and cost of greenhouse gas control, the effect of increased use of renewable energy sources, the costs and benefits from increased energy efficiency, and the impact of regulations relating to the use of innovative or reformulated energy sources. Since energy supplies and costs, demand for specialized energy services, and other energy market features vary greatly across the United States, regional versions of the model can be used to account for different geologies and other characteristics and focus on key areas most relevant for policy analysis.

Unit energy consumption (UEC) is estimated for each NAICS sector in the industrial demand module. The quantity of energy necessary to generate one dollar's value of shipments or one unit of physical output is specified as UEC. Technological change in the manufacturing process allows for lower energy intensity; this is assumed to come about through a learning-by-doing process—that is, as experience is gained in the technology, production costs decrease. Industrial innovations can be selected and deployed because of a variety of reasons other than their energy consumption characteristics, such as process improvements to enhance product quality, changes to increase productivity, or changes in reaction to the competitive environment. Future reductions in unit energy consumption are calculated using technology possibility curves, and future energy savings are estimated for both new and existing processes and facilities.

In older facilities, energy gains arise from progressive improvements driven by energy-saving measures, retrofits of certain technologies, and the closure of inefficient older facilities. Estimated UEC values for state-of-the-art (SOA) and advanced technologies are also provided. The most recent and proven technologies available at the time of investment decision—that is, the SOA—are chosen. Estimated results are then compared with UECs of the base year to compute an index of relative energy intensity, calculated as the energy use of a new process relative to base-year energy use. The efficiency benefit for new facilities depends on the installation of the SOA technologies appropriate for that sector. When new technologies are accessible for a specific process, a second, occasionally more significant, round of considerable improvements may occur. Industrial energy consumption is affected by increased energy efficiency in new and old facilities, the industry's growth rate, and the retirement rate for old plants (EIA 2022).

NEMS has been widely used. For instance, Brown and Baek (2010) study energy efficiency impacts of a portfolio of energy and climate policies to mitigate electricity and biomass price increases while increasing energy security and lowering CO_2 emissions. They evaluate three different national policy scenarios focusing on the forest products sector: a renewable electricity standard, a carbon policy, and incentives for industrial energy efficiency. They also explore the potential impacts of such market shifts on biomass and electricity costs, energy use, and CO_2 emissions.

Table C.3. Global Change Assessment Model (GCAM)

Type	Optimization/ simulation Partial equilibrium	**Industry sectors**	Iron and steel Chemicals Aluminum Cement Fertilizers Other industry
Approach	Bottom-up		
Spatial resolution	Global (32 regions, 300 subregions)		
Temporal resolution	5 years to 2100		

Developed by the Pacific Northwest National Laboratory, GCAM is a multisector integrated model that analyzes both human and Earth system dynamics (GCIMS). The model adopts a set of assumptions and then analyzes them to provide a complete picture of pricing, energy, commodity, and other flows across regions and in the long term. It represents five distinct interacting and interrelated systems: macroeconomics, energy, agriculture and land, water, and physical earth. The energy-economy system runs in 32 regions globally, the land system is split into more than 300 subregions, and the Earth system module is global. Market equilibrium is the main guiding concept of GCAM, in which representative agents decide how to distribute resources based on pricing and other potentially relevant information. These representative agents communicate with one another through markets. To ensure that supplies and demands are balanced throughout all these markets, GCAM solves for a range of market prices. The GCAM solution process entails optimizing market pricing until this equilibrium is achieved. Given that GCAM is a dynamic recursive model, choices made today do not consider future events.

The energy system module in GCAM models nine detailed industrial sectors: six manufacturing sectors (iron and steel, chemicals and petrochemicals, aluminum, cement, fertilizers, and other industry) and three nonmanufacturing sectors (construction, mining energy use, and agricultural energy use). International trade is not modeled. Physical outputs (Mt) and general terminology are used to express the output of the detailed industry sectors. The remaining industrial sectors are represented as “other industries” and are consumers of generic energy services and feedstocks. The iron and steel sector is divided into three subsectors: basic oxygen furnace (BOF), electric arc furnace with scrap (EAF), and EAF with direct reduced iron (DRI). Each subsector has several competing technologies, including fossil fuels with and without CCS, electricity, hydrogen, and biomass. The chemicals and petrochemicals sector is divided into two parts: chemical energy usage and feedstocks. The aluminum manufacturing process consists of two major steps: alumina refining, which involves refining bauxite ore into alumina, and aluminum smelting, converting alumina to aluminum. There are several competing methods for alumina refining, including coal, refined liquids, gas, and biomass with and without CCS. GCAM contains a model for cement manufacturing that measures both fuel and limestone-derived CO2 emissions. Most of the key fossil fuel and low-carbon technologies that are expected to be available at least until 2050 are represented in the model. In GCAM, mitigation is modeled as a move from high- to low-carbon technologies based on relative costs, emissions constraints, and carbon prices.

In a recent application, Peng et al. (2021) investigate twelve mitigation scenarios that differ along two dimensions: national mitigation effort and subnational policy approach. The first is measured by four national US total greenhouse gas (GHG) emissions objectives for 2050. The second is represented by three levels of variability in the constraints of state-level climate policy, represented as a uniform carbon price calculated by equalizing the marginal abatement cost (MAC) across states in GCAM-USA. The MAC indirectly evaluates industries’ and households’ willingness to pay to reduce carbon emissions in a given state. A greater MAC means a higher carbon price and, as a result, stricter climate policy actions. Peng and colleagues validate the widespread conclusion in the literature that deep decarbonization often necessitates decarbonizing the electrical sector first before moving on to harder-to-abate sectors such as industry, residential, and transport.

Table C.4. Regional Model of Investment and Development (REMIND)

Type	Nonlinear programming Optimization	**Industry sectors**	Cement Chemicals Iron and steel Other industry
Approach	Hybrid		
Spatial resolution	Global (11 regions)		
Temporal resolution	5 years until 2060, 10 until 2110, 20 until 2150		

REMIND is a multiregional model developed by Potsdam Institute for Climate Impact Research. It is based on the General Algebraic Modeling System (GAMS), which incorporates the economy and a detailed description of the energy sector. It employs nonlinear optimization to create welfare-optimal regional transformation paths of the energy-economic system under climate and sustainability constraints for 2005–2100. Under the presumptions of perfect agent foresight and internalization of external effects, the solution conforms to the decentralized market outcome. With a specific focus on the scaling up of innovative technologies, such as renewables, and their integration into energy markets, REMIND can be used to analyze technological possibilities and different policy approaches for climate change mitigation (Baumstark et al. 2021).

The industry module simulates the total final energy demand and emissions of the industry sector and its subsectors: cement, chemicals, iron and steel, and all remaining industry energy demand ("other industry"). These shares are fixed at 2005 levels for each region. The constant elasticity of substitution production function is used to determine whether fuel switching is attractive depending on final energy prices and the final energy carriers' substitution elasticities. Three MAC curves for CCS in the cement, chemicals, and iron and steel sectors have been generated from the literature and used in all industrial module realizations (Kuramochi et al. 2012). To compute industry CO2 emissions and capture levels, sector-specific MAC curves for CCS are applied to emissions calculated from energy use and emissions factors based on the endogenous CO2 price. Process emissions from the production of cement are counted in the cement emissions for which CCS is relevant and are based on an econometric estimate of cement production. The integral below the MAC cost curve equals the industry CCS costs by subsector (Baumstark et al. 2021).

Table C.5. Modular Energy System Simulation Environment (MUSE)

Type	SImulation Partial equilibrium	**Industry sectors**	Aluminum Iron and steel
Approach	Bottom-up		Chemical
Spatial resolution	Global (28 regions)		Cement Pulp and paper
Temporal resolution	5–10 years to 2050–2100		Other industry

MUSE, developed by Imperial College London, models a partial equilibrium of the whole energy system, which includes the extraction of resources like oil, biomass, or renewables (in supply sectors), the resource transformation into energy vectors (in power systems and refineries), and the consumption of energy vectors for fulfilling society needs (in demand sectors) (Giarola et al. 2022). With its agent-based structure, the model is used to describe decision goals and strategies of key players in each sector, and thus it shows that business and consumer decisionmaking can produce macro-level inefficiencies in the energy system. From the technology description, the model is bottom-up and technology-rich; it models each technology performance, costs, and emissions and records technology stock, investments, operating costs, and energy use. The level of technological detail necessary to characterize the technologies and agents requires access to large datasets of technoeconomic and socioeconomic information, which may not always be publicly available for all countries.

MUSE demand sectors include industry, agriculture, buildings, and transport. In addition to iron and steel, industry also covers nonmetallic minerals, nonferrous metals, pulp and paper, and chemical and petrochemical products. These other subsectors are grouped together as “other industry.” In the hard-to-abate industry sectors, existing technologies represent the base year stock, which models existing facilities installation, operating production levels, energy consumption, and emissions aggregated at a regional scale. The existing capacity is linearly decommissioned; this, alongside the capacity needed to meet future demand, is then replaced by new assets, taking into consideration evolving legislation, fuel and carbon prices and the availability of advanced technologies.

The model first forecasts future demand for industrial commodities on a worldwide scale with a regional disaggregation using historical patterns. Then the production of material goods is modeled using a merit-order method based on the investor’s decision goal, which could be net present value maximization or cost minimization. As a result, until the demand for material goods is satisfied, the processes with the highest profits are used to primarily cover the demand. The quantity needed of each different fuel is calculated based on the combination of technologies being employed. The decarbonization of industry sectors may occur through (1) energy efficiency; (2) electrification in the iron and steel industry; (3) fuel switching, with biomethane and biomass options available for all industries, and hydrogen available for cement and the iron and steel industry; or (4) advanced technologies, which include electric furnace and the smelting process in the iron and steel sector, calcium looping in the cement sector, and the integration of CCS in all the standard sector technologies with a higher installation cost and greater energy consumption.

One relevant application of the industry model is presented in Budinis et al. (2020), which models the decarbonization of the Chinese ammonia industry. This may occur via the integration of CCS in addition to fuel switching, investigating the potential uptake of negative emissions obtained from the combination of bioenergy with CCS. The methodology is has an agent-based formulation, which aims to simulate real investment strategies in the energy sector made by agent-investors in China. By classifying the market share into small versus large enterprises and international versus state-owned companies, the work shows that despite the availability of CCS, there are barriers preventing technology innovation, which can be related to the decisionmaking process and the capital access of industries.

Table C.6. The Integrated MARKAL-EFOM System (TIMES)

Type	Optimization	**Industry sectors**	Aluminum
Approach	Bottom-up		Iron and steel
Spatial resolution	Global (15 regions)		Chemical
Temporal resolution	10 years to 2100		Cement
			Pulp and paper
			Other industry

The TIMES model, developed by Imperial College London and the Grantham Institute, is a model generator that combines technical engineering detail and economics in energy modeling (Loulou and Labriet 2008). Although the TIMES model generator has different realizations at a national level (such as the UKTM, the TIMES model for the UK) and at a global scale (such as TIAM-Grantham or TIAM-UCL), the modeling approach is a least-cost intertemporal optimization. TIMES assumes perfect foresight, which means that all investment choices in each milestone year are optimized with the assumption of complete knowledge of future occurrences.

We describe here the energy system granularity of TIAM-Grantham as reference. The model incorporates all the phases from raw resources into the delivery of energy services requested by energy consumers via the chain of activities that transform, transport, distribute, and convert energy. On the supply side, it includes fuel mining, primary and secondary production, and external imports and exports. Energy is given to the demand side via various energy carriers, which are segmented into residential, commercial, agricultural, transportation, and industrial sectors.

Energy efficiency, electrification, and fuel switching are the available decarbonization options in TIAM. Among the advanced technologies, the model includes the following:

- in the iron and steel sector, blast furnace with direct coal injection, blast furnace with top-gas recycling, blast furnace with top-gas recycling and CCS, blast furnace with CCS, Corex smelting process, Corex with CCS, DRI with CCS, DRI with hydrogen, on-site power generation with recycled gases, on-site power generation with CCS
- in the nonmetallic mineral sector, cement precalciner with CCS, cement whole plant with CCS
- in the chemical and petrochemical sector, chemical production with CCS, ethylene process in chemical sector with CCS, hydrogen for ammonia production with CCS, ethylene and propylene process with CCS
- in the pulp and paper sector, steam generation in pulp and paper (coal- or gas-fired) with CCS, process heat in pulp and paper (coal- or gas-fired) with CCS
- in all the energy-intensive industry sectors, combined heat and power (using coal, gas, or recycled gases) with CCS
- in other industries, process heat with CCS

One of the recent model applications is presented by Napp et al. (2019), who focus on the challenges posed by decarbonization in industry. The analysis concludes that substantial investments in advanced technologies are required to achieve a scenario that is consistent with limiting global warming to 1.5°C. Key advanced technologies in the industrial sector include hydrogen-based steel, electrification, and CCS from cement production.

Table C.7. IMAGE

Type	Simulation	**Industry sectors**	Aluminum Iron and steel Chemical Cement Pulp and paper Other industry
Approach	Bottom-up		
Spatial resolution	Global (26 regions)		
Temporal resolution	Yearly to 2100		

IMAGE is an integrated framework developed by PBL Netherlands Environmental Assessment Agency for modeling interactions between human and natural systems (PBL 2021). The model includes two primary systems: the Human system and the Earth system. The socioeconomic or Human system illustrates how human activities that are important for sustainable development have evolved over time. Environmental changes are described by the Earth system. The effects of human activity on the Earth system and the effects of environmental change in the Earth system on the Human system make the two systems interdependent. The spatial resolution for socioeconomic processes is composed of 26 regions chosen for their importance to global environmental and development challenges, as well as the high level of consistency within these regions. The model framework is well suited to large-scale (global) and long-term (until 2100) assessments of human-environment interactions. The impacts of human activities on natural systems and natural resources are assessed, as well as how such impacts inhibit the availability of ecosystem services to sustain human development.

Focusing on the interaction between the Human and Earth systems, IMAGE defines emissions as a function of activity levels in the energy system, industry, agriculture, and land cover and land use changes, as well as projected abatement measures. The model represents key greenhouse gas emissions and a variety of air pollutants. It is calibrated to current global emissions inventories, with its settings adjusted to reproduce the state of the world from 1970 to a final base year. Changes in emissions factors over time are calculated based on the storyline, and the model may assume that emissions factors remain constant or decline over time in parallel with economic progress.

The energy model for the industry sector contains three categories: cement, steel, and other industrial activities. IMAGE includes extensive demand models for cement and steel. Exogenously specified emissions factors are multiplied by activity levels to compute emissions. Other industrial activities, such as copper production and solvent manufacture, have activity levels that are formulated as a geographic function of industry value added. Emissions are computed by multiplying activity levels by emissions factors. For the steel and cement industries, the heavy industry submodule is included. The activity in the generic structure of energy demand is described in terms of metric tons of cement and steel, both of which can be traded. Trade demand can be met from production that combines a variety of technologies. Costs and energy use per unit of production are two characteristics of each technology, and both gradually decrease over time. The multinomial logit equation used to determine the actual mix of technologies in steel and cement production leads to a larger market share for the lowest-cost technologies. Energy efficiency increases because of these technologies' autonomous development. The technology selection represents the price-induced improvement in energy efficiency. Price plays a role in fuel substitution, but technology type also plays a role because some technologies can only use certain types of energy carriers.

Sharmina et al. (2020) compare sector-specific analyses of four key sectors that are challenging to decarbonize with economy-wide modeling of 1.5°C and 2°C scenarios: aviation, shipping, road freight transport, and industry. To analyze and monitor the progress of mitigation in these sectors, the authors create and implement a novel framework. They find that in the 1.5°C and 2°C scenarios of the IMAGE model, emissions reductions result from significant reductions in CO_2 intensities and lower energy intensities, with relatively slight demand reduction in the activity of these sectors. Several additional actions and policy levers that could significantly reduce emissions are identified but not explicitly included in the modeled scenarios. These options for demand reduction include moving the industry toward a circular economy.

Table C.8. Material Economics Modelling Framework

Type	Simulation	**Industry sectors**	Steel
Approach	Bottom-up		Cement and concrete
Spatial resolution	European Union		Plastic
Temporal resolution	5 years to 2050		Ammonia

Cement and concrete, plastics, steel, and ammonia are all covered under the Material Economics Modelling Framework (Material Economics 2019). The modeling approach starts by estimating future activity levels. A baseline scenario for 2050 demand is predicted using a variety of models. The primary tool for steel is a dynamic material flow analysis, together with estimates about future saturation levels for steel stock in various end-use sectors. Activity levels for plastics, cement, and ammonia are based on expected building, mobility, food production, and other activity scenarios. The baseline scenario assumes no significant changes in material intensity or industrial structure. No change in net imports is envisaged because the goal is to define an EU net-zero CO_2 industrial system.

The second stage is to establish a variety of low-CO_2 manufacturing approaches. The analysis describes each process's technical maturity, investment needs, energy and feedstock inputs, other operational expenses, mass balance, and CO_2 emissions. Energy input costs are calculated for commonly used energy-economic scenarios developed by the International Energy Agency and other organizations. CO_2 emissions include not just emissions from power generation, but also carbon contained in items that may be discharged as CO_2 at the end of their useful life. Along with the production side, the assessment employs a variety of models to investigate prospects for the circular economy: enhanced material efficiency and increased material circularity. A packaging model characterizes 35 types and calculates prospects for reduced material consumption and replacement with other materials. The third component is a description of end-of-life material flows and manufacturing pathways that use them as inputs for the manufacture of new materials.

A dynamic materials flow model is employed for steel to anticipate the future availability of steel scrap. For plastics, a variety of end-of-life flows are anticipated based on stock levels and product lifetimes; these are evaluated for recycling and recovery suitability, including influences on yields, quality, and the consequent effective substitution of new production. Chemical recycling is defined as a new plastics production method, with an emphasis on high-carbon mass balance approaches. Plastic end-of-life incineration is also modeled, and CO_2 emissions are calculated. The potential for cement recycling of concrete particles and unhydrated cement recovery is calculated. A scenario analysis combines these three components. All scenarios are designed to achieve near-zero CO_2 emissions from the industrial output by 2050. Backcasting is used to build five-year paths that account for capital stock turnover, progressive increases in technical maturity, building lead times, and other constraints.

Material Economics (2019) investigates various strategies to maintain EU steel, plastic, ammonia, and cement output while achieving net-zero emissions. It estimates the possible effects of various solutions and determines that emissions from those industries may be decreased to zero by 2050, supporting the conclusions of the paths outlined in European Commission (2018).

Table C.9. Energy-Environment-Economy Global Macro-Economic (E3ME)

Type	Macro-econometric	**Industry sectors**	NACE 2-digit
Approach	Top-down		
Spatial resolution	Global (61 regions)		
Temporal resolution	Yearly to 2050		

E3ME is a global, macro-econometric model developed by Cambridge Econometrics to address the world's key economic, social, and environmental issues (Cambridge Econometrics 2019). The model has a high level of disaggregation, allowing for an exhaustive analysis of sectoral and country-level effects from a variety of scenarios. Social impacts are significant model outputs. Another distinguishing feature is the econometric specification, which solves problems with macroeconomic models and offers a solid empirical foundation for research. The model can accurately examine both short- and long-term implications and is not constrained by many of the restrictive assumptions that are typical in computable general equilibrium models. Analyses of the world's economies, energy systems, emissions, and material demands are also included in E3ME. This makes it possible for E3ME to represent these components in a non-linear interaction with two-ways feedbacks.. E3ME includes 61 worldwide regions, with full sectoral breakdowns in each, and forecasts annually through 2050. It is commonly used at the national, European, and global levels, as well as for broader European and global policy analyses. E3ME is based on the ESA95 system of national accounts, along with balances for energy and material demands, as well as environmental emissions flows. It also includes detailed historical datasets, time series that span the period since 1970, and sectoral disaggregation based on the NACE classification of economic activities at the two-digit level.

E3ME is composed of three modules: economy, environment, and energy. The model's economic module is solved for each region. Most economic variables are addressed at the sectoral level. Although single-country solutions are feasible, the entire system is addressed simultaneously for all industries and areas. Unless there are restrictions on available supply, demand determines production and employment. The key explanatory variables for aggregate energy demand are economic activity in each of the energy users, average real energy prices for each energy user, and technological variables, which are represented by investment, R&D spending, and spillovers in major industries that manufacture energy-consuming machinery and vehicles. For each of the energy consumers in the model, emissions data for CO2 from energy use are accessible, and coefficients are calculated from historical data. This establishes the connection between energy use and emissions. Process CO2 emissions, such as those from the cement and chemicals industries, are explicitly included in the model but are tied to production from those industries rather than energy use. Other emissions are treated in a less detailed way, and findings are often not broken down by industry.

Gramkow and Anger-Kraavi (2019) analyze a change in Brazil's economy while contributing to the Paris targets, using the manufacturing sectors as an example. E3ME is used to project Brazil's growth outlook up to 2030 with and without a portfolio of fiscal policies that promote low-carbon investments. The research shows that the right combination of strategies can assist in modernizing and decarbonizing the Brazilian manufacturing sectors and enable the nation's economy to grow more quickly while reducing CO_2 emissions.

Table C.10. Industrial Sector Energy Efficiency Model for Iron and Steel (ISEEM-IS)

Type	Linear programming Optimization	**Industry sectors**	Iron and steel
Approach	Bottom-up		
Spatial resolution	United States, China, India		
Temporal resolution	2010–50		

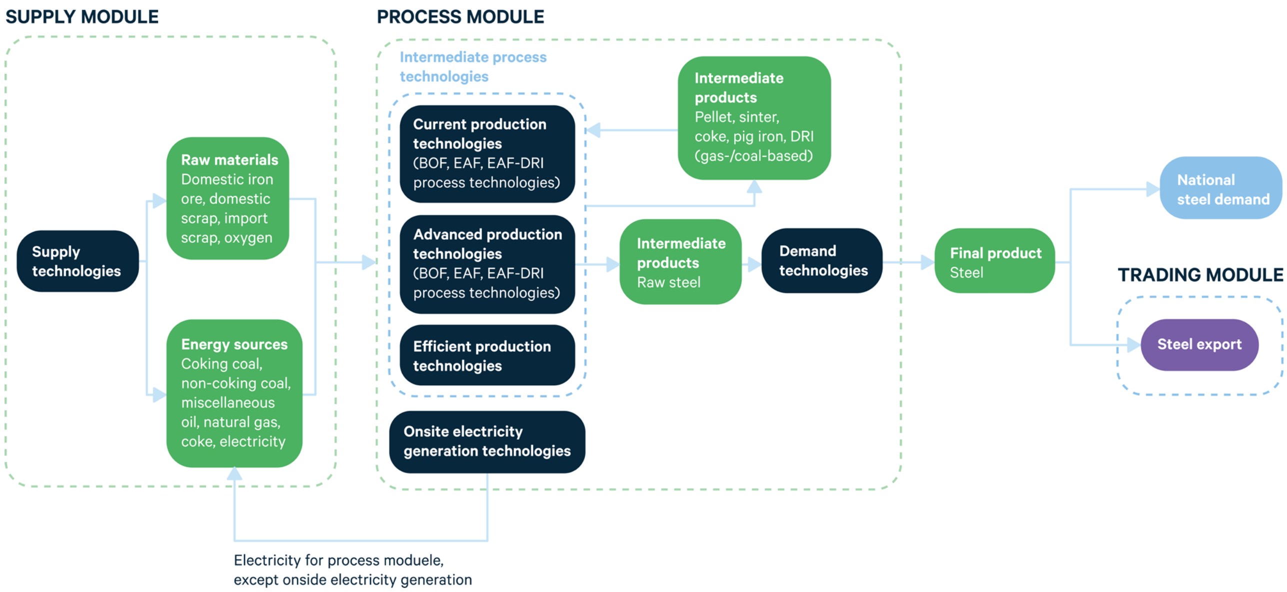
ISEEM-IS, developed by the Lawrence Berkeley National Laboratory, is a bottom-up optimization energy modeling framework for representing impacts of energy policies on US iron and steel production (Figure C.1). It is a linear programming optimization model that minimizes the costs of production over a set of predefined industrial constraints across a set of plants defined by technologies. The modeling framework analyzes the use and potential improvements of technologies in the US iron and steel sector with respect to reducing carbon and GHG emissions, as well as wider economic implications of such energy and environmental policies. It incorporates international trade, specifically from India and China; energy and emissions policies; and the key assumption that production technologies change and improve gradually over time.

ISEEM-IS's main strength is its technological detail and the endogenous representation of investment and deployment of new or refined technologies of production and supply. Each technology has its own set of constraints, requirements, parameters, and rates of growth or change. The model divides production technologies into three categories: current, advanced, and energy-efficient. Current production technologies are those that are currently in use in the industry, such as basic oxygen furnace and electric arc furnace; advanced production technologies represent autonomously improved versions of current production technologies; and energy-efficient technologies are those that improve energy efficiency of current production technologies but are associated with extra costs. The full list of production technologies included in ISEEM-IS can be found in Karali et al. (2013, Appendixes A and C). Despite the technological detail, the energy-efficient technologies are limited to methods and processes of production in iron and steel and do not include other emissions reduction technologies that are production-adjacent, such as CCS. The ISEEM model structure can be applied to other industrial sectors but requires huge amounts of data that might not always be available.

Karali et al. (2013) use the model to investigate the impact of carbon reduction options on the US iron and steel sector under a set of specific scenarios. They also examine how local policies and emissions reduction strategies would affect trade with, production in, and CO2 emissions from China's and India's iron and steel sectors. The policy scenarios impose reductions in global emissions of 10, 20, and 30 percent under three variations of the model: (1) without commodity or carbon (allowance) trading (ER), (2) with commodity trading but without carbon trading (ET), and (3) with both commodity and carbon trading (EC).

One of the key findings of Karali et al. (2013) was how carbon emissions reduction policies interact with not just domestic production but also international production and trade flows both of the commodity produced (steel) and of carbon. For example, under the trading scenarios, the authors find that production partially shifted out of the United States to China and India, as it was less expensive to import than to invest in energy-efficient technologies domestically. With respect to the baseline in 2030 under the EC- and ET-30 scenarios, US imports increased by about 55 percent, and US production decreased by about 25 percent. Furthermore, under the trading scenarios, while China's and India's energy intensity levels are much reduced, those of the United States remained unchanged from the base scenario levels, as there was little to no incentive to switch to energy-efficient technologies in the United States.

Figure C.1. Production Flow Diagram of the Iron and Steel Sector in the ISEEM-IS Model



Source: Karali et al. (2013)

Table C.11. Universal Industrial Sectors Integrated Solutions (U-ISIS)

Type	Linear programming Optimization	**Industry sectors**	Cement Pulp and paper
Approach	Bottom-up		
Spatial resolution	United States with demand and supply regions		
Temporal resolution	2010–50		

U-ISIS is a bottom-up sector-based dynamic linear programming optimization modeling framework developed by the US Environmental Protection Agency (EPA). The model optimizes total surplus with respect to various constraints, including supply, demand, costs of production, technologies available, and energy policies instituted by the US government. The model incorporates multiple industries within a multimarket, multiproduct, multipollutant, and multiregion emissions trading framework. It analyzes optimal sector operations to meet demand and pollution reduction requirements over a specified period of time, while taking into account plant-level economic and technical factors and costs, including production capacity changes, fixed and variable production costs, transportation costs, import costs, emissions costs, and energy intensity and efficiency.

The main strength of U-ISIS is its ability to model industry pollution generation pathways and methods for abating emissions resulting from those pathways through both mitigation and prevention. The model includes methods for tracking multiple pollutant streams—as well as multiple pollutants—associated with controlled and uncontrolled emissions, pollution prevention measures, and other control-related effects. For the cement industry, pollutants include criteria pollutants, hazardous air pollutants (HAPs) such as mercury or hydrochloric acid, CO_2, nitrogen oxides (NO_x), sulfur dioxide (SO_2), and particulate matter. The generation pathways include cement manufacturing, quarrying operations for raw materials, kiln operations, and fuel combustion. The model already includes in its base scenario the extant regulatory requirements with respect to pollutants and can run scenario analyses for a variety of policy scenarios to address these emissions pathways and abatement options, including emissions limits, cap and trade, and emissions taxes under long- and short-term horizons (decades and annual) and regional or national requirements. U-ISIS has an incredible amount of plant-level detail—but that comes at the cost of lengthy and regular calibration and recalibration of the modeling framework. Furthermore, the model's existing user interface restricts the kind of scenario that can be run. It is unclear from the documentation how flexible the interface is, such as how difficult it would be to add a technology or scenario not already within the interface, or how necessary it is to run the model.

The U-ISIS model was first used by EPA to examine the US Portland cement industry, with a focus on how policies for emissions reduction affect the industry (EPA 2013). EPA later adapted the model to examine the US pulp and paper industry (Bhander and Jozewicz, 2017). For the cement industry, it addressed the development of efficient and effective policy options for managing emissions and air quality resulting from all steps of cement production. The model demonstration for pulp and paper focused on identifying optimal industry operation through the selection of cost-effective controls to meet demand while complying with emissions reduction requirements and calibrating a baseline business-as-usual scenario. The demonstration also showcased three scenarios for NO_x emissions reductions: fuel substitution, installation of controls, and implementation of energy efficiency measures.

Table C.12. Hybrid Technological Economic Platform (HYBTEP)

Type	Optimization and simulation	**Industry sectors**	Aluminum Iron and steel Chemical Cement Pulp and paper Other industry
Approach	Bottom-up and top-down		
Spatial resolution	Multinational or single country		
Temporal resolution	2010–50		

HYBTEP is a combination of the bottom-up TIMES model (see Appendix C.6) and the top-down CGE General Equilibrium Model for Economy, Energy, and Environment (GEM-E3) (Fortes et al. 2014). GEM-E3 is a dynamic recursive CGE model that solves for the equilibrium price of goods, services, labor, and capital to clear all markets and optimize behavior of economic agents simultaneously. Both models are multinational but can be adjusted to model a single country. The HYBTEP framework creates a soft link between the two systems, solving them concurrently and exchanging information between them.

HYBTEP's main strength is that its soft-link methodology allows users to perform integrated assessments of climate and energy policy instruments with detailed technology profiles for the energy sector, which is something that neither top-down CGE models nor bottom-up models can do on their own. Soft linking maintains the structure and individual strengths of each model while eliminating many of the drawbacks. It incorporates an extensive group of technologies and economic responses, allowing for greater understanding of the impacts and effects of various energy and climate policies. Despite these strengths, HYBTEP does have a few limitations, mostly inherited from the two models it links—in particular, the assumption of perfectly competitive markets and optimistic views of deployment of future technologies.

The platform was used to provide insights into the advantages of the hybrid system through examining the macroeconomic effects of various climate policies in Portugal. These policy scenarios were run relative to a calibration scenario (which was not a business-as-usual scenario, given the way TIMES optimizes the energy system) and included a current policy regulation scenario (CPR), a CO_2 price scenario (TAX), and a renewable energy support scenario (RES). The CPR scenario reflected the current state of energy and climate policies, including reductions in GHG emissions, increases in renewable energy consumption, and improvement in energy efficiency. The TAX scenario added to the CPR scenario a domestic carbon tax (set at the highest level indicated in an EU roadmap for transitioning to a competitive low-carbon economy) on GHG emissions from energy consumption instead of the emissions caps from the Emissions Trading System (ETS) and non-ETS sources. The RES scenario added a monetary incentive for renewable energy (biofuels, solar and biomass consumption, renewable electricity) to the CPR assumptions.

Table C.13. FORECAST

Type	Simulation	**Industry sectors**	Paper and printing
Approach	Bottom-up		Nonmetallic mineral products
Spatial resolution	Multinational or single country		Nonferrous metals
Temporal resolution	2010–50		Iron and steel
			Chemicals
			Other industry

The FORECAST model, developed by the Fraunhofer Institute for Systems and Innovation Research, is a bottom-up simulation model for the development of long-term scenarios for future energy demand in the industrial sectors, services, and households (Fleiter et al. 2018). It is a multinational model that can be adjusted for a single country and can disaggregate results down to the district level if desired. The model incorporates plant-level data and includes both energy-intensive industrial sectors and less energy-intensive subsectors and applications. Its main output is a time series of final and useful energy demand and the related GHG emissions under a high level of disaggregation regarding energy carriers, subsectors, end uses, and technologies, presented by country and scenario.

One of the core strengths of the FORECAST model is that it incorporates a high level of technological detail, policy parameters, and transition paths and costs in an integrated approach. FORECAST has six submodels: macro, energy-intensive processes, space heating and cooling, electric motors and lighting, furnaces, and steam and hot water. Its industrial subsectors include paper and printing, nonmetallic mineral products, nonferrous metals, iron and steel, chemicals industry, food and drink and tobacco, engineering and other metal, and other nonclassified. The simulations are conducted at the individual subsector level (e.g., iron and steel), where energy-intensive processes are considered explicitly, and other technologies and energy-using equipment are modeled similarly across all subsectors. Further, the model can calculate comprehensive transition-decarbonization scenarios for an individual country's entire industry sector through a broad scope of mitigation options. However, the diverse methods used to gain sectoral and technological detail reduce transparency and render the interpretation of results more difficult. FORECAST is written in Visual Basic.

FORECAST can address numerous questions related to energy demand and GHG emissions, specifically in the context of technical change. These questions include scenarios for future demand of individual energy carriers, calculations of energy savings potentials and their impacts on GHG emissions, abatement cost curves, ex ante and ex post policy impact assessments, and low-carbon transition scenarios. The mitigation options include energy efficiency (incremental and radical change), fuel switching (to renewable and low-carbon energy carriers), CCS, circular economy and recycling, and material efficiency and substitution.

Two examples of FORECAST's use are a study of the cement industry in Taiwan and analysis of energy efficiency and an analysis of a decarbonization pathway for Germany's industrial sectors. In the Taiwan case, Huang et al. (2016) find that adoption of energy-efficient technology can result in 25 percent savings for electricity and 9 percent savings for fuels, of which 91 percent could be implemented cost-effectively under an assumed discount rate of 10 percent. In the Germany case, Fleiter et al. (2016) consider two scenarios: a reference scenario reflecting current policies, economic, and technological trends and a transition scenario achieving a GHG emissions reduction in industry of 83 percent by 2050 (with a GHG emissions reduction in the entire economy of 80 percent). Under the transition scenario, electricity demand is reduced by 16 percent and fuel demand by 32 percent by 2050; biomass use increases; coal use is phased out in all industry sectors except iron and steel; use of alternative materials increases in the paper, cement, glass, and aluminum sectors; and CCS mitigates about 35 metric tons of CO_2e in 2050, with total emissions reduced from 140 metric tons in 2010 (the base year) to 75 metric tons of CO_2e by 2050 versus 110 metric tons of CO_2e under the reference scenario.

Appendix D. Examples of Applications Using Different Models

D.1. World Energy Models

For the *World Energy Outlook*, WEM uses a scenario approach to look at potential changes in the energy sector, modeling the world for 26 regions. Four scenarios were simulated in depth for the *World Energy Outlook 2021* (see Appendix C.1).

D.2. NEMS

Huang and Eckelman (2020) model material flow economy in the United States.

Huang and Eckelman (2021) estimate pollutants from industry in the United States.

Brown and Baek (2010) estimate renewable fuel standards impacts on US industry.

Arora et al. (2018) estimate taxation recycling impacts on US industry.

Ruth et al. (2000) estimate impacts of market-based climate change policies on the US pulp and paper industry.

D.3. GCAM

Liu et al. (2015) use the GCAM-USA version to explore the water-energy nexus (multisector analysis). The United States is represented at a state level.

Peng et al. (2021) estimate the effects of state and national carbon policies (multisector analysis). The United States is represented at a state level.

D.4. REMIND

Luderer et al. (2012) employ a version of the REMIND model to examine Asia's participation in the global effort to mitigate climate change.

D.5. MUSE

Budinis et al. (2020) model the decarbonization of the Chinese ammonia industry.

D.6. TIMES

Napp et al. (2019) use the TIAM version and focus on advances in energy demand sectors, including best available technologies in industry. This study models the world and represents the United States as one region.

Fais et al. (2016) focus on decarbonization options for UK industry.

D.7. IMAGE

Qui et al. (2022) focus on direct air capture implications for the power sector. This study models the United States as one region.

Chen et al. (2021) analyze multisector carbon neutrality; industry discussed aggregated. This study models the world and represents the United States as one region.

Sharmina et al. (2020) include hard-to abate sectors and circular economy for industry. This study models the world and represents the United States as one region.

Kermeli et al. (2019) focus on the cement industry. This study models the world and represents the United States as one region.

D.8. Material Economics Modeling Framework

Material Economics (2019) uses this framework to investigate various strategies to maintain EU steel, plastic, ammonia, and cement output while achieving net-zero emissions.

D.9. E3ME

Bachner et al. (2020) model decarbonization of iron and steel industry in Europe.

Gramkow and Anger-Kraavi (2019) model investments in Brazilian industry decarbonization.

D.10. ISEEM-IS

Karali et al. (2013) investigate the impact of carbon reduction options on the US iron and steel sector.

D.11. U-ISIS

EPA (2013) exmaines the US Portland cement industry using U-ISIS. Bhandar and Jozewicz (2017) apply the model to the pulp and paper sector.

D.12. HYBTEP

Fortes et al. (2014) apply HYBTEP to analyze three climate and energy policy scenarios in Portugal.

D.13. FORECAST

Fleiter et al. (2016) conducts an analysis of a decarbonization pathway for Germany's industrial sectors.

Huang et al. (2016) studies the cement industry in Taiwan.