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Is the industrial sector hard to decarbonize or hard to model? A comparative analysis of industrial modeling and net zero carbon dioxide pathways

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ABSTRACT

This paper examines the results of the Energy Modeling Forum Study 37 on Deep Decarbonization & High Electrification Scenarios for North America (EMF 37), with specific focus on industrial decarbonization pathways. Broadly, industrial decarbonization can be delivered through a wide range of actions such as energy efficiency, circular economy, electrification, low-carbon fuels, feedstocks, and energy sources, and carbon capture utilization and sequestration (CCUS). Remaining positive emissions in the energy system can be offset by carbon dioxide removal (CDR). The extent to which these options are, or are not, included in the models will impact the extent to which industrial decarbonization is projected to contribute to achieving an economy-wide net-zero climate policy. If adequate actions and technological levers are included in the model structure, but are more expensive than other options, in particular CCUS and CDR, then projected industry emissions reductions play a smaller role in meeting a net-zero constraint. The distinction between "hard to decarbonize" and "hard to model" has significant policy implications. If industry is hard to decarbonize, policies should focus on innovative and cost-effective industrial technologies, CDR, or both. If industry is hard to model, there may be overlooked opportunities for decarbonization that require further exploration. There is no consensus across the models in the study regarding both the level of decarbonization that could be achieved in industry or the pathways to achieve it. We caution against drawing conclusions solely from existing models and recommend rigorous and coordinated modeling efforts to better capture industrial innovation and decarbonization strategies.

1. Introduction

Stanford University's Energy Modeling Forum (EMF) coordinates among energy modelers and issues reports on emerging energy topics in related to the economy, climate, and the environment. EMF Study 37 focuses on analysis of pathways for deep decarbonization and increased electrification of energy systems for North America (*will be referred to EMF 37 from hereon*). The EMF 37 invited teams of researchers to run sector-specific and economy-wide models under a variety of decarbonization scenarios with a focus on achieving net-zero carbon dioxide (CO_2) emissions by 2050. The results from the participating models were compiled into a database to facilitate comparison across the models and scenarios. Browning et al. [1] summarized the goals of the EMF 37, described the scenario design, presented high-level results and insights across the energy system, and laid the groundwork for follow-up analyses ranging from broader policy implications [2] to health and air pollutant impacts [3] and finally various sectoral analyses such as this paper. The study results served as the main foundation of the Mitigation Chapter of The Fifth National Climate Assessment [4], which is the US Government's preeminent report on climate change impacts, risks, and responses. The Chapter provided alternative feasible pathways to reduce greenhouse gas emissions and adapt to climate change.

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In 2021, the U.S. industrial sector consumed 24 exajoules (EJ) of primary energy and 3.6 EJ of electricity, accounting for 35 % of total U.S. delivered energy consumption and 33 % of total U.S. energy consumption [5]. Fossil fuels are currently the main source of energy for industry in the U.S. accounting for about 80 % of industrial energy consumption. Historically, fossil fuels have been particularly suitable for providing the high-temperature heat required by heavy industry production processes at relatively low cost. Therefore, the industrial sector is a significant contributor to total greenhouse gas (GHG) emissions in the U.S. Fig. 1 presents the historical role of industrial emissions relative to the rest of the economy and by source within industry. According to U.S. Environmental Protection Agency's (EPA) recent GHG inventory [6], total economy-wide GHG emissions reached 6340 million metric tons (MMT) of CO_2 equivalents in 2021 (Fig. 1A), and around 23 % of these emissions are due to industrial activities (Fig. 1B).

Over the last thirty years, industrial emissions have seen a modest decrease, although the industrial production increased over that period. However, the pace of reduction in GHG emissions from high emitting industries is still insufficient to meet a goal of net zero CO_2 by 2050 [7, 8]. There are two major components of industrial emissions, one resulting from combustion of fossil fuels, and the other being process related. Within direct industrial emissions, as seen in Fig. 1B, fossil fuel combustion is the single largest source of emissions. The industrial sector also uses electricity purchased from the grid. When emissions associated with electricity use are included in the totals, industry's contribution to U.S. GHG emission increases significantly.

Industries classified as energy-intensive include food and beverage, chemicals, metals, non-metallic minerals (cement, lime, and glass), forest products, and mining. They are the top industries that are viewed as "hard to decarbonize," as they release process emissions (almost a third of CO_2 emissions, Fig. 1B) as well consume high amounts of fossil fuel for process heat. Process emissions, driven by non-combustion related chemical reactions, often occur at high temperatures ranging from 800 – 1500 F. They can be avoided only by fundamentally altering the processes used to make these products or should the produced CO_2 is captured and stored geologically for significant periods of time. Process emissions therefore act as a major challenge to achieving near-zero or net-zero emissions in the industrial sector.

For instance, in iron and steel industry, iron ore (Fe_2O_3) needs to be reduced by a carbon-heavy fuel in blast furnaces to make pure molten iron (Fe). Industry uses coal to make carbon-heavy coke, which in turn both used to provide high temperature heat in the furnace, also acts as a reducing agent. The oxygen in the iron ore combines with the carbon in the coke to create pure molten iron and process results in CO_2 emissions. Molten iron, is then charged in a basic oxygen furnace (BOF) to produce steel. For each MT of steel made via BOF, 1.8 – 2.3 MT of process CO_2 is released in addition to combustion emissions [9]. Another way to make steel is in electric arc furnaces (EAFs), where an electric arc between electrodes and charge metals such as direct reduced iron (DRI) and scrap steel is made to melt the metals. Besides electricity, EAFs can be powered by natural gas or hydrogen (specifically for DRI). Although, the majority of world steel production relies on coke-fired blast furnace/-BOFs, around 70 % of U.S. steel production is EAF-based [10]. EAF steelmaking is also a more flexible process with the ability to ramp production up or down as the market requires. Despite consuming significant amounts of electrical energy during the melt phase, EAF steelmaking, whether using scrap or DRI exclusively, can be up to 10 % more energy efficient than primary BOF steelmaking [11] and can significantly reduce direct and upstream CO_2 emissions from steel production. We note that the quality of steel is directly influenced by scrap content and quality. As such, in applications that require high-quality steel such as aviation, wind turbines, and automotive bodies, the production route would ultimately be driven by quality considerations and not just energy or emissions.

Similarly, in the cement sector, where limestone is heated in a cement kiln, calcination process occurs at very high temperatures, and the calcium carbonate in limestone breaks down into calcium oxide and CO_2, emitting about 0.5 MT of CO_2 as a byproduct per MT of clinker (a

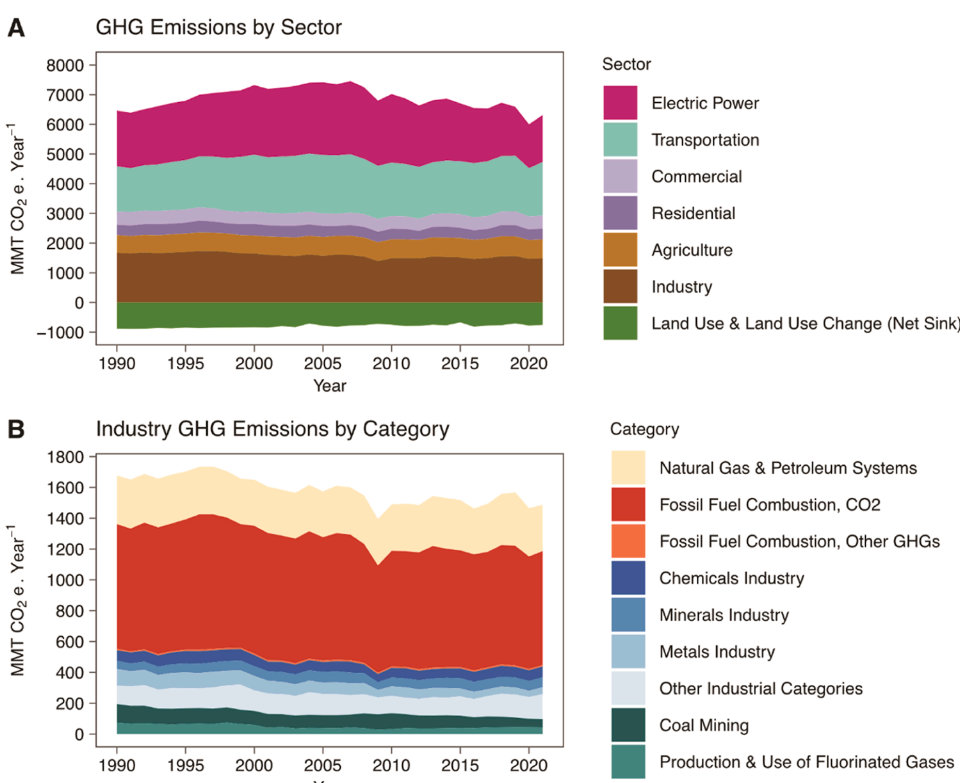

Fig. 1. (A) U.S. greenhouse gas emissions (GHGs) broken down by economic sector and (B) U.S. industry sector emissions broken by category. Data obtained from U.S. Environmental Protection Agency.

pre-cursor to cement) produced [12]. The fuel requirements of cement kilns are flexible as long as a fuel can provide high-temperature heat and is cost-effective. Historically, coal has been the largest source of heat in the cement sector along with waste products such as tires because of their cost advantage, although manufacturers in the U.S. are increasingly looking to natural gas and waste biomass to reduce cost and emissions [9]. However, even with such efficiency and fuel switching measures, the CO_2 from calcination of the limestone, which accounts for about 60 % of the cement process emissions, still needs to be abated either by using alternative cement chemistries or feedstocks such as calcined clay, supplementary cementitious materials like fly ash and steel slag, and carbonated calcium silicate and/or by deploying carbon capture [13,14].

The U.S. Department of Energy's (DOE) Industrial Decarbonization Roadmap report identifies 4 major pillars of technological and strategic interventions to reduce industrial emissions – (1) enhancing energy and material efficiency, (2) electrification of fuel combustion-based processes (with implicit progress towards low-carbon electricity production), (3) switching fossil-based fuels and feedstocks with lower carbon alternatives, and (4) using end-of-pipe technologies such as carbon capture and utilization. There are many technical and non-technical challenges associated with these approaches. These include development, deployment, and commercialization of technological innovations, adoption of new technologies by industry, socio-economic and policy dimensions (both domestic and international), permitting and regulatory barriers, and other real-world or engineering implications [9,15,16]. In addition to these, another significant challenge with decarbonizing industrial products is that the majority of the energy intensive sectors' products such as steel, aluminum, chemicals and petrochemical products are traded internationally yielding a potential risk for carbon leakage without proper regulatory or policy mechanisms [17].

A series of studies outside EMF37 have outlined potential sector-specific decarbonization pathways. These include pathways for iron and steel [9,18,19], chemicals [9,20,21], ceramics [22], glass [23], pulp and paper [9,24], food and beverage [9,25], cement [9,26,27], and refineries [9,28]. With heterogeneity of industrial sector, these studies have significant value and contribution however many policy makers analyze energy sector as a whole and would like to make informative decisions on how to prioritize within the industry sector and identify cost-effective abatement measures. Worrell and Boyd [29] used industry specific studies like these and employed a detailed accounting exercise found carbon reduction pathways.

Furthermore, there are some studies exploring the role of hydrogen [30] and carbon capture, utilization, and storage (CCUS) [31,32], or a combination of both [33], and carbon dioxide removal (CDR)in the context of industrial decarbonization. These decarbonization pathways include use of hydrogen either for feedstock or fuel, and CCUS in the industrial sector, especially for applications in iron and steel, cement, and chemicals. In the iron and steel sector, use of hydrogen in the DRI process could potentially reduce emissions. To reduce carbon emissions from cement production, capturing the CO_2 via CCS is a viable alternative. In the chemicals sector, petroleum is the dominant fuel for feedstock, followed by natural gas. Main concerns with these technologies is that they may not be compatible with retrofitting existing stock of technologies. Moreover, a large capital investment requirements, high maintanance costs, low capacity factors associated with high maintanance needs and uncertain future commercial readiness could be a real challenge to meeting industrial decarbonization goals. Policies that could ease implementation could include capital incentives, research and development programs, revenue enhancements, resource availability enhancements, trade exposure reduction, infrastructure support, and recycling promotion initiatives.

According to U.S. Energy Information Administration's (EIA) 2023 Annual Energy Outlook (AEO) [5], non-energy intensive manufacturing relies mainly on electricity and natural gas. While these sectors show a large variation in processes used, many use relatively low temperature heat, which means these industries prime candidates for electrification and increased energy efficiency measures [29,34]. Non-energy intensive manufacturing will become more economically important in the U.S. (see Macroeconomic Indicators in AEO 2023) and consume a larger share of industrial energy consumption in the future. One of the examples of non-energy intensive manufacturing industry is computer and electronic products which includes manufacturing for power electronics needed for electric vehicle and renewable energy technologies.

Several themes need be considered on the industry front such as feasibility of industry-specific energy and material efficiency (including substitution and reuse of production materials, recycling; new materials and processes) options, electrification, switching to low-carbon fuels, alternative feedstocks such as biomass and hydrogen, CDR options, carbon capture utilization and sequestration (CCUS), trading and leakage issues, behavioral and economic considerations. CDR may include CCUS and direct air capture (DAC), and land use and land use change and forestry (LULUCF) offsets. It is from this lens that the industrial sector is frequently characterized as "hard to decarbonize."

Literature on modeling and industrial trends highlight a critical question; whether industry is "hard to decarbonize" or "hard to model" or both. Decision makers rely on modeling and planning for the decarbonization strategies to inform policy. A wide variety of modeling and assessments are done to provide insights for future policy. The extent to which various decarbonization options are, or are not, represented in the industrial component of these assessment models will influence the insights gathered from the models regarding the contribution of industry decarbonization on economy-wide net-zero climate policy. When we combine the diversity of activities that could lead to industrial decarbonization with the possible limitations of the models themselves we see through the lens by which we hypothesize the industry as "hard to model." To address this, we provide context in the form of an overview of the industrial modeling within the participating modeling frameworks, then compare the results of the decarbonization scenarios, and discuss the technical, policy, and modeling challenges of industrial decarbonization. We seek to find a consensus across the models regarding both the level of industrial decarbonization or the pathways to achieve this. We also examine participating models' structure to see if any patterns emerge from these results.

The goal of this paper is to (a) provide an overview of how EMF 37 participants represent the industry sector in their respective models, (b) identify alternative CO_2 emissions reductions pathways for industry based on model ensemble results, and (c) discuss the role of industry in the context of rest of the energy system with respect to achieving system level net-zero CO_2 goals by 2050. Although the EMF 37 focus is on North America, many of the modeling frameworks presented results for United States. Thus, this paper examines the insights from four scenarios from EMF 37: the reference case (*Reference*), the constrained net-zero CO_2 by 2050 case (*Net Zero*), the industrial advanced action case (*Net Zero+ Industry*), and the advanced action for all sectors (*Net Zero+*) specific to U.S.

2. Methods

2.1. Scenario design and analysis boundaries for industry modeling

This paper examines four scenarios from EMF 37 Study specifically focusing on results for U.S.: the reference case (*Reference*), the constrained net-zero CO_2 by 2050 case (*Net Zero*), the industrial advanced action case (*Net Zero+ Industry*), and the advanced action for all sectors (*Net Zero+*). The primary focus is on the difference between the *Reference* case and the *Net Zero* case. The *Reference* case assumes a common set of initial historical population and economic assumptions based on the U.S. Energy Information Administration's Annual Energy Outlook (AEO), unless those drivers are fully endogenous in a particular model. The *Net Zero* case achieves net-zero CO_2 emissions by 2050. The *Net Zero* cases assume policies and limits are in place to require net zero emissions by the target year of 2050, but does not specify the nature of those policies. *Net-Zero+ Industry* refers to the advanced assumptions for the industrial sector only, while *Net-Zero+* refers to advanced assumptions for all sectors, including industry. The EMF 37 team included sectoral study groups that provided guidance on assumptions for the advanced action cases. The guidance from the industrial sector working group is in the Supplementary Note 1. The guidance from the other working groups targeted for buildings, transportation and carbon management are provided in the Supplementary Materials of Browning et al. [1].

To achieve Net Zero CO_2 emissions, modeling groups have flexibility to implement range of possible policy options. Most models do not explicitly reflect all the possible policies. In most cases, *Net Zero* scenarios are modeled as an explicit constraint in reducing energy system-level CO_2 emissions. This implies that the industrial sector itself need not be net-zero in 2050. The models can rely on negative carbon offsets to achieve net zero emissions by 2050. For the models that do not explicitly represent LULUCF, an assumption on 800 million metric tons of carbon dioxide is included for CO_2 offsets.

The model teams were instructed to assume no leakage in industry resulting from a carbon price or a climate policy. Leakage of emissions via shifting production elsewhere is a viable option to reduce emissions in a particular sector or region of the world. This problem is unique to industry because the energy services and associated emissions from buildings and transportation are tied to a location, but the production of energy/carbon intensive goods are not. Here, our goal is to identify potential decarbonization pathways for industry, should the projection of industrial output levels stay similar across scenarios. Through the scenario analysis, we identify how much industry contributes to carbon emission growth (*Reference*), how much industry contributes to decarbonization goals (*Reference* vs *Net Zero*).

2.2. Industry sector representation in the EMF 37 models

The energy system models that participated in the EMF 37 study are diverse in geographical coverage, modeling capabilities, industrial coverage, future technology portfolio representation including techno-economic parameterization of these technologies. The models that submitted results to EMF 37 are listed in Table 1 with the sectoral, spatial, and temporal coverage of each, included underlying modeling approach including how the model reaches equilibrium, the decision foresight and demand and technology choice mechanisms. Based on model's equilibrium approach (general vs. partial); foresight (myopic vs. perfect) and underlying technology choice functions and/or methods (linear programming (LP) or logit function vs. constant elasticity of substitution (CES) function), we clustered them into three categories: (1) General-Myopic-CES, (2) Partial-Perfect-LP, and (3) Partial-Myopic-Logit.

In the early stages of the EMF 37, the study called for participation from more models. Owing to time constraints and other unforeseeable matters, not all models submitted results. Initial effort was to gather information on and analyze the industrial model structure of the models. Each modeling team described their industry characterization in two categories: (1) level of aggregation of industries, and (2) modeling techniques employed to project industrial energy demand. Twenty two modeling teams submitted answers. The goal was to document differences among industry modeling structure, disaggregation levels, equilibrium approach, foresight, and technology choice methodology. We asked each modeling team to present their model's aggregation or disaggregation in the form of a mapping to the Industrial Demand Module (IDM) of the U.S. EIA's National Energy Modeling System (NEMS) [35].

NEMS is the primary government-led energy and emissions modeling platform in the U.S used to project energy supply, demand, and prices in several scenarios that provide insights into the future of the U.S. energy system evolution. EIA uses NEMS to generate scenarios for energy system evolution to be published in the Annual Energy Outlook (AEO) every year. EIA defines the industrial sector as manufacturing, agriculture, construction, and mining [35]. The IDM estimates U.S. energy consumption by energy source (fuels and feedstocks) in the AEO for 15 manufacturing and 6 nonmanufacturing industries. The IDM classifies manufacturing industries into energy-intensive manufacturing industries and non-energy intensive manufacturing industries (Table 1). The IDM models manufacturing industries through either a detailed process-flow or end-use accounting procedure. The nonmanufacturing industries are modeled with less detail because processes are simpler and fewer data are available. Table 1 presents the crosswalk for the industry coverage of NEMS through the North American Industry Classification System (NAICS).

The level of aggregation and disaggregation of industries along with modeling methods varies across the modeling teams, the industry representation for models in EMF 37 are contrasted with NEMS IDM. Key insights from this activity are incorporated into the Table 2. The industrial energy models in EMF37, use a variety of methods to project results: (1) aggregate only, by energy type; (2) end-use service accounting; (3) detailed process flow for key energy intensive sectors; (4) hybrid methods. Since future economic activity, associated energy use, and GHG mitigation opportunities vary across the different industries, the level of disaggregation of industrial energy demand within the models can influence the modeling of economy-wide decarbonization scenarios. Details regarding non-participating models are included in Table S1 in the Supplementary Materials to illustrate the broad range of industrial representation in models used for energy and climate policy analysis. There is a diversity across the models in all dimensions of industrial aggregation, representation of energy, and model structure/foresight as well as input data. For instance, there are General, Myopic, CES models that are highly aggregated in terms of energy and industry detail, and ones that are highly disaggregated in terms of industry using process flows for energy. Diversity of design occurs in every dimension of the model attributes including inputs. "One size fits all" does not describe industrial energy model design. EMF 37 modelers have not gone through model input data harmonization.

In addition, models have options to include CDR technologies. U.S. DOE defines CDR as wide array of approaches that remove CO_2 from the atmosphere including DAC coupled to durable storage, soil carbon sequestration, biomass carbon removal and storage, enhanced mineralization, ocean-based CDR, and afforestation/reforestation. CDR does not refer to point source carbon capture from the fossil fuel-based power sector or industrial sector as these are classified under the umbrella of CCUS. The CDR options and CCUS technologies included in the models are also listed in Table 2. In addition to the diversity of model design, each model calibrates to a base year for energy supply, transformation, and demand, and some also calibrate to energy prices. The base year energy and economic data are obtained from different sources. Although the formal base year of the EMF 37 study is established as 2020, not all models calibrate to this year. The base year ranges between 2010 and 2020 across the models. The available historical data for energy, prices, and environmental parameters do not align in most instances for at least the industrial sector. For instance, the most recent detailed survey of U.S. manufacturing energy is the 2018 Manufacturing Energy Consumption Survey (MECS) [36]. EIA's Annual Energy Review compiles aggregate industrial sector indicators on an annual basis. Our survey has found that not all models update to most recent data regularly. Furthermore, prices fluctuate between different base years, introducing further divergence in projections. The goal of the study was not to harmonize all inputs and generate model ensembles. The inputs to models are numerous and difficult to quantify with certainty during the design process. Models generate very specific outputs synthesized from hundreds—perhaps thousands—of assumptions and data inputs of how the technologies will perform. However, EMF 37 provided guidelines in scenario structures and model calibration tips.

EMF 37 provided study participants a precise taxonomy for energy

Table 1
List of models who submitted scenarios for the EMF 37 study.

					Carbon Management Options							Industry
Model Name	**Institution**	**Spatial Resolution**	**Equilibrium Approach & Foresight**	**Base-End Years; Timestep; Technology Choice**	**DAC**	**Biofuels**	**BECCS**	**H2**	**Syn. gas & liquids**	**RNW NG**	**CCS**	
ADAGE	RTI International	US+7 global regions	General; Myopic	2010-2050; 5-year time steps; **CES**	X	X						13 energy including food, energy intensive manufacturing, other manufacturing, services, households; 24 non-energy sectors
GENeSYS-AnyMOD	TU Berlin	US, Canada, and Mexico	Partial; Perfect	2020-2050; 5-year time steps; **LP**	X		X	X				Single industry sector
EC-MSMR	Environment and Climate Change Canada	Canada, Mexico, US + 13 other regions	General; Myopic	2014-2050, 5-year time steps; **CES**	X	X	X	X		X		4 energy 15 non-energy
EP-RIO	Evolved Energy Research	27 US regions (aligned with EPA eGRID - Alaska and Hawaii aggregated)	Partial; Perfect	2021-2050; 5-year time step; Mixed; **LP** in electricity and fuel, **logit** in end-use	X	X	X	X	X			20 industry sectors represented via eight service categories (heat, HVAC, lighting, machine drive, refrigeration, support, transport, and other)
EPA-TIMES	US EPA	9 US regions	Partial; Perfect	2010-2050, 5-year time steps; **LP**	X	X	X	X				20 industry sectors + refining
EPS	Energy Innovation	US	Partial; Myopic	2020-2050, 1-year time steps; **Logit**	X	X		X				25 manufacturing sectors (including energy)
FARM	USDA	US, Canada + 11 other world regions	General; Myopic	2011-2101, 5-year time steps; Mixed: **Logit** for electricity generation shares; **CES** otherwise		X	X					6 energy-intensive; 1 other industry
FECM-NEMS/ OP-NEMS	OnLocation	US; subnational aggregation varies by submodule	Partial; Near-perfect (electricity, liquid fuels), Myopic (demand)	2021-2050; 1-year time steps; Mixed: **LP** in power and liquid fuels; **MIP** for CO2 pipeline and storage; **Logit** in demand models	X		X	X			X	15 manufacturing; 6 non-manufacturing; refining; 4 Census regions
GCAM	PNNL	Canada, Mexico, US, +29 other regions	Partial; Myopic	2015-2100; 5-year time step; New investment: **logit** based on expected profitability; Operating costs are accounted for existing stock.	X	X	X	X		X		6 manufacturing; 3 non-manufacturing
GCAM-USA	Univ of MD and PNNL	50 US states, Canada, Mexico+29 other regions	Partial; Myopic	2015-2100; 5-year time step; New investment: **logit** based on expected profitability; Operating costs are accounted for existing stock.	X	X	X	X		X		3 (Cement, Fertilizer, and All Other Industry)
gTech (Navius Research)	Navius Research	Canadian Provinces + US	General; Myopic	2015-2050; 5-year time steps; **CES**	X	X	X	X				34 non-energy industrial sectors; 9 agriculture & 24 energy sectors
MARKAL-NETL	NETL	9 US Census regions	Partial; Perfect	2005-2075; 5-year time steps; **LP**	X	X	X	X	X		X	7 non-energy; 9 industrial energy carriers
NATEM	Esmia Consultants	13 Canadian regions; 9 US Census regions + CA, TX, NY; Mexico	Partial; Perfect	2016-2060; 2- to 5-year time steps; **LP**	X	X	X	X	X			7 non-energy; 8 industrial energy carriers
TEMOA	North Carolina State University	9 US regions	Partial; Perfect	2020 to 2050; 5-year time steps; **LP**	X	X	X	X	X			2 sectors; Manufacturing: 9 end-uses; Non-manufacturing: 6 end-uses
US-REGEN	EPRI	16 US regions	Partial; Perfect	2015-2050; 5-year time steps; Mixed; **LP** in electric and fuels sectors, **logit** in end-use sectors	X	X	X	X	X			37 non-energy sectors
USREP-ReEDS	MIT-NREL	USREP: 12 US regions	General; Myopic	2017-2050; 5-year time steps; Mixed; **CES** in USREP; **LP** in ReEDS	X	X	X		X		X	5 energy; 6 non-energy

Aggregate only, by energy type
Energy service
Detailed process flow (iron & steel and cement) + Energy service demand (rest of industry)
Detailed process flow (iron & steel and cement) + Aggregate only, by energy type (rest of industry)
Partial, Myopic, Logit
General, Myopic, CES
Partial, Perfect, LP

Table 2
Industry coverage of NEMS industrial demand module by NAICS code.

Energy-intensive manufacturing		Non-energy-intensive manufacturing		Nonmanufacturing	
Food products	311	Metal-based durables industries		Agriculture: crop production	111
Paper and allied products	322	Fabricated metal products	332	Other agricultural production	112, 113, 115
Bulk chemicals group		Machinery	333	Coal mining*	2121
Inorganic	325,120, 325,180	Computer and electronic products	334	Oil and natural gas extraction	211
Organic	325,110, 325,193, 325,194, 325,199	Electrical equipment and appliances	335	Metal and other non-metallic mining	2122–2123
Resins	325,211, 325,212, 325,220	Transportation equipment	336	Construction	23
Agricultural chemicals	325,311, 325,312	Wood products	321		
Glass and glass products	327,211, 327,212, 327,213, 327,215, 327,993	Plastic and rubber products	326		
Cement and lime	327,310, 327,410	Balance of manufacturing	312–316, 323, 3254–3256, 3259, 3271, 327,320, 327,330, 327,390, 327,420, 3279 (except 327,993), 3314, 3315, 337, 339		
Iron and steel	331,110, 3312, 324,199				
Aluminum	3313				

Source: Table A-1. IDM Industries and NAICS Codes of the NEMS Industrial Demand Module, U.S. Energy Information Administration [35]

and emissions accounting with regards to “industry”. However, there are often complications involving the energy and emissions accounting within any given model for the “industrial sector.” In the EMF 37 study, manufacturing is included in industry, but non-manufacturing industries are represented differently in the different models. For instance, one model represented energy use in agriculture and construction through off-road vehicles usage, and the amounts are reported in the transportation sector. Mining includes both energy and non-energy mineral mining, so energy use in energy production may be modeled in the energy supply side of some models and elsewhere for non-energy minerals. Next, we present the results from our analysis of the results for various EMF 37 scenarios as submitted by the participating modeling groups.

3. Results

3.1. *Reference case*

Different representations and scopes of the industry sector and different base-year calibrations result in significant differences within the models. Fig. 2A presents final energy use in the industrial sector (including historical and projections) for the four scenarios reported by EMF 37 models. According to EIA, the industrial sector consumed 24 EJ of primary energy and 3.6 EJ of electricity in 2021 [5,6]. The industrial energy demand in 2020 in the *Reference* case across models range between 15 and 27 EJ with median of 21.47 EJ. The industrial energy

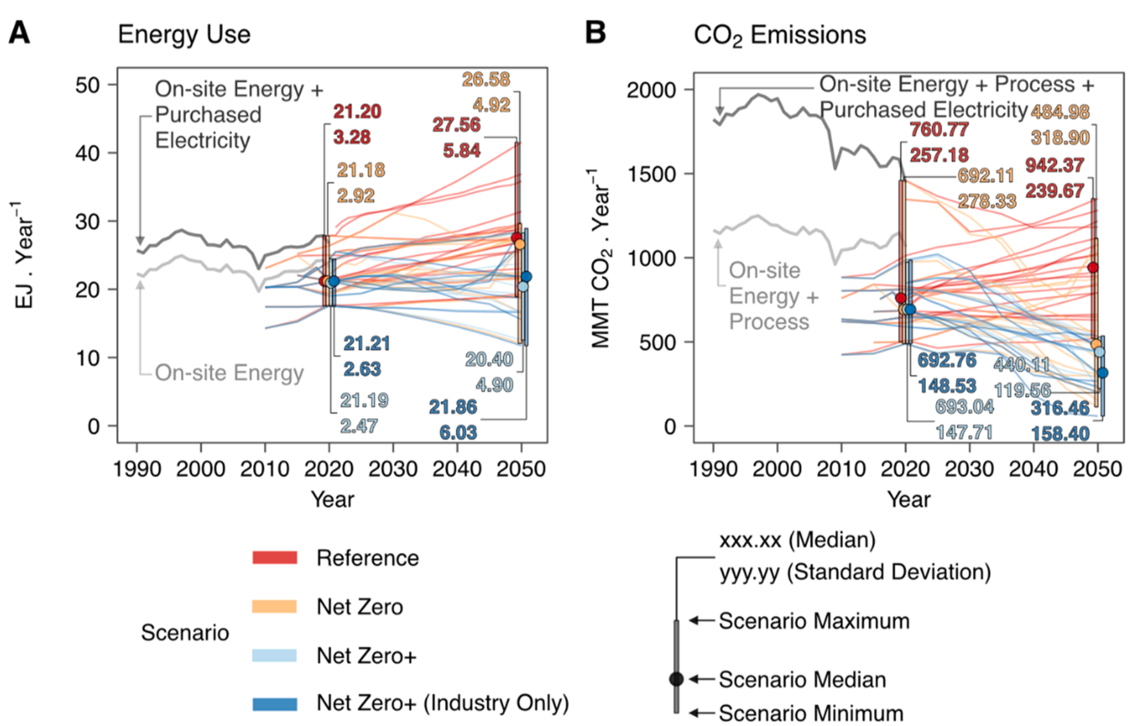

Fig. 2. Industrial Final Energy (A) and CO2 Emissions (B): Comparison to Historical and EMF 37 model ensembles. The historical (1990–2020) values are based on EIA [37] and EPA [38], and the EMF37 Projections (2020–2050) are from model ensembles.

consumption increases in the *Reference* case across all models reaching a median of 27.81 EJ by 2050.

In the Reference case, there is no significant change in the fuel mix to meet the increased final energy use. Fig. 3 presents the industrial final energy use by fuel type by model for the scenarios. Although there are similarities across the distribution of fuels such as use of oil, gas and electricity, the absolute numbers vary. The apparent divergence in the historic energy consumption values is due to variations in the energy accounting such as representation of fuel types in models and how total consumption is allocated to individual industries as discussed above. For instance, final energy use corresponding to coal mining (NAICS: 2121) and oil and gas systems (NAICS: 211) are included in the industrial energy balance in the models such as EC-MSMR, EPS, GCAM, US-REGEN, USREP-ReEDS, whereas although represented in models, this balance was excluded in the industrial sector reporting of EPA-TIMES, FARM, and MARKAL-NETL models.

According to EIA's latest Manufacturing Energy Consumption Survey (MECS), final energy consumption in energy-intensive industries is around 63 % of total industrial energy consumption [36]. Table S2 of the Supplementary Materials provides a detailed breakdown of industrial fuel and electricity consumption for each industry in 2018. We compiled the energy consumption between energy-intensive and non-energy intensive industries across the models and presented in Fig. 4. We observed that across the models, this attribution to energy-intensive vs non-energy intensive industries in their base years varies significantly (Fig. 4). Most models with General equilibrium, myopic, CES traits allocate the majority of final energy consumption (e.g., ~78 % in ADAGE) to energy-intensive industry whereas FARM and USREP-REEDS (Fig. 4A) do not distinguish between energy-intensive and non-energy intensive. No common trend is observed in partial equilibrium, myopic, logit models (Fig. 4B). The attribution to energy-intensive industries is much lower than the values reported in MECS which was around 63 %. The partial equilibrium, perfect foresight, LP models do not report the split between energy-intensive and balance final energy use. However, based on the detailed model survey (Table S1), we can infer that these models include representation for energy-intensive and non-energy intense industries. For instance, EPA-TIMES model is calibrated to MECS 2018 data, so we assumed their 2020 value (Ref20) corresponds to MECS 2018 split. In Fig. 4C, the EPA-TIMES Ref20 energy-intense industry contribution is denoted in yellow. Furthermore, EPA-TIMES, MARKAL-NETL and US-REGEN are calibrated to MECS. As a result, there is a common trend in these models.

Direct industrial CO_2 emissions (mostly due to fossil fuel combustion) in the *Reference* case increase steadily across all models (Fig. 2B). Direct CO_2 (Scope 1) emissions are measured from sources that industry sector owns or controls. The electricity related emissions are accounted separately. The large reliance on fossil fuels (Table S2 and Fig. 2) is main contributor of the CO_2 emissions along with process related (non-combustion) emissions. Across all the modeling scenarios, by 2030, the range of industrial CO_2 emissions is: 446 $MtCO_2$ – 1304 $MtCO_2$ with median 7698 $MtCO_2$, and 58 $MtCO_2$ – 1352 $MtCO_2$ by 2050 with median 520 $MtCO_2$ (Fig. 2B). The variation in 2030 emissions can be attributed to variation we observed for final energy use due to calibration differences and industry coverage as well as allocation of fuel use within industry for energy-intensive industries versus the rest of industry (Fig. 4). In *Net Zero* cases, industrial CO_2 decreases in the bulk of models. CO_2 emissions in industry in decarbonization scenarios with industrial advances assumptions are between 447 $MtCO_2$ and 924 $MtCO_2$ by 2030 (with median 605 $MtCO_2$) and between 59 $MtCO_2$ and 536 $MtCO_2$ by 2050 (with median 316 $MtCO_2$).

3.2. *Net Zero scenarios*

The International Energy Agency (IEA) states that the key for industrial decarbonization is decoupling of industrial production from CO_2 emissions [39]. As we outlined earlier, the industrial decarbonization can be achieved via (1) Energy and material efficiency improvements, (2) switching to lower-carbon fuels and feedstocks, e.g., natural gas for coal or zero-carbon hydrogen or biomass for fossil fuels generally, (3) industrial electrification supplied by low and zero carbon electricity sources and (4) adoption of carbon capture, utilization, and storage in industry. One caveat to note is that the net carbon benefit of CO_2 utilization is a topic of ongoing research. Whether utilization of CO_2 leads to net negative emissions depends on several factors including source of the CO_2, lifetime and fate of the end-product(s) made using captured CO_2, and GHG emissions from displaced products and processes.

Fig. 2 underscores the first challenge we observed in comparing the industrial sector energy and emissions projections from EMF 37. Significant differences in the base year energy, emissions, and fuel mix accounting yield projections in the future under both the *Reference* and *Net Zero* case(s). This makes the comparison of levels across the models' projections rather difficult. Fig. 5 attempts to address the differences in level via either indexing to a base year or computing fuel shares. In the *Reference* case, the median of total industrial energy growth is about the same as AEO2023 energy growth projections from 2020–2050. The *Net Zero* scenario shows increased electrification (Fig. 5C) and increased use of biomass (Fig. 5E). The *Net Zero+* scenario results are very similar to those of the *Net Zero* case, and therefore is excluded from the discussion.

Median average annual industrial energy consumption growth in the *Reference* case is 0.75 % from 2020 to 2050. This level is consistent with the historical growth in industrial energy consumption. In the *Net Zero* case, median average annual industrial energy consumption growth rate for the same period is lower at 0.24 %. The reader should keep in mind that the value of shipments projections for industrial output is an exogenous input to the models. In the *Reference* case, the median of energy shares across the models changes very little between 2020 and 2050. Notably, further electrification does not occur among the models, nor is there a significant increase in hydrogen adoption: one model uses a trivial amount of hydrogen in 2020, and one more model adopts low levels of hydrogen by 2050.

In the *Net Zero* case, there are significant changes in energy share. The median share of electricity increases by 10 percentage points by 2050 to 26 %, with maximum share of 42 % by 2050. Six models project hydrogen consumption by 2050; all but two of those models' shares are 5 % or less. The maximum hydrogen shares in 2050 is 19 %, and that model also adopts bio-based energy sources while shares of liquids and gas decline significantly. In this model, nearly 50 % of industrial energy is provided by either bio-based sources or hydrogen. The *Net Zero+* case results are similar to the *Net Zero* case.

Another way to address the baseline accounting issues when comparing across models may be to focus on the individual models' differences between the *Reference* and *Net Zero* cases. Fig. 6 illustrates the annual growth rates between 2020 and 2050 for final energy, direct CO_2 emissions, electricity, and non-electricity (such as fuel and feedstock). Fuels and feedstocks are computed subtracting electricity total from final energy. Most models have modest to no growth (0–1 %) in final energy in the *Reference* case, which occurs as efficiency gains partially offset industrial production increases. All but three models show no growth in direct emissions in the *Reference* case. The difference in total energy and emissions can be partially explained by the relative growth in non-electric and electric energy. Direct CO_2 emission arise from non-electric energy use. Any CO_2 emission from purchased electricity use is accounted for outside the industrial sector in the EMF reporting scheme. When comparing the *Reference* case growth to net-zero, about one-third of the models show a decline in total energy growth rates between the two scenarios, while almost all show a decline in the growth rate of emissions. About half of the models have increases in electricity growth rates and declines in fuel and feedstock growth rates. Few models reduce total energy consumption from energy efficiency. Some models exhibit much larger direct industrial decarbonization, some of which may be attributable to moving away from fuels

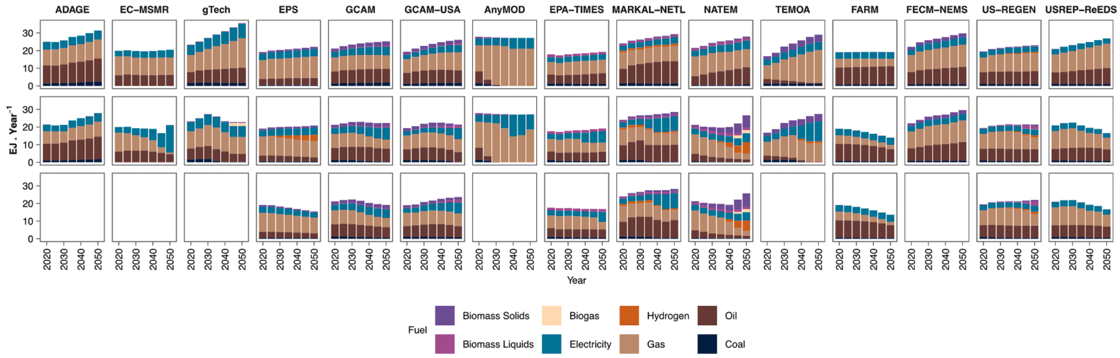

Fig. 3. Industrial final energy use by fuel types for Reference, Net Zero, Net Zero+ scenarios.

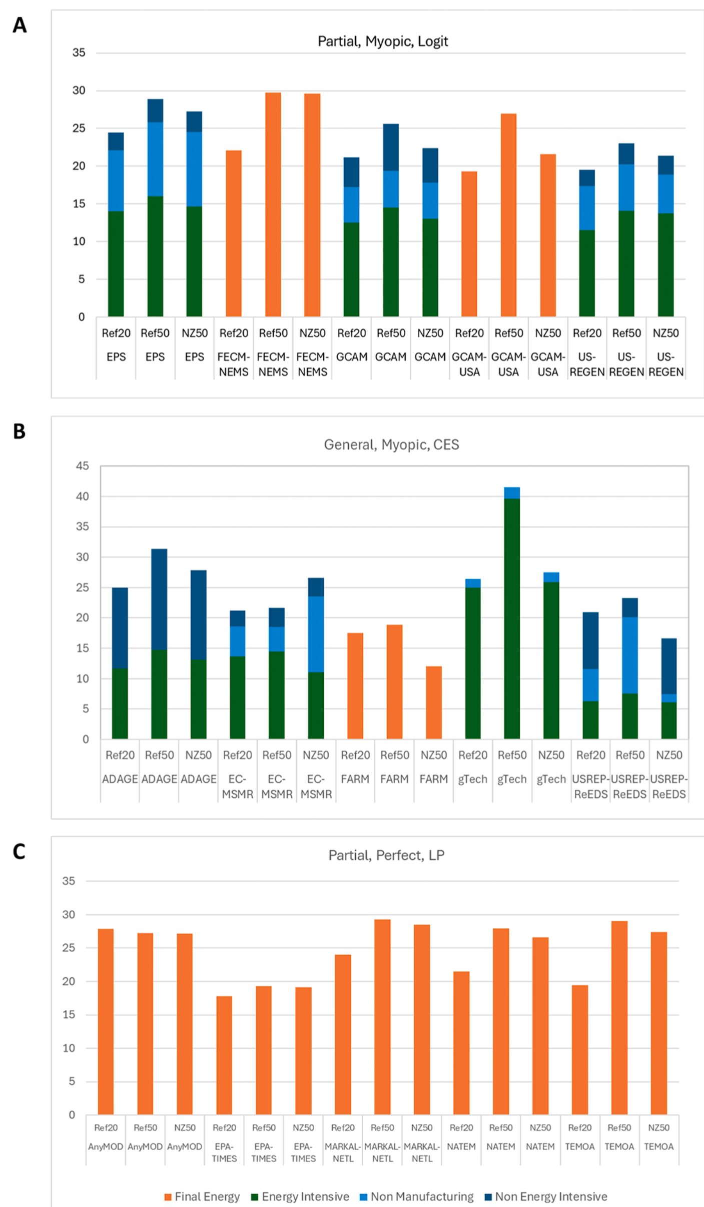

Fig. 4. Energy-intensive industry final energy use contribution to total industrial final energy use in 2020 for Reference case (Ref20) and in 2050 for Reference (Ref50) and Net Zero (NZ50) cases reported from (A) Partial, Myopic, Logit model ensembles; (B) General, Myopic, CES model ensembles and (C) Partial, Perfect, LP model ensembles.

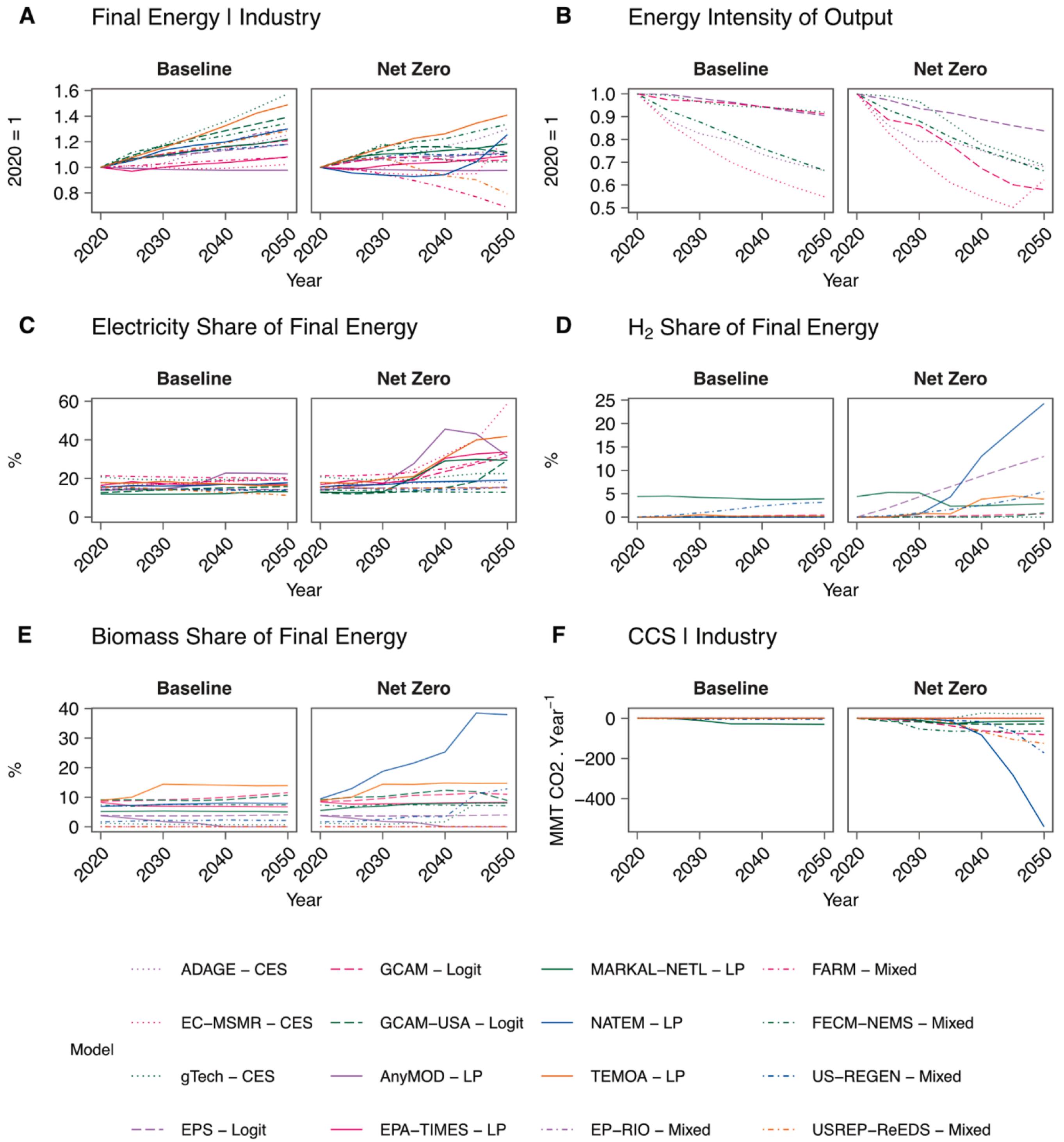

Fig. 5. Comparison between Reference and Net Zero Scenarios: (A) Final Energy Use in Industry; (B) Energy Intensity of Output; (C) Electricity share of Final Energy in Industry; (D) Hydrogen share of Final Energy in Industry; (E) Biomass Share of Final Energy in Industry; (F) emissions captured from CCS. Model descriptors after model names in the legend indicate whether the model uses a constant elasticity of substitution (CES), logit function, linear programming (LP), or a combination (mixed) of the approaches in selecting technologies.

and toward low and zero carbon electricity. Browning et al. [1] documents the rapid grid decarbonization in most all EMF 37 models.

Using average annual growth rates over the entire period may oversimplify the results because rates may vary within the projection period. Breaking the net-zero scenario growth rates into two fifteen-year time periods (2020–2035 & 2035–2050) illustrates whether growth rates change over time. Fig. 7 shows that differences exist for growth rate in CO_2 and the underlying energy types, but not for total energy. Total energy demand growth tends to be stable over time; but changes in CO_2 emissions "accelerate" for about half the models; electricity and fuel demand changes accelerate for quarter of the model results, with the differences for fuel use growth being rather small. Since reported changes in CO_2 emissions are direct emissions, these results are the combination of lower fuel use and carbon content of fuels. This acceleration in changes in CO_2 emissions likely reflects model structure regarding foresight, capital turnover constraints, or the way a net-zero

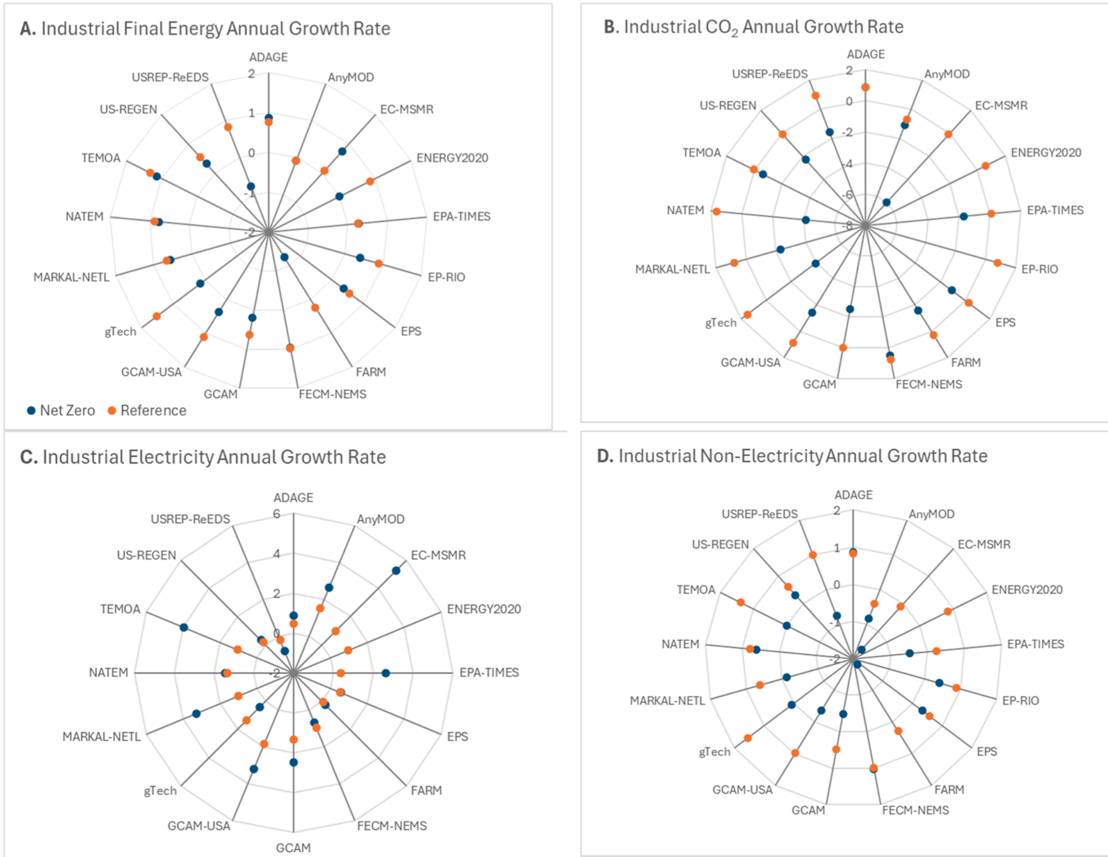

Fig. 6. Comparison of model specific growth rates for final energy, CO_2 emissions, electricity use and fuel use.

requirement is implemented in each model.

Using growth rates for the levels of energy and emissions ignores possible differences in the growth rate of industrial activity, whether physical quantities, gross dollar value, or dollar value-added. Some models have endogenous activity and many are exogenous. Only six of the models provided the underlying economic activity for industry to the EMF-37 database. Even in the case of the two models that reported using exogenous activity there were differences. While the guidance for EMF 37 for exogenous activity is to calibrate to the Reference Case of the *Annual Energy Outlook* for 2022. One model team choose the low-economic growth case instead of the reference case. In the *Reference* case those underlying economic growth rates ranged from 0.7 % to 2.4 % per annum, and the average growth rate is 1.6 %. This means that the levels of energy demand and direct emissions can vary widely across the models based on these underlying assumptions or endogenous forecasts. Those models with higher economic growth would tend to put upward pressure on emissions and require larger reductions to meet net zero. Of the four models using endogenous activity only one exhibited different total industrial activity growth in the *Net Zero* case; others were within +- 0.1 % of the *Reference* case. This means that changes in industrial output was not an important driver of emission reductions in the net zero results, at least for models where that information was reported.

In addition to above comparison, we computed percent changes between *Net Zero* and *Reference* case for following indicators: (1) total energy growth, (2) increased efficiency, (3) electrification, and (4) direct decarbonization. Models with higher baseline emissions or underlying activity forecasts will have impacts on the energy system beyond the industrial sector due to higher emissions generally. Change ratio can illustrate the main components of each model's assessment of the net zero energy carbon system for industry. Fig. 8 integrates these five metrics as outlined below for each model into a single figure; the models are grouped based on model structure.

1. Total energy growth: Ratio of final energy in industry for *Reference* case in 2050 to final energy in industry for *Reference* case in 2020
2. Increased Efficiency: Ratio of final energy in industry for *Net Zero* case in 2050 to final energy in industry for *Reference* case in 2050
3. Electrification: Ratio of total "fossil" for *Net Zero* case to *Reference* case in 2050
4. Direct decarbonization via low carbon fuel switching, CCUS, etc.: Ratio of CO_2 emissions for *Net Zero* case to *Reference* case in 2050.
5. Marginal cost of decarbonization: reported carbon price is included in dollars per million metric tons of CO_2.

If the values are less than one, this means some decarbonization is happening in the *Net Zero* Case. The differences between the ratios reflect different basic pillars of decarbonization. Since all models achieve net zero, this cost (or price) reflects the overall marginal cost of achieving net zero system-wide while also reflecting the contributions from the four industrial pillars of decarbonization, if any.

We observed that the distribution of these ratios for all five measures is roughly symmetric across the models, meaning the average and the median are similar. The largest difference between the average and the median is for the *Reference* case growth and direct emissions (7 %). Average *Reference* case growth in final energy (blue bars) is 16 %; average reductions in total energy (orange bars), fossil (grey bars), and CO_2 emissions (yellow bars) are 12 %, 20 %, and 39 % respectively. This might suggest that these median values could be considered a consensus forecast, but that is not the case. The models are all very different in both the levels of decarbonization and the projected pathways. In addition, larger reductions are needed to offset the higher growth in final energy in *Reference* case (blue bar) in some of the models.

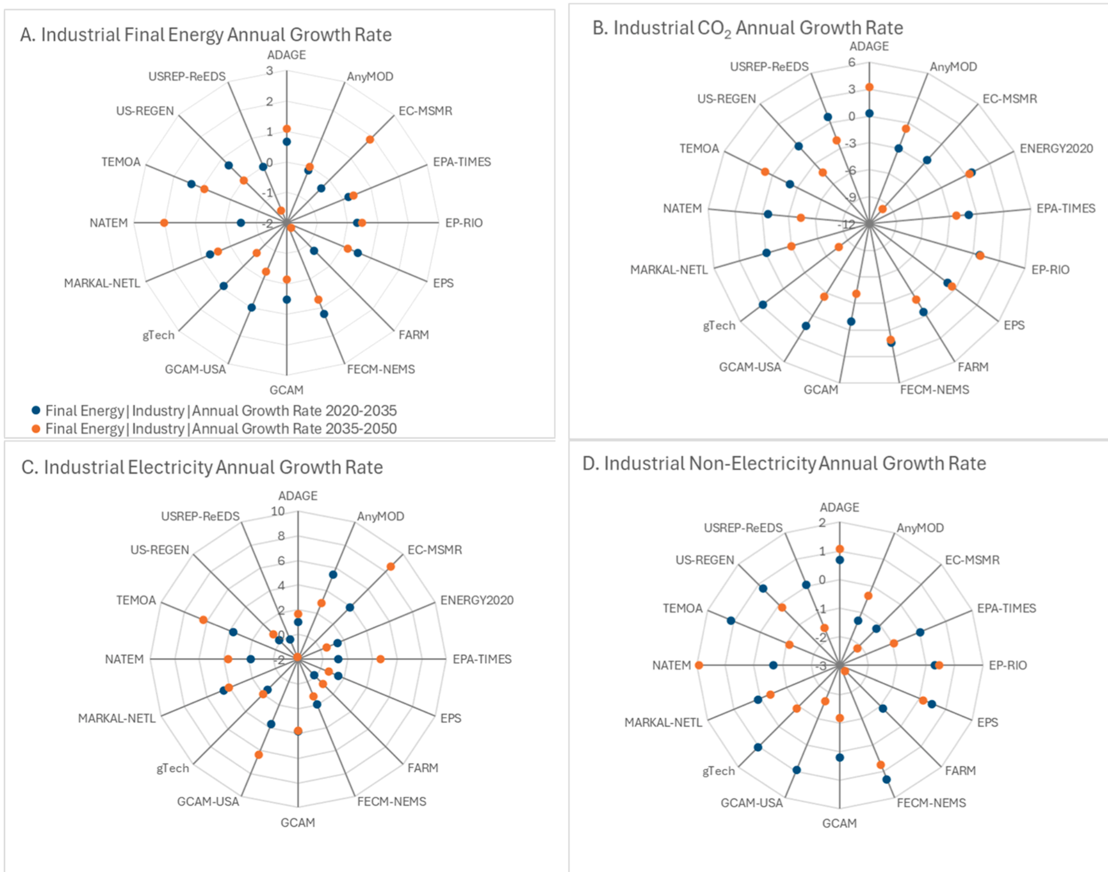

Fig. 7. Comparison of model specific growth rates for total energy, emissions, electricity and fuels in the net zero case for the near-term (2020–2035) and long-term (2035–2050) time frames.

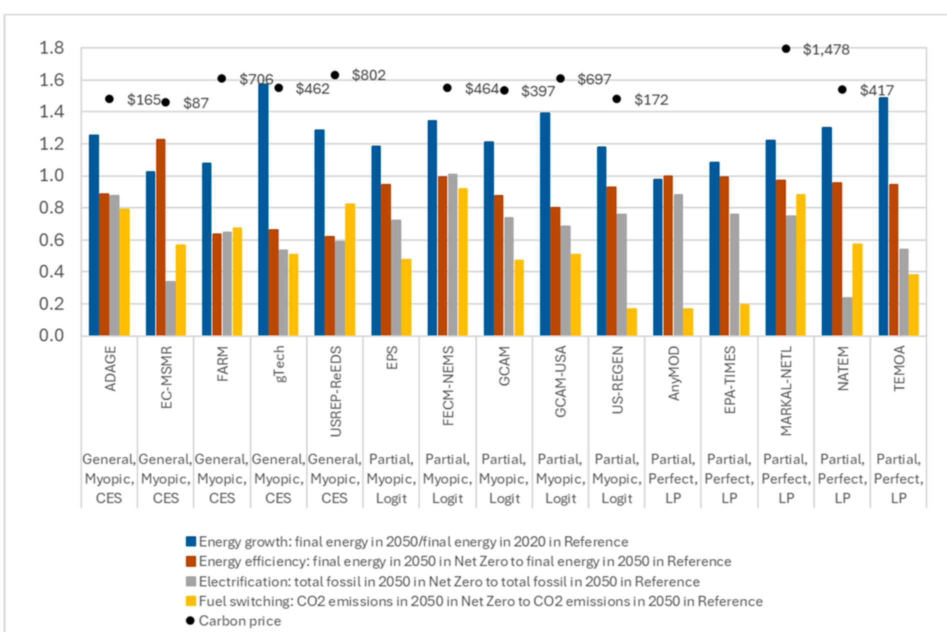

Fig. 8. Comparison of model specific change ratios between the Reference and Net Zero cases for total energy, fuels, and emissions in 2050, including the reported marginal cost (carbon price).

Comparing the grey and orange bars shows that eight models (FECM-NEMS, EP-RIO, US-REGEN, ADAGE, EPS, gTech, USREP-ReEDS, NATEM) have about the same or only slightly larger reductions (<5% difference) in fossil energy compared to total energy, implying that these models have fuel shares in the Net Zero case that are similar to the *Reference* case, so d*o not exhibit significant electrification in their forecasts*. These models are mainly logit and CES, suggesting that this approach may have limited representation of electrification. Of these eight, only two (gTech and USREP-ReEDS), exhibit substantive reduction in total final energy (energy efficiency), while the electric to non-electric mix stays roughly the same. For those remaining models, four of which are LP based, the median reduction in fuels compared to total energy is 25 %. This suggests that LP models may have more representation of electrification pathways.

Comparing the yellow and grey bars reveal seven models (ADAGE, FARM, USREP-ReEDS, EP-RIO, FECM-NEMS, AnyMod and TEMOA) exhibiting little direct decarbonization of fuels, meaning switching to low carbon fuels. The reduction in direct emissions is within 10 % of the reduction in fuel use. Interestingly, TEMOA and FARM show an increase in emissions relative to non-electric energy, exhibit direct decarbonization of fuels. The average reduction (difference between the orange and gray bars) for the remaining models is 41 %. We observe no correlation with direct decarbonization in industry and structure of the models.

When we analyze the reported carbon prices, we observe median prices of $206/tonne and $439/tonne in 2040 and 2050, respectively (Fig. 8). In half of these reporting models, carbon prices rise rapidly after 2040. If the grid is largely decarbonized, then the incremental cost of electricity would also reflect in the marginal costs of that decarbonization. Several models did report a price for electricity that reflects this marginal cost, compared to *Reference* case median electricity prices increase 32 % in 2050 compared to price of electricity in 2020. With the increase in electric prices, we might expect some models not adopting electrification.

To explore the relationship between the change in these three decarbonization metrics relative to the carbon price, we can look at the correlation coefficient between the change in final energy, the change in fuel use, and the change in emissions between the *Reference* case and the *Net Zero* case in 2050 for each model. When all models that reported a price are included, the correlations are rather low. If the upper and lower price outliers are excluded, then the correlation is –0.69 for final energy and –0.66 for fuels and feedstocks. However, the correlation with the change in direct CO_2 emissions is zero, regardless of the treatment of outliers. This may reflect optimistic assumptions about low carbon fuels such that lower the prices leads to increase in the adoption of those fuel types.

4. Discussion

4.1. Industry's role on getting to Net Zero

Fig. 8 shows the wide range of direct emission reductions across the models; three models reduce emissions by more than 80 % and four models reduce emissions by less than 20 % from the *Reference* case (average is 39 %). This lack of consensus on industry's contribution toward a net zero constraint implies that models with smaller reductions in the industry reach net zero by substantially relying on reductions from other sectors. Alternatively, some models rely more on CDR options to provide negative emissions. To put the contribution of industry in context, we must also consider the emissions from other sectors. One way to consider this is how much each sector contributes to "residual" emissions, i.e., positive direct emissions that are offset by other means.

In the *Net Zero* cases, all models result in some residual CO_2 emissions and relied on emission offsets [1]. In the scenario design, an exogenous assumption of 800 MMTCE of land use sink is included in the models that do not represent LULUCF. In addition to this exogenous assumption, all models rely on some level of CDR such as DAC, BECCS, or CCS. The contribution of positive emissions across sectors that lead to the "demand" (or need) for CDR vary across the models. In 2050, the median of industry contribution to residual emissions is 28 %. Transportation is highest at 38 %. The buildings and the power grid reduce CO_2 emissions most, resulting in 12 % and 6 % median contribution to the residual emissions, respectively. Industry has the highest standard deviation of these residual emission shares (0.20), so there is less agreement amongst the models about the role of industry regarding residual emissions. We observed a range of *net-positive emission shares* for industry and also a wide range of the of net-positive emission levels overall for the models. We hypothesized that, models resulting in higher industry share of emissions may also have higher net-positive emissions overall. To measure this, we take the total positive emissions from each model, subtract 800 MMT of CO_2 to reflect LULUCF and compare this to the *Reference* case emissions.

Fig. 9 plots the industry share of emissions against the ratio of the net-zero scenarios' positive emissions less the land sink divided by *Reference* case emissions. The denominator of the ratio is a measure of "how close to zero?" the models project emissions are without need for CDR and/or CCUS. The lower the number the closer they are to net-zero relative to the *Reference* case. Industry shares vary widely, from near 10 % to over 60 %; there is little consensus about the role of industry. The median share is 27 %. In aggregate, the positive emissions that must be offset by negative emissions (DAC, etc.) range from zero to almost 60 %; the median is 18 % and the average is 23 %. These shares already account for exogenous LULUCF assumption. The model with the highest share of industry emissions has a low percentage of net-positive emissions. The models with the highest net zero share have about average industry contribution. There isn't any relationship between the industry share and total net positive emissions. The correlation coefficient between these two metrics across the models is 0.11 indicating weak correlation. When model structure is considered, there is still no discernable pattern for CES and Logit models. However, across the Partial, Perfect, LP models, the R-squared value is 0.68 indicating moderate to strong correlation. This suggests that industry is a meaningful contributor to residual positive emissions in these models. However, we know from the model surveys that some of these models lack bottom-up characterization of advanced technologies employing electrification and low carbon fuels, etc., the absence of which drives the demand for negative emissions technologies. From this perspective, it could be concluded that industry is "hard to model," although it is difficult to ascertain whether and to what extent bottom-up modeling of industrial technologies in these models would indeed reduce the demand for negative emissions.

4.2. Modeling challenges

The extent of industrial sector decarbonization, or lack thereof, contributes to net positive direct emissions that must be offset by CDR or CCUS technologies resulting in negative emissions. Other things equal, when industry contributes to the demand for CDR and/or CCUS then the options for direct industrial decarbonization that are included in the models are either more expensive than CDR or constrained in some fashion. The level of this demand could be overestimated, should the models exclude particular industrial decarbonization pathway.

Based on the results presented above, any reduction in fossil energy that exceeds the reduction in total energy implies a forecast shift in the fuel/electricity mix. This may not be "electrification" per-se but could simply be the price incentive to reduce direct carbon emission from fuel and feedstocks via efficiency, since most models project modest increases in the cost of electricity, but the inherent carbon content of fossil fuels, even natural gas, results in a large increase in final cost. Switching from fuel to electricity for process heat may also be associated with increased efficiency. In addition, there could be technological advancements in how the goods are made such as a greater share of

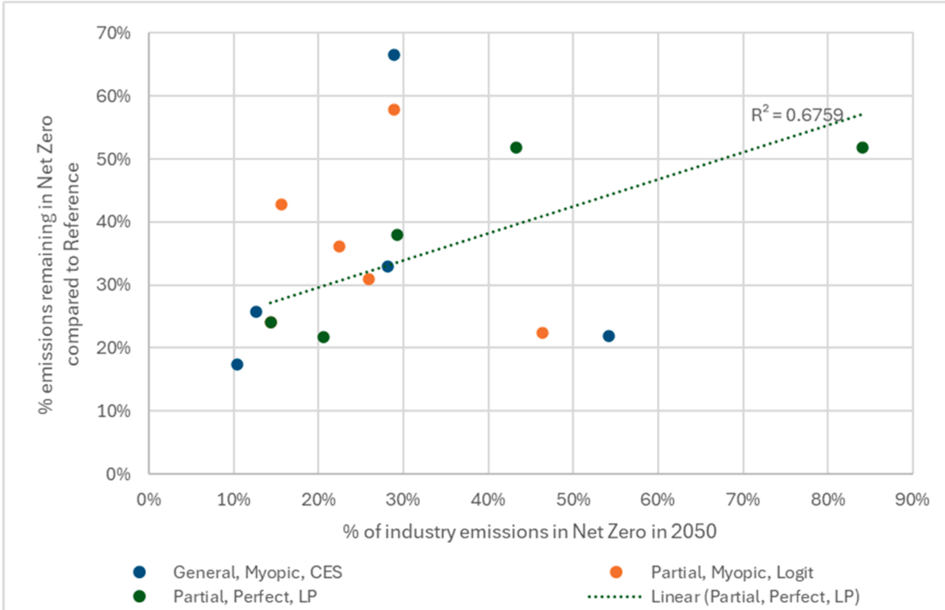

Fig. 9. Net positive emissions relative to the Reference case compared to the industrial share of net positive emission in 2050, by modeling approach.

electricity consumption in metal-based durables. Finally, the industrial decarbonization can be achieved when the demand for goods decline as the production slows down. Within the context of EMF 37, most of the models do not capture endogenous changes in value of shipments. Also, many models lack detail on multiple pathways to produce one good. In the rest of this section, we explore the modeling challenges for both direct reductions (energy efficiency) and electrification (switching from fuel to electricity for heat) from the view of two major model types: (1) “top down” models using parametric estimates of elasticities, e.g., CES, and (2) “bottom up” or “technology rich” models that use LP or logit models and incorporates cost and performance to assess technology choice.

4.2.1. Direct reductions (energy efficiency)

Top-Down models (CES): The increase in price in fossil fuels relative to electricity can lead to increased adoption of electricity. However, low price elasticities (in absolute value) will blunt any price effect. Price elasticities based on empirical studies tend to have rather low own price elasticities and focus on electricity only [40–42]. These papers contradict with studies by Boyd and colleagues finding own price elasticities that range from -0.5 to -1.0, with most being closer to unity [43–45]. The primary difference between the various studies with low elasticities and the studies by Boyd and colleagues is the latter studies use plant level data with industry specific estimates and estimate both electricity and fossil fuel elasticities. Some other plant level studies do exist, though they focus on estimation of efficiency and not price elasticities [46,47].

The prevalence of relatively low-price elasticities in the models is exacerbated by the fact that U.S. industry has never faced sustained high electricity or natural gas prices. Historically, electricity prices have been relatively stable, and natural gas prices have spiked briefly before returning to a lower long-term trend. Therefore, it is not possible to predict know how industry will react with sustained high energy prices since we have not observed long term trends. While electricity prices are not expected to rise substantially in the net-zero scenarios,[1] the full cost of natural gas, which includes the marginal cost of carbon or “carbon price,” would rise to levels that are not historically experienced. This complicates the calibration of this class of models to a history of low stable prices with the need to forecast demand in a future of significant and consistently increasing fossil fuel prices.

Bottom up (LP and logit): Within these modeling frameworks, efficiency is represented through technology’s fuel efficiency and capability of model to switch to technologies that consume less energy to meet the energy service demand in the industry. Fuel efficiency does lower emissions but doesn’t eliminate them in the long term. While electricity efficiency doesn’t necessarily provide lower emissions in the industrial sector as the emissions are accounted part of the grid. It does lower the demand for electricity, reducing incurred costs and stress on the grid. Fuel switching opportunities might be limited in the industrial sector, specifically for the sectors that require high temperature heat. That said, improvements in boilers, industrial heat pumps, insulation, and motors may offer benefits, but that is more likely for industries needing low- to mid- temperature heat [48–50]. Within the participating models in EMF 37, few models distinguish demand by temperature, most likely due to data limitations. Higher temperature processes tend to be more industry specific, placing additional challenges on the models to represent the details of kilns, furnaces, chemical crackers, etc.

4.2.2. Electrification

Top-Down Models (CES): Switching from fossil fuels to electricity to generate heat is suggested as a viable decarbonization approach as the power grid also becomes decarbonized. However, representing this substitution in a traditional production/cost function framework, such as the CES framework, has major challenges. These include data relating to energy services and the assumption of symmetry in the substitution potential. That implies that electricity can be substituted for fuel and vice versa. However, fuel/electricity substitution is not symmetric. In some cases, fuel/electricity substitution is effectively impossible. As pointed out by Steinbucks [51], certain energy services, such as lighting and motive power, are exclusively electric, or nearly so. It is impractical to expect otherwise, no matter what the relative prices of electricity and other energy sources. Certain chemical processes are inherently electric. Non-substitutability of fuel for electricity in these cases while assuming symmetric substitution implies that comparing aggregate data on energy use for electricity and fuel will mask opportunities to substitute electricity for fuel for process heat. Similarly, the symmetry that is imposed

[1] For the small number of models that report electricity prices the increase from the reference case is much smaller than the carbon price effect on natural gas.

by popular mathematical models like CES imply that it is possible that fuel could replace these exclusively electric energy services. Production functions that have a variable elasticity of substitution might be able to address this problem [52–54], but these functions lack the computational simplicity needed for solving most CGE models.

Combining these data issues and the simplifying mathematical assumptions inherent in CES models with relative prices that have been mostly stable for many years, the result is empirical studies that tend to find little or no substitution potential between fuel and electricity in individual industries, for example [43–45]. However, under a net-zero climate policy the relative price of natural gas vs electricity would rise well beyond any historical experience. Most EMF models predict only a modest rise in the final cost of electricity, but the implicit cost of carbon would drive up the price of natural gas; for each $100 per ton of carbon the price of natural gas would rise $5.30/MMBtu. With a median carbon price of ~$400, the final cost of natural gas including a carbon price would rise by more than $21/MMBtu. This increase in relative prices has no historical analog on which to base a statistical model.

Bottom up (LP and logit): Electrification of energy service demands within industry presents multiple challenges [55]. The demand for heat drives much of the demand for energy and fossil fuels in the industrial sector. The heat and temperature requirements for industry can vary significantly across industries. McMillian and Ruth [34] characterized heat demand profiles of 14 top-GHG emitting industries and concluded that 30 % of demand can be substituted for alternative sources. Furthermore, McMillian et al. [56] do attempt to address this issue in the context of solar heat for low and medium temperature processes. Schoeneberger et al. [57] studied electrification of boilers in the U.S. Despite a considerable increase in renewables and a 40 % decrease in coal-based electricity in their reference grid case, the fuels required for electricity from boiler electrification still exceed the fuel savings from conventional boilers. Furthermore, Gilbert et al. [58] presented a framework to calculate levelized cost of heat that can be applied to steam boilers, ethane crackers and glass furnaces. They found that main driver for technology choice is fuel cost, and natural gas is likely the cheapest fuel source in the U.S. even after paying for carbon capture, and dramatic reductions in the cost. Since many LP and logit-based models represent technology in a bottom up manner via calculating levelized cost of each technology meeting the industrial heat demand, these alternatives could be represented in LP and logit-based models. In the modeling results, we haven't observed much electrification in the industry, the models either have strict constraints that limit the penetration of these technologies, or alternative technologies are not represented at all.

5. Final remarks

Along with examining the energy and emission implications of the EMF37 model results, this paper investigated the role of model structure and level of aggregation in industry sector via reported results from four scenarios: *Reference, Net Zero, Net Zero +* and *Net Zero + Industry,* with the primary emphasis on the first two scenarios since only a few models ran the latter two scenarios with advanced assumptions. While examining the results, we contemplated the following question "*Is the Industrial Sector Hard to Decarbonize or Hard to Model?*".

The models and scenario results can play a significant role in the formulation of policy, therefore it is important to understand the insights about *hard to decarbonize* and *hard to model* where the conclusions could yield very different implications for climate policy. When a policymaker understands that industry is *hard to decarbonize,* the policy implication is that new industrial technologies from accelerated R&D, emissions offsets from CDR, or both will be required. This would be reflected in a particular type of policy focus. When industry is *hard to model,* this implies that there may be missed or misunderstood opportunities in industrial decarbonization that should be further explored before or concurrent to developing specific types of technologies and policies. In this paper, we highlighted policy implications in the context of industrial sector, Bistline et al. summarized broader policy implications of the EMF37 study [2].

Unsurprisingly perhaps, there is no consensus in the results to answer this far-ranging question. It is a fact that specific basic material manufacturing sectors with large direct process emissions and high-temperature processes, e.g. cement, primary steel, basic chemicals (olefins and ammonia), etc. only have a few, or relatively expensive, options to decarbonize. These examples by themselves suggest that industry may be *hard to decarbonize* – that is, hard to reach zero CO_2 emissions individually in these basic materials industries without significant investments and transformative changes in innovative technologies that can produce these commodities at cost and quality parity with incumbent technologies.

However, these industries comprise only a portion of current and future emissions. Individual sectors need not achieve zero on their own. Almost all EMF models project some level of net positive emissions that are offset by LULUCF or other negative emissions technologies. If a sector's share of net positive emissions is indicative of how hard it is to decarbonize, then the median results across EMF 37 ranks industry "2nd hardest" at 28 %, with electric power (6 %) and buildings (12 %) decarbonizing "more easily" and transportation (38 %) the "hardest.[2]" There is more variation across models in the industrial share of net positive emissions than in other sectors, implying less consensus. However, there is no correlation between positive total emissions and the industry share. In other words, when models projected positive emissions are highest, industry is not always the culprit. There is pronounced disagreement across the models about the magnitude of decarbonization, measured by the share of positive emissions, and the pathways that might, or might not, result in decarbonization.

The comparisons throughout the paper cannot account for the fact that the industrial energy and emissions accounting in the base year of the various EMF models show marked discrepancies, which clearly impact projected levels, shares, and rates of change. This paper is unable to determine the extent to which the diversity regarding industry's contribution toward net zero is due to these accounting issues. While the paper looked broadly at model design to see patterns in results, e.g., that CES models tended to have less electrification, the paper cannot account for the myriad of details in the way the models handled the industrial sector.

The lack of consensus in industrial sector results across the EMF models on a wide range of issues, including things as simple as the base year accounting framework, leads to the conclusion that industry is ***very hard to model.*** The results provide no consensus regarding a particular path to decarbonization, both in terms of level of decarbonization and the pathways used to achieve it. Moreover, some pathways to industrial decarbonization are not particularly evident in the model results. Inclusion of extensive electrification options and changes in materials use/production, i.e., "circular economy" are two examples of pathways that are underrepresented in the models, if at all. Part of this is due to the complexity of the industrial sector: there are many different sector specific decarbonization measures possible because industries use different processes and energy sources to produce goods. Modeling even the major form of decarbonization in industry is a challenge. In term of "hard to decarbonize," some industries cannot use some decarbonization pathways, e.g., the prospect of electrifying cement production appears to be remote due to the high temperature requirements.[3] Finally, unlike

[2] Due rounding errors and representation of numbers as medians, the total might not add up to 100.

[3] We note that there have been recent advances made in electrification of pyroprocessing and electrochemical routes for cement production, although such technologies are still far from being proven at technical and commercial scales to be considered as viable options, particularly in the timeframe of this study.

the buildings or transportation sectors, where the broad outlines of pathways to decarbonization are better understood, decarbonization is much murkier for industry. Many technologies have not been invented or cannot be used in their current form for some industries. For instance, application of industrial heat pumps may meet low and medium temperature requirements, but to meet high temperature heat for the most energy intensive industries is problematic. Advances in the next decades may raise the temperature at which the heat pump delivers energy services and may also improve the economics for heat pumps in industry generally. However, until then, the uncertainty of decarbonization pathways for industry remains.

Other research suggests a range of options that can result in industrial deep decarbonization [29]. This study employs an accounting approach in its assessment and does not reduce industry entirely to zero emissions either. One decarbonization option to explore is a shift toward a circular economy where final products at the end of their life are recycled into new products. The circular economy will induce structural shifts in the composition of industry away from the most energy and carbon intensive activities.

Energy efficiency's role in these results is mixed. It is clear from the very low or near zero growth in total energy in the *Reference* case that efficiency plays a role in reducing the amount of carbon reduction that is required by 2050 in the absence of a net-zero policy. However, efficiency that reduces fuel use does not, per-se, result in complete decarbonization, only reducing the need for negative emission technologies. Almost all model results project that CDR is required to mitigate the remaining net-positive emissions. Industry's contribution to these net-positive emissions varies widely, so the models don't have any consensus about how far, or how much farther, efficiency might reduce this. Electricity efficiency doesn't reduce emissions from a zero-carbon grid, but can reduce the strain on, and possibly the cost of, the grid to decarbonize, particularly on infrastructure costs. However, it is not clear which of the EMF 37 models, if any, reflect grid infrastructure costs in the net-zero projections.

Care should be taken about drawing climate policy conclusions for industry from the current suite of models. The level of residual emissions projected by many models might lead to the policy conclusion that industry is hard to decarbonize. While there are carbon intensive sectors that pose industry specific challenges, industry is also hard to model, and the results may not fully reflect the range of decarbonization pathways that are available to industry at the level of marginal costs projected in the study. Industry has a long history of innovation and adoption of new energy and material technologies that have emissions implications, in the long-term, capturing those innovations in a formal model will require rigorous thought and coordinated effort among the industrial energy modeling community.

6. Future research directions

Industrial electrification is another mechanism for industrial decarbonization, given that the model results project that the grid will be decarbonized by 2050. Electrification is particularly applicable to less energy intensive, lower temperature industries, but also some energy-intensive processes such as steel. Research directions will vary based on the type of model. For CES and logit models, better parameterization can capture the asymmetry of electricity and fuel substitution. For technology rich models, further research is needed to include many industrial electrification paths as possible in the technology portfolio, such as electric boilers and electric heat pumps.

We observed carbon prices that are high enough to support CDR may lead to accelerated retirement of existing technology capital stock. While vintage specific data is not readily available, myopic bottom-up models may be able to consider accelerated retirement, at least for capital stock that exists in the beginning of the analysis time-period. To the extent that efficiency (particularly for fuel) and retrofit/accelerated retirement are not included in the bottom-up models then industrial decarbonization is likely underestimated.

The lack of historic and sustained relative high price ratio of natural gas to electricity has complicated efforts to model and incorporate into CES models. To model this accurately, the demand for heat might be "exogenously" phased out at a given high relative natural gas to electricity price. This phaseout will cause a concomitant increase in electricity use. Under what level of relative prices will induce fuel-to-electric substitution requires more research. Industries with low and medium temperature needs are more amenable to electrification. Disaggregation of industries according to NAICS could provide a proxy for the heat requirements and facilitate better modeling of opportunities [57]. A study analyzing process flows and temperatures for select industries such as those presented by Brown et al. [59] can also lend insight to differential temperatures in these industries.

In many of the energy systems models, circular economy technologies and practices that represent extensive recovery and recycling of materials are absent or modeled insufficiently [60]. This suggests an opportunity to model industrial activity in physical units in at least some industries along with endogenizing the output to allow for feedback mechanisms. Endogenizing manufacturing output would be a major undertaking, however, requiring a detailed modeling approach to material substitutions, recycling, and reuse.

Expanding scenarios, such as richer industrial CO_2 reduction and electrification scenarios, can drive compositional changes to the industrial sector. Such scenarios can provide incentives for early retirement of industrial capacity and include high carbon taxes or government incentives for industrial electrification. Such scenarios can highlight how far compositional changes to the industrial sector can go to lessen the pressure on decarbonization in other sectors, particularly transportation.

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Declaration of competing interest

The authors declare the following financial interests/personal

relationships which may be considered as potential competing interests:

Gale Boyd reports financial support was provided by US Environmental Protection Agency. Sarang Supekar, Nadejda Victor reports financial support was provided by US Department of Energy. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.egycc.2025.100190.

Data and code availability

The complete database from the Energy Modeling Forum 37 study is available at 10.23719/1531685.

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