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# Resource use, physical flows, and costs of select technologies and facilities in U.S. chemicals, cement, iron and steel, food, and non-manufacturing industries

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**Abstract**

We present a structured dataset that characterizes select technologies and facilities across U.S. industry. This dataset enables consistent, cross-sector techno-economic and energy/emissions characterization of U.S. industrial production for modeling and benchmarking analysis. The dataset covers six manufacturing sectors—ammonia, cement, ethanol, ethylene and propylene, iron and steel, and food, and three non-manufacturing sectors—agriculture, mining, and construction. Organized as an industry-level JSON array, the dataset integrates standardized assumptions, characterizations of incumbent and emerging technologies, and inventories of existing facilities. The assumptions harmonize units and prices, normalize operating costs using common feedstock and fuel baselines, apply chemical engineering plant cost index factors to capital costs, and index all cost values to 2018 USD. For manufacturing sectors, the dataset provides facility-level inventories including 36 ammonia, 97 cement, 201 ethanol, 35 ethylene and propylene, and 102 iron and steel plants. Also included are state-level food production and energy intensities. For non-manufacturing sectors, the dataset catalogs 18 technology options rather than facility inventories, documenting qualitative benefits and low/average/high estimates of potential resource use, emissions, and cost reductions. Data sources include publicly available datasets from federal agencies, industry, and academic literature. The dataset supports energy systems optimization, capacity planning, integrated assessment modeling, and benchmarking analysis.

**Keywords:** foundational industrial dataset, energy systems modeling, industrial energy analysis, facility-level data

## 1 Background & Summary

The U.S. industrial sector[1] has a significant economic and resource footprint, generating about 19 trillion USD of value added (17% of national GDP) [1] while consuming 30.9 quadrillion Btu (32,600 PJ) of primary energy (30% of the total energy consumed in the economy) [2]. Industrial processes are highly complex and diverse, spanning hundreds of subsectors with distinct feedstocks, production methods, and technologies. Compounding this complexity is the variability in technologies, capacity, and energy and economic characteristics observed across facilities within any given subsector. Analysts rely on a range of U.S. federal, state, industry group, and other independent datasets to describe industrial production economics, feedstocks, and mass/energy flows. Despite their breadth, these datasets remain fragmented, inconsistently defined, and often aggregated [3].

Several federal datasets provide information on U.S. industrial energy use, physical inflows and outflows of resources, products, and wastes, and facility characteristics. Each dataset is typically developed through different regulatory authority and for different purposes, therefore exhibiting critical differences in resolution, methodology, and scope. The Manufacturing Energy Consumption Survey (MECS), for instance, conducted every four years by the U.S. Energy Information Administration, provides statistics on energy use by fuel, end use, and NAICS code[2] at national and regional-level aggregation [4]. While MECS is a core resource for industrial energy analysis, its public data does not include facility-level energy use characteristics and it lacks feedstock information. State Energy Data System (SEDS) compiles fuel sales and consumption at the state level, but its industrial statistics are mainly derived from energy producers, aggregated across NAICS codes, and do not resolve patterns at the facility or subsector level [5].

Environmental reporting offered insights into facility-level utilization, an attribute that was generally lacking from other datasets. The U.S. Environmental Protection Agency (EPA) Greenhouse Gas Reporting Program (GHGRP) offers facility-level annualized operational data in the form of greenhouse gas (GHG) emissions data indexed by Facility Registry Service (FRS) ID [6, 7]. GHGRP offers valuable facility-level coverage, but reporting is mandatory only for large emitters ($\geq$25,000 $tCO_2e$ per year), leaving most of the roughly 300,000+ U.S. industrial establishments unrepresented [8]. It excludes data on electricity purchases, production capacity, and process technologies. Coupled with the use of mixed units for various energy and mass exchanges, identification of other facility-level attributes is challenging. EPA's National Emissions Inventory (NEI) also provides annualized operational data in the form of estimates of pollutant emissions from combustion and processes but lacks the comprehensive facility-level detail needed for energy and material inputs-focused modeling [9].

Plant trackers developed by the non-profit Global Energy Monitor (GEM) represent a non-governmental independent data initiative. They provide information on capacity, technology, and production attributes for iron, steel, and cement plants, but

[1] Includes manufacturing, mining, construction, and agriculture industries.

[2] The North American Industry Classification System (NAICS) standardizes classification of businesses by industry across the U.S., Canada, and Mexico using 6-digit numbers.

omit feedstock and energy intensity data. The Association of Iron & Steel Technology (AIST) furnace reports provide insight into capacity, technology, and recycled content, but they are limited in availability, coverage, and consistency [10]. Life cycle assessment (LCA) databases such as GREET provide generic or representative subprocess-level estimates for feedstock and energy use, but typically do not provide facility-specific inventories; facility-level data are primarily needed for benchmarking, spatially explicit analysis, and capturing operational heterogeneity [11]. Many sector-specific LCA studies present aggregated product- or process-level results rather than facility-specific characteristics [12]. Other data sources are incomplete, proprietary, or inconsistent in scope. A notable advancement in facility-level industry characterization is the Foundational Industrial Energy Dataset (FIED) developed by McMillan et al. [13], which integrates FRS, NEI, and GHGRP data to derive unit-level estimates of energy use, physical inflows and outflows, and design capacity, geospatially referenced to latitude and longitude. While FIED represents a significant step toward harmonized facility-level characterization, its reliance on NEI, GHGRP, and FRS data means that reported attributes do not always align with actual facility capacity, technology details, or operations compared to GEM, industry association reports, or company disclosures.

Taken together, these datasets offer valuable but fragmented perspectives of industrial operations. They vary considerably in scope, units, reporting frequency, and system boundaries—and none provide a unified facility-level view of energy use, physical flows, technology, and capacity. Aggregation, confidentiality, inconsistent classifications, and missing operational details (e.g., vintage and utilization rates) create persistent data barriers for facility- and technology-specific modeling. These limitations force reliance on generic assumptions, restrict facility-level analysis, and reduce alignment between plant-level data and sectoral models, making the industrial sector challenging to model. To address this challenge, this study develops a harmonized, high-resolution dataset for seven major U.S. industrial subsectors—iron & steel, cement, ammonia, ethanol, ethylene & propylene, food, and non-manufacturing industries, which includes mining, construction, and agriculture. The dataset standardizes technology characteristics (performance, energy, physical flows, costs), compiles facility attributes (location, capacity, technology details), and is designed for interoperability and reuse through structured schema, GIS-ready coordinates, consistent economic units, and modular extractability. This contribution establishes a foundation for more transparent, reproducible, and robust industrial analysis.

## 2 Methods

The development of this U.S. industrial facilities and technologies dataset in this work followed a systematic approach to data collection, curation, harmonization, and validation, tailored to the specific characteristics of each sector. A consistent methodological framework was applied across five manufacturing industries with facility-level inventories (iron and steel, cement, ammonia, ethylene and propylene, and ethanol), while a modified structure was adopted for the food sector, and a distinct technology-level structure was applied for the three non-manufacturing industries–agriculture, mining, and construction. A 'technology-level' record represents a technology option with applicability and estimated impacts (energy/resource/cost), not a facility inventory. Data for manufacturing industries was built upon the U.S. Department of Energy Industrial Technology Office's Transformative Pathways for U.S. Industry report (hereafter referred to as "DOE Pathways" report or analysis) [14], and was significantly expanded by incorporating information from a wide array of supplementary sources. These sources notably include GHGRP [6], MECS [4], U.S. Geological Survey (USGS) Mineral Yearbooks [15], FIED datasets [13], academic and scientific literature including life-cycle assessment models such as GREET [16] and technology-specific LCA studies, industry-specific reports from industry associations and international agencies including AIST, American Cement Association, and the International Energy Agency (IEA), company disclosures (annual reports, sustainability reports, press releases), and independent tracking initiatives such as the Global Energy Monitor (GEM) plant trackers [17].

The curated information was organized in a structured JSON array. For the five manufacturing industries–iron and steel, cement, ammonia, ethanol, and ethylene/propylene–each entry contains four sections: author list, assumptions, emerging technologies, and existing facilities. Technology characteristics were standardized per unit of product and include energy intensities, physical flows, capital expenditures (CAPEX) and operating expenditures (OPEX), and technology readiness levels. The references cited in Table 1 and following section cover the principal categories of sources used–federal surveys and datasets, industry reports, LCA databases, and peer-reviewed LCA and techno-economic analysis literature). However, the JSON dataset section for each sector contains additional references linked to individual data points. These are included directly in the dataset to ensure full traceability.

Facility characteristics were captured at the plant level, including identifiers, geographic location, production capacity, and process technology. The food sector followed the same JSON structure but used a modified design wherein the emerging technologies section covers heating options such as low- and high-temperature heat pumps, while its existing facilities are aggregated in capacity by state and subsector, which includes animal slaughtering, dairy, fruit and vegetable, grain and oilseed milling, and sugar industries. For the three non-manufacturing industries, the dataset catalogs 18 operational technologies across agriculture, mining, and construction, grouped into six categories. Each technology records energy production or savings, cost or income effects, and impacts to physical flows. Impacts are taken directly from literature where available, and for specific technologies that offset the use of purchased electricity (e.g., agrivoltaics, irrigation hydropower, on-farm anaerobic digestion, and retrofit horticultural lighting with LEDs), changes in emissions are derived by multiplying reported energy savings or production by U.S. EPA's reported average emission factor of 373.5 kg $CO_2$/MWh [43] for the U.S. electricity mix in 2024.

Because the dataset integrates information from heterogeneous sources, a harmonization process was applied to ensure consistency across sectors. All quantitative parameters were converted into standardized physical and economic units, e.g., energy in GJ/t product and costs in \$/t (2018 USD). Emerging technologies for manufacturing sectors, defined as technologies with minimal to no market share in U.S. commercial-scale production facilities, were selected and their characteristics modeled based on the DOE Pathways report. Technology performance metrics were expressed per unit of product output: energy intensity in gigajoules per metric ton (GJ/t), with electricity converted to GJ from kilowatt-hours using a

**Table 1** Summary of key data sources and supplementary data used for each manufacturing industry.

| Industry | Energy & feedstock intensity | Physical outflows | CAPEX & OPEX | Location, identifiers, capacity & production |
|---|---|---|---|---|
| **Emerging and Existing Technology Characteristics** | | | | |
| **Iron & Steel** | DOE Pathways Report [14]; GREET [16]; FIED [13]; USITC [18] | DOE Pathways Report [14] | Zang et al. [19]; Krüger et al. [20]; Bhaskar et al. [21] | FIED [13]; GHGRP [6]; GEM Steel Tracker [17]; AIST [10]; ArcelorMittal [22]; USGS [15] |
| **Cement** | DOE Pathways Report [14] | DOE Pathways Report [14] | IEA Cement Tech Assessments [23]; GEM Cement Tracker [17]; LEILAC [24]; NETL TEAs [25] | FIED [13]; GHGRP [6]; GEM Cement Tracker [17]; CemZero [26]; LEILAC [24]; USGS [15]; company sustainability reports |
| **Ammonia** | DOE Pathways Report [14]; IEA Ammonia Roadmap [27]; Ammonia Energy Assoc. [28] | DOE Pathways Report [14] | Ammonia Energy Assoc. [28, 29]; Mining Weekly [30]; QCIntel [31] | FIED [13]; GHGRP [6]; USGS [15]; company disclosures; company websites |
| **Ethanol** | DOE Pathways Report [14] | DOE Pathways Report [14] | NETL TEA Updates [25]; Shapouri and Gallagher [32]; Gallagher et al. [33] | FIED [13]; GHGRP [6]; RFA Outlook [34]; Ethanol Producer Magazine [35]; company websites |
| **Ethylene & Propylene** | Ren et al. [36]; Gu et al. [37]; DOE Pathways Report [14] | Ren et al. [36]; Gu et al. [37]; DOE Pathways Report [14] | Ren et al. [36]; Vora et al. [38] | GHGRP [6]; Oil & Gas Journal Survey [39]; industry news [40] |
| **Food** | DOE Pathways Report [14]; MECS [4] | – | – | By state and subsectors (animal slaughtering, dairy, fruit & vegetable, grain & oilseed milling, sugar); Dong et al. [41] |
| **Cross-cutting Characteristics** | | | | |
| **TRL (all industries)** | IEA ETP Clean Energy Tech Guide [42] | | | |

conversion factor of 277.78 kWh/GJ; feedstock intensity in metric tons per metric ton of output; and physical outflows in metric tons of a resource or waste per metric ton of output. Where available, values from established LCA datasets, published literature, industry reports, and sector-specific expert input were compared against the DOE Pathways report values to ensure that the DOE Pathways values did not contain any outliers. Technology readiness levels (TRLs) were standardized across sectors using the IEA Energy Technology Perspectives

Clean Energy Technology Guide [42]. Established and incumbent commercial technologies, including those documented in the existing facilities dataset were assigned TRL of 9.

Economic attributes were standardized to a 2018 baseline year, chosen for consistency with recent DOE industrial technology roadmapping reports that use 2018 as their reference year [14**?** ]. Capital expenditures (CAPEX) were expressed as 2018 USD per unit of annual production capacity, while operating expenditures (OPEX) were separated into fixed and variable components. Fixed operating expenses (OPEX) include costs such as labor, maintenance, and overhead. These are typically expressed either as a fraction of capital expenditures (CAPEX) or as dollars per ton of output capacity. In this dataset, we have converted all fixed OPEX values to dollars per ton of output at 100% capacity utilization, using the corresponding plant capacity reported in each data source. This standardization ensures that data from different references can be compared consistently. The plant capacity and fixed OPEX as a ratio of CAPEX data is also recorded for reference. Variable OPEX per physical unit of production was calculated as the product of energy and feedstock intensities and their respective prices using equation 1, where $VOM$ is the annual variable O&M cost, $EI_i$ and $FI_i$ represent the energy and feedstock intensities of fuels and materials per unit of product output, and $P_i$ and $P_j$ are the prices of energy and feedstock used in a production process. $CAPEX$ per unit of annual capacity was harmonized across studies using equation 2, with units expressed in 2018 USD per metric ton-year. Reported capital costs from diverse sources were converted into this common metric and normalized to 2018 USD using the Chemical Engineering Plant Cost Index (CEPCI) [44].

$$VOM = \sum_i (EI_i \times P_i) + \sum_j (FI_j \times P_j) \tag{1}$$

$$CAPEX = \frac{Total\ Investment}{Annual\ Production\ Capacity} \tag{2}$$

Fuel and feedstock prices from literature and average market values were converted to USD/GJ or USD/t using higher heating values and densities [11]. Purchased electricity prices were converted from cents/kWh to 2018 USD/GJ using EIA Electric Power Monthly data [2], while hydrogen prices were drawn from DOE Hydrogen Program records [45]. Scrap, dolomite, graphite electrodes, and oxygen were normalized using reported U.S. market prices, adjusted to 2018 USD [46].

Facility-level attributes were harmonized to support geospatial and cross-sectoral analysis. Each facility was assigned a standard identifier using its FRS ID and/or GHGRP ID, geographic coordinates, and process technology tags developed to describe the type of production technology (e.g., electric arc furnace). Location data were taken directly from federal and research databases when available, and otherwise supplemented through manual searches of company disclosures, association reports, and commercial online data sources. Production capacity was expressed uniformly in metric tons per year (t/yr). Nameplate capacity is not equivalent to actual throughput; where available, both are recorded and users should treat production/throughput/utilization rate of nameplate capacity as the operational measure. Missing values were supplemented using industry association databases, plant trackers, and/or corporate sustainability reports. When utilization rates were not directly reported, they were approximated using USGS industry averages or estimated by comparing facility-level energy consumption reported in FIED with modeled full-capacity energy requirements, based on the harmonized energy intensity and production capacity.

The integration of data from various sources inevitably resulted in conflicting or inconsistent information. To address these discrepancies and maintain high data quality, a two-pronged approach was implemented. Significant errors in datasets (resulting from incorrect reporting, outdated information, or demonstrable inaccuracies) were identified through cross-verification with other credible sources or consultation with industry experts and replaced with more reliable and validated information. For example, facility capacity data from industry association reports, USGS annual yearbook, and companies' financial reports were cross-referenced. Discrepancies were resolved by prioritizing information from the companies' most recent financial reports with the assumption that they represent the most accurate estimate of their facility's actual capacity.

When various datasets provided different values for a particular parameter, and no single source could be definitively deemed more trustworthy or accurate than the others, all data points from each credible source were presented. For instance, reported CAPEX values for hydrogen-based direct reduced iron ($H_2$-DRI) vary across studies. Bhaskar et al. [21] report costs normalized to hydrogen production capacity, while Zang et al. [19, 46] provide CAPEX tied to installed steelmaking capacity. CAPEX estimates from both sources were converted into 2018 USD per ton of crude steel capacity with adjustments made for exchange rates, inflation indices, and process normalization assumptions. Harmonized values were stored in parallel JSON arrays, one containing numerical values and another referencing original sources, to preserve transparency and traceability. This approach allows users of the dataset to select the data that best aligns with their specific analytical requirements, assumptions, or regional focus.

# 3 Data Record

An integrated dataset containing resource use, physical outflows, and cost characteristics of major technologies (incumbent and alternative) in 6 manufacturing and 3 non-manufacturing industries, including data on facility-level details or regionally-aggregated capacities where available, is published as a single JSON file in a Dryad data repository [47]. Data record details corresponding to each industry are discussed next.

## 3.1 Ammonia

Key data sources for the ammonia industry technology and facility-level dataset include the DOE Pathways report [14], EPA GHGRP [6] database, the FIED dataset [13], USGS Mineral Yearbooks [15], and the International Energy Agency's Ammonia Technology Roadmap [27]. Supplementary data were drawn from the Ammonia Energy Association [28, 29] and trade press [30, 31].

Technology characteristics are defined per metric ton of ammonia produced. Energy and feedstock intensities for production technologies such as steam methane reforming (SMR), coal gasification, and electrolysis were taken from the DOE Pathways report [14]. Cost data (CAPEX, OPEX) were drawn from techno-economic assessments [28–31] and normalized to 2018 USD using Chemical Engineering Plant Cost Index (CEPCI). CEPCI is a composite cost index used to adjust historical CAPEX estimates to a common reference year for cost harmonization. Users can escalate values to other years using CPI (general dollars) and/or CEPCI (capital costs) from the 2018 model year. TRLs for conventional production technologies such as SMR are assumed to be 9, while emerging production technologies such as methane pyrolysis, autothermal reforming (ATR) with CCS, and renewable $H_2$-based ammonia synthesis were assigned TRLs from the IEA ETP Clean Energy Technology Guide [42]. Facility-level data cover 36 ammonia plants across 20 states, dominated by natural gas-based SMR (92.1%), with the remainder as coal gasification (3.9%) and ammonia synthesis only (4.0%). Attributes include facility identifiers (GHGRP ID, FRS ID), geographic coordinates, production capacity, and reported utilization, supplemented from USGS yearbooks [15] and company disclosures.

### 3.2 Cement

Primary data sources for cement include the DOE Pathways report [14], project-level studies such as CemZero [26] and Leilac [24], the American Cement Association's (ACA) Plant Information Summary [48], and USGS Mineral Yearbooks [15]. Additional references on carbon capture and process efficiency were used to parameterize emerging technologies [23, 49, 50].

Cement production is modeled as two steps: clinker production and cement grinding (with the dataset structure allowing for inclusion of raw material preparation). Technology characteristics are defined per metric ton of clinker or cement depending on the step. Conventional dry and wet kilns form the baseline, while emerging technologies include kilns with CCS and indirect heating-based pre-calciner. Energy intensities were taken from the DOE Pathways model [14] and cross-checked against data from the ACA [48] and USGS [15]. CAPEX and OPEX data were drawn from feasibility studies [23, 25, 50, 51] and industry techno-economic benchmarks [24, 26], adjusted to 2018 USD. TRLs for commercial plants are set at 9, while emerging technologies (e.g., indirect calcining) follow IEA ETP Guide [42]. Facility-level data include clinker and grinding plants. Production capacity is expressed in metric tons per year, with clinker-to-cement ratios assumed to be the dominant cement product ratio at each facility. A national average ratio of 0.8982 [14] was used where facility-specific data were missing. Utilization rates were derived from USGS yearbooks [15], supplemented by GEM cement trackers [17] and company sustainability disclosures.

### 3.3 Ethanol

Ethanol technology and facility data was based on the DOE Pathways report[14], FIED [13], GHGRP [6], the Renewable Fuels Association (RFA) [34], Ethanol Producer Magazine (EPM) plant data [35], and techno-economic assessments from NETL [25], Gallagher et al. [33], and Shapouri and Gallagher [32]. Technology characterization is defined per metric ton of ethanol. Conventional dry mill (95.5% of U.S. capacity) and wet mill (4.5%) processes are included, along with emerging routes such as electrified heating, biomass gasification, and CCS-equipped dry mills. Energy intensities were based on DOE Pathways report [14] and were disaggregated by fuel and process type. CAPEX and OPEX data were taken from techno-economic studies [25, 32, 33], normalized to 2018 USD. Variable OPEX was calculated by multiplying fuel and feedstock prices by reported intensities, while fixed OPEX was estimated as a fraction of CAPEX. Facility-level data include 201 ethanol plants across the U.S., with attributes such as facility ID, location, technology type, capacity, and utilization rates. Reported capacity data were obtained from RFA and EPM datasets [34, 35], and utilization estimates were benchmarked against GHGRP energy data [6] and EIA [52].

### 3.4 Steam Cracking for Ethylene and Propylene

Key data sources for ethylene and propylene include the 2015 Oil & Gas Journal (2015 facility dataset) [39], EPA facility datasets [53], GHGRP [6], Statista [54], and peer-reviewed studies [36–38, 55]. Technology characteristics are expressed per metric ton of ethylene produced, with steam cracking (ethane- and naphtha-based) as the dominant U.S. technology. Facility capacities for ethylene and propylene production were derived from Oil & Gas Journal [39] and harmonized using feedstock yield data from Yang et al. [55]. Facilities are classified by dominant feedstock (ethane vs naphtha/mixed liquids) based on public information, e.g., Oil

& Gas Journal [39] and recent facility-specific disclosures [40]. Many crackers operate blended feeds and slates can vary over time, which is a limitation of this approach. CAPEX and OPEX data were compiled from techno-economic studies [36–38, 55]. Existing steam crackers are assigned TRL = 9, while emerging routes were assigned TRLs from the IEA ETP Guide [42]. Facility-level data include 35 plants across six states, with attributes covering GHGRP IDs, geographic location, production capacity, and feedstock split. Utilization rates were benchmarked against Statista's reported U.S. production totals [54] and GHGRP energy data [6]. While costs are reported in 2018 USD, facility capacity/feedstock attributes reflect the most recent publicly available information (through 2025 where available), with facility start year recorded for user filtering.

## 3.5 Iron & Steel

Iron and steel data sources include the DOE Pathways report [14], GREET [16], FIED [13], GHGRP [6], the IEA Iron and Steel Technology Roadmap [56], Global Steel Plant Tracker [17], USGS Mineral Yearbooks [15], AIST furnace roundups [10], peer-reviewed articles [19, 19, 57], and industry news and announcements. Steel production is modeled as a two-step process: ironmaking (using a blast furnace (BF) or direct reduction furnace (DR), for instance) in per unit mass of iron and steelmaking (using a basic oxygen furnace (BOF) or electric arc furnace (EAF), for instance) in per unit mass of crude steel. Conventional iron & steel production routes include blast furnace–basic oxygen furnace (BF-BOF), natural gas–direct reduced iron–electric arc furnace (NG-DRI-EAF), and scrap–electric arc furnace (scrap-EAF). Emerging iron & steel production routes include hydrogen-direct reduced iron–electric arc furnace($H_2$-DRI–EAF), molten oxide electrolysis (MOE), and aqueous electrolysis (AqE), with CCS considered ancillary. Energy and feedstock intensities were drawn from the DOE Pathways report [14]. The total energy and cost of crude steel production depend on the recycled content characterized by the scrap-to-iron ratio in EAF, which was modeled from AIST furnace roundups [10]. Where scrap rates were not reported, industry averages were assumed as 25% for BOF and 85% for EAF.

Capital expenditures (CAPEX) and operating expenditures (OPEX) were compiled from techno-economic assessments [19, 21, 46, 56], and industry announcements [22, 58–62], and the values were normalized to 2018 USD. Fixed OPEX was typically expressed as a percentage of CAPEX, although some studies reported absolute fixed values; in such cases, the two components were combined, and total fixed OPEX was calculated as the sum of the CAPEX-based fraction and any reported fixed amounts. Variable OPEX was derived from the product of fuel and feedstock intensities and the corresponding prices. Technology readiness levels (TRLs) were harmonized using the International Energy Agency's Energy Technology Perspectives Clean Energy Technology Guide [42], with commercial technologies assigned TRL = 9. Facility-level data cover 102 facilities across 31 states. Attributes include facility IDs, geographic coordinates, capacity, technology, and scrap ratio. Reported capacities were cross-referenced with GHGRP [6], FIED [13], GEM [17], and company disclosures [22]. Utilization rates were estimated from FIED energy consumption data and compared against modeled full-capacity requirements, constrained to not exceed 100%.

## 3.6 Food

Food industry data were drawn from MECS [4], GHGRP [6], USDA cost-of-production surveys [63], and reports and peer-reviewed articles [64, 65]. The dataset distinguishes five food subsectors: animal slaughtering, dairy, fruit and vegetable processing, grain and oilseed milling, and sugar manufacturing. Emerging technology characterization focused on performance improvements in low- and high-temperature process-heat, including hot water and steam heat pumps, electric boilers, and renewable natural gas/biogas boilers. Technology performance characteristics were obtained from the CARB report from California's energy intensive industrial sectors [65]. TRLs for these technologies were adopted from the IEA ETP Clean Energy Technology Guide [42], with established boilers assigned TRL = 9 and emerging technologies assigned values according to reported maturity.

Unlike the other sectors described thus far, existing food industry capacity is modeled at an aggregated state–subsector level rather than as individual plants. Attributes include production volume and estimated energy intensity. State-level production by subsector was taken from Dong et al. [41], while energy intensities and fuel types for processes such as conventional boiler use, CHP/cogeneration, process heating, process cooling and refrigeration, machine drive, other process uses, and facility HVAC were derived from the DOE Pathways report [14].

### 3.7 Non-Manufacturing

The non-manufacturing sector data covers 19 resource-saving technologies for agriculture (11), mining (3), construction (3) industries, respectively, and one technology related to off-road machinery that applies to all three subsectors. For each technology, the dataset provides a description including its energy or resource saving potentials and impacts to these reductions, including cost/income, where data are available. For instance, one technology in the agriculture subsector, Agrivoltaics (on-site solar), could avoid 100–200 MWh/year of purchased electricity with a installation cost of $150,000–350,000 [66–68]. Other technologies in the agriculture sector include irrigation hydropower-hydro-mechanical system and irrigation hydropower-hydroelectric system [69, 70], agricultural residues and processing wastes [71], on-farm anaerobic digester [72–74], electrification or alternative fuels for tractors [68, 75, 76], conservation tillage [67, 68, 75–78], precision agriculture/nutrient management [65], retrofit horticultural lighting (excluding livestock barns) with LEDs [68], and reduction of food loss and waste (avoided overproduction) [79]. The mining industry technologies include truck electrification [80], in-pit-crushing [81], and trolley assist system conveyors [81]. The construction industry technologies include hybrid excavators, electric excavators, and electric dumpers [82]. Retrofitting off-road machinery with diesel emission controls is applicable in all three subsectors to significantly reduce NOx and particulate matter emissions [76, 83].

## 4 Data Overview

Salient technological attributes synthesized from the data record contained in the accompanying dataset to this paper [47] are summarized in Figures 1–3. Figure 1 shows the spatial distribution of facilities across the United States, with bubble area depicting installed production capacity and color depicting the primary production technology. Figure 2 summarizes the distributions of industry-specific costs broken down by capital expenditure (CAPEX), fixed OPEX, and variable OPEX for various technology–feedstock combinations as obtained from numerous sources. Figure 3 presents the electricity and fuel and feedstock energy intensities for each technology in 5 of the 6 manufacturing industries (excluding food), with fuel contributions disaggregated by source (coal & coke, natural gas, hydrogen, fuel oil, NGL & naphtha, steam, and other fuels and feedstocks).

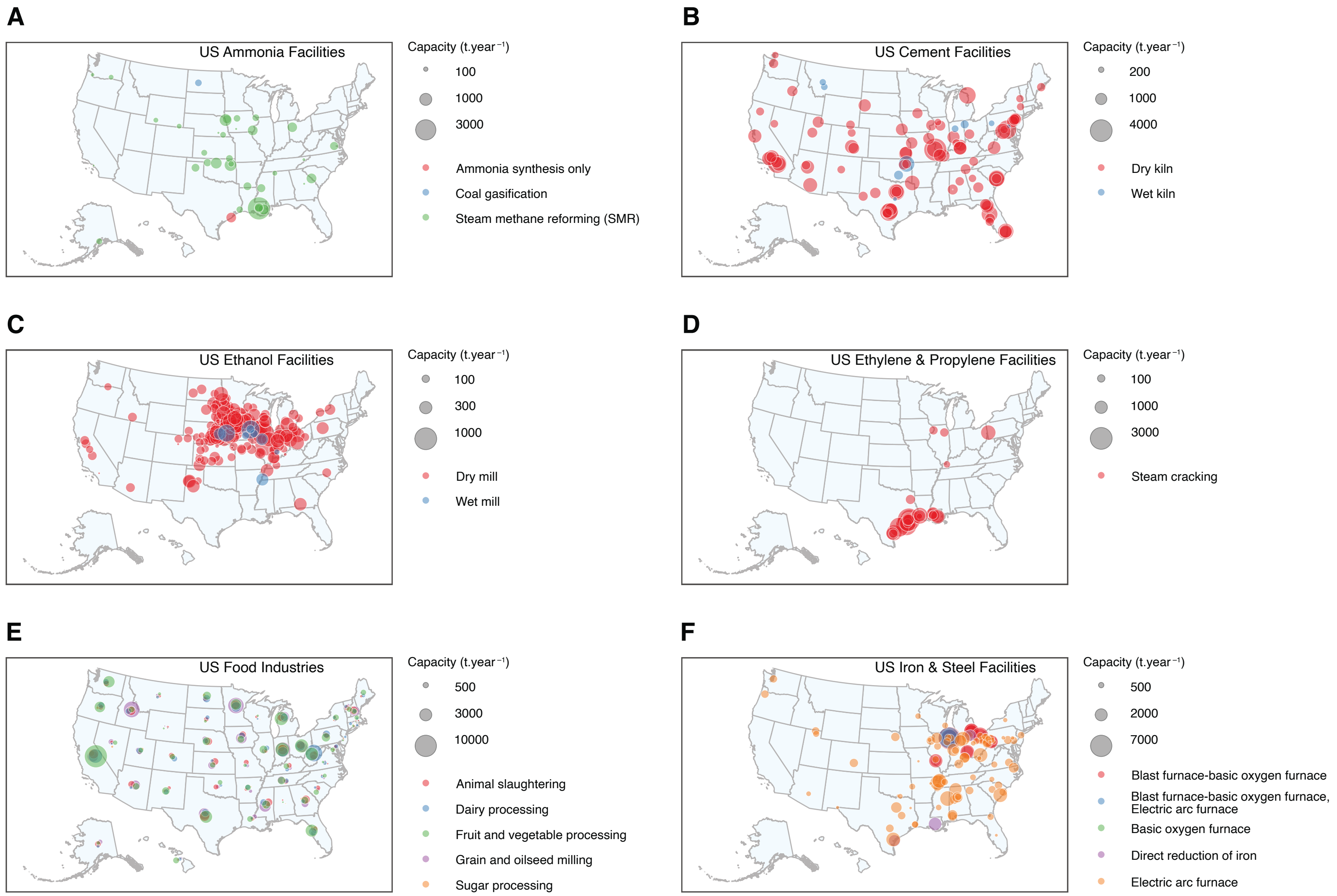


**Fig. 1** Spatial distribution and technological makeup of existing facilities across six industries, listed alphabetically: (A) Ammonia, (B) Cement, (C) Ethanol, (D) Ethylene & Propylene, (E) Food, and (F) Iron & Steel. Each bubble represents a single facility and its area is scaled by installed production capacity. Colors indicate the primary installed technology at a facility.

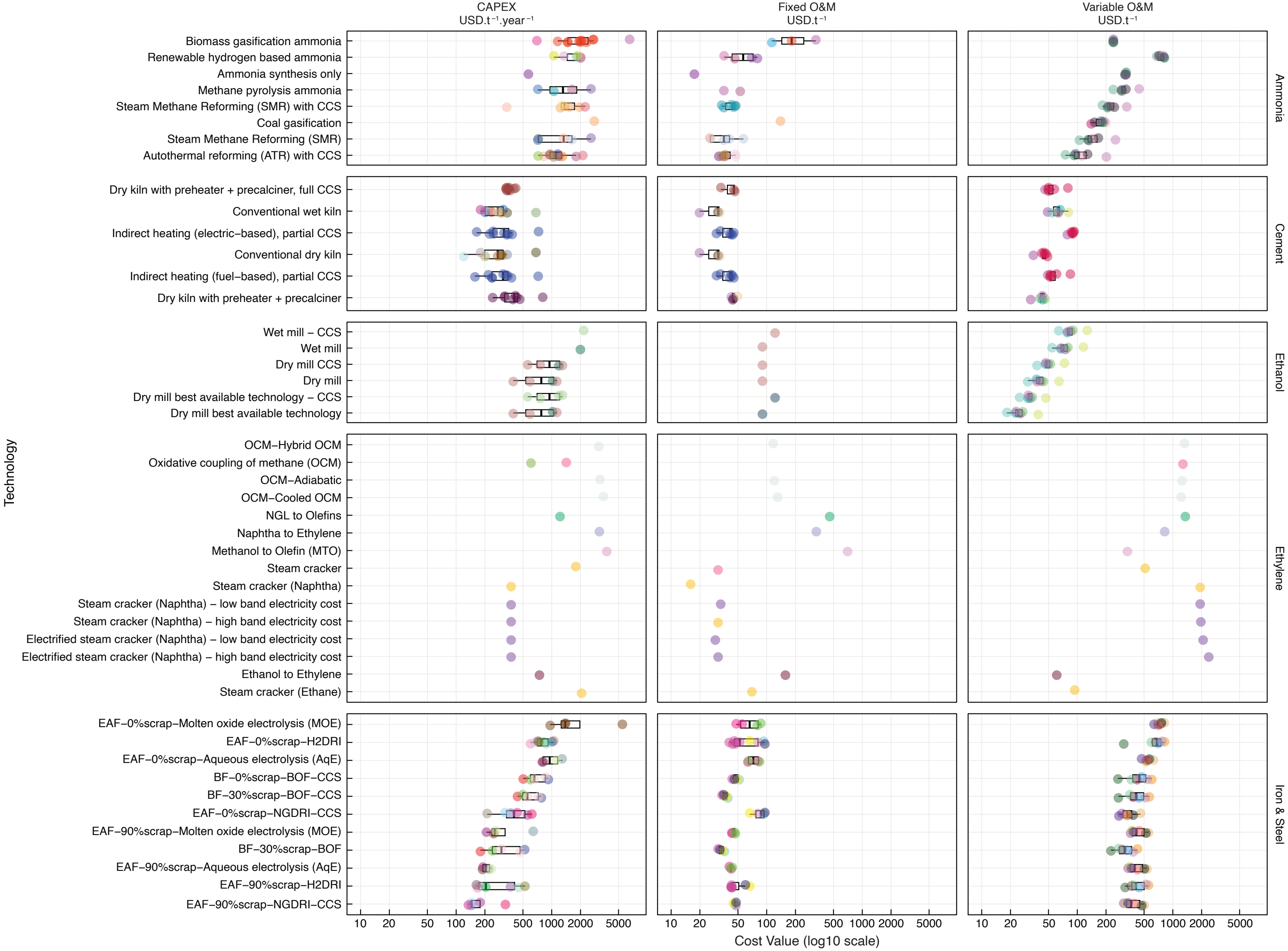


**Fig. 2** Capital (CAPEX) and fixed and variable operation and maintenance (O&M) costs of technologies in 5 manufacturing industries examined in this study (food is excluded because it is represented as state–subsector archetypes rather than facility-level cost points). Each bubble corresponds to a single data point. Bubble colors correspond to an individual data source, the legend for which is excluded for brevity. Box plots are shown for technologies containing 3 or more data points for a given cost category.

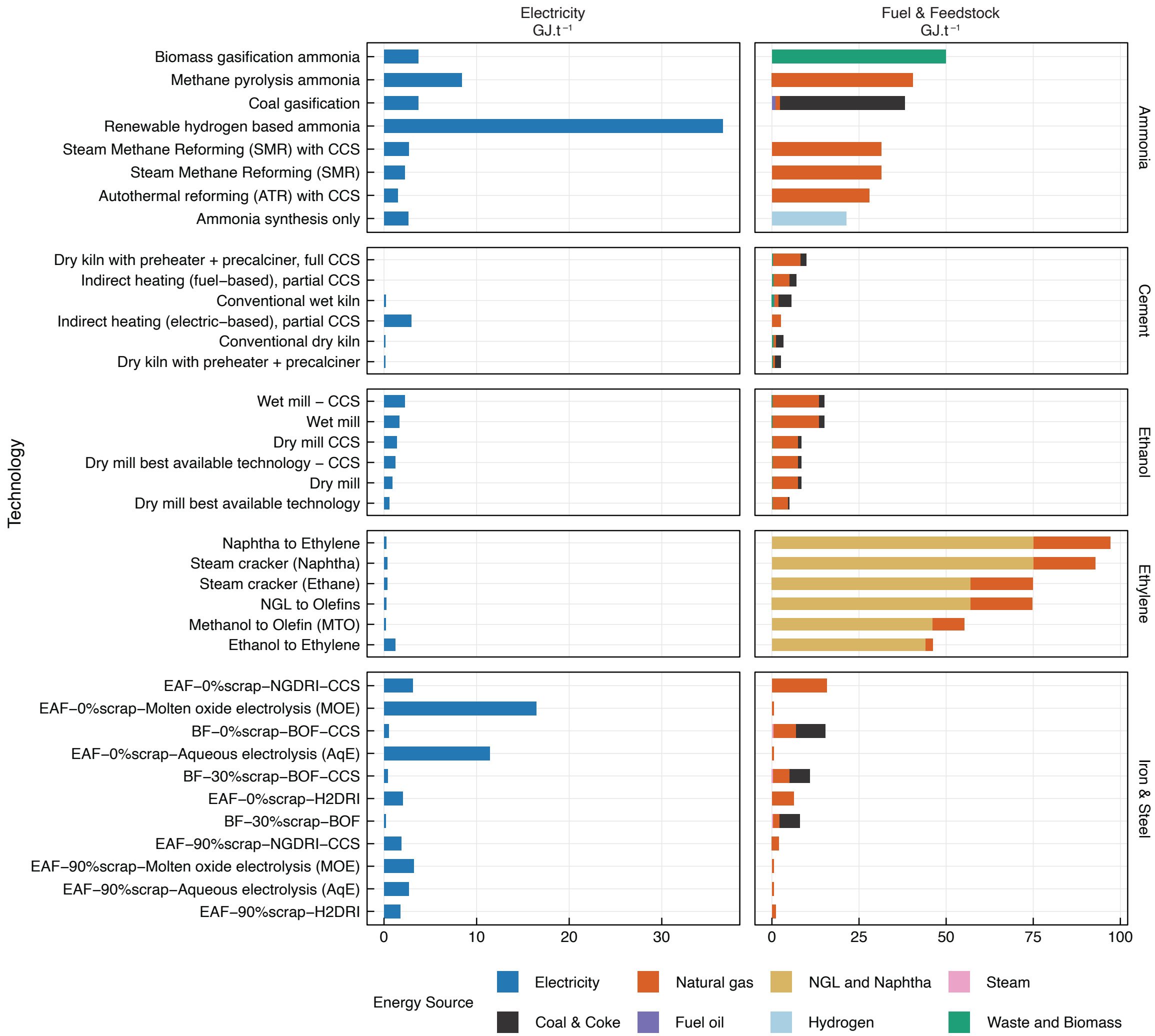


**Fig. 3** Electricity and fuel and feedstock energy intensities (GJ/t) of technologies in 5 manufacturing industries. Values are obtained from the DOE Pathways report [14].

# 5 Technical Validation

We applied a staged validation workflow that emphasized harmonization, cross-referencing, and transparent provenance. GEM plant trackers [17] were used as one external reference point for facility coverage and technology tags in the core manufacturing sectors, alongside GHGRP [43], FIED [13], USGS [15], industry yearbooks [35], and operator disclosures [22]. When sources differed in scope or definitions (for example, asset status or process boundaries), we aligned records to a common vocabulary and noted inconsistencies in the reference. When equally credible sources disagreed and a single best estimate was not evident, we aligned records to a common vocabulary and preserved alternatives with reference. Targeted issues were reviewed with subject-matter experts where feasible.

Facility records were linked across sources using names, locations, and standard identifiers, then screened for duplicates and boundary mismatches. Coordinates, capacities, and status were compared across GEM, federal datasets, and operator filings. Where recent company reports were available, they were treated as the most likely representation of current conditions; otherwise, we retained multiple sourced values with citations. Utilization was taken from reported data when available and otherwise inferred from federal production, energy, or emissions records, with follow-up checks when implied values appeared outside typical ranges.

Technology attributes were standardized to common physical units and mapped to a controlled vocabulary consistent with DOE and IEA frameworks [23, 27, 56]. Performance metrics compiled from roadmaps, LCA models, industry reports, and peer-reviewed TEA/LCA studies [16, 36, 46] were screened against sectoral ranges; apparent outliers were rechecked and either corrected or flagged. Technology readiness levels were harmonized to a single scale across sectors. Where reputable sources reported materially different performance for the same technology, multiple values were retained with explicit assumptions and references.

Economic parameters were normalized to a single price year in line with DOE industry transformative pathways analysis [14]. Reported costs stated on different capacity or boundary bases were converted to a shared denominator using standard indices and exchange rates, with original units and years preserved in the metadata. Fixed and variable operating costs followed standard techno-economic conventions, and energy and material prices were converted to common units using federal and industry sources.

# 6 Usage Notes

The following examples describe the most commonly envisioned applications of this dataset. We note that these use cases were not executed or validated in this work. The datasets could: (1) screen and compare energy and feedstock intensities, process characteristics, indicative costs, TRLs, and other technology attributes with an industry for techno-economic assessments; (2) assess spatially-resolved profiles of industrial resource use; (3) develop networked representations of manufacturing facilities and their characteristics for supply chain analysis; and (4) serve as inputs to spatially-resolved production capacity planning models and integrated assessment models.

# 7 Code Availability

The dataset [47] acompanying this paper is published in a data repository on Dryad (https://doi.org/10.5061/dryad.djh9w0wcz). The README.md file in the repository documents schema, assumptions, and recommended data aggregation and extrapolation steps.

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## Author Contributions

S.S. conceptualized the data framework and acquired funding support for the project. Y.Z. and S.S. wrote the main manuscript, supervised the project team, and prepared figures 1 – 3. J.Z., I.O., G.A., L.Y., and Y.Z. curated the data record for ammonia, ethylene & propylene, and ethanol industries. S.S., I.O., S.N., Y.Z., U.S., and T.R.H. curated the data record for cement industry. Y.Z. and S.N. curated the data record for iron & steel industry. U.K., P.R., K.A., and T.H. curated the data record for food industry. N.C. and T.H. curated the data record for non-manufacturing industries. H.E.D. and S.S. characterized all carbon capture pathways and P.P. characterized all hydrogen pathways used in manufacturing industries. Y.Z. and D.T. performed technical validation of the datasets. All authors reviewed the manuscript.

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