ARTIFICIAL INTELLIGENCE FOR CLIMATE CHANGE MITIGATION ROADMAP (SECOND EDITION)

CHAPTER 5:

MANUFACTURING SECTOR

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The manufacturing sector makes products on which the modern world depends. Billions of tons of steel and cement are used in buildings, bridges and roads each year. Chemicals, including ammonia, provide fertilizers and other essential building blocks for modern society.[1]

At the same time, the manufacturing sector is responsible for roughly one third of global greenhouse gas (GHG) emissions. Steelmaking has the largest carbon footprint in the manufacturing sector, followed by cement-making and then chemicals. The remaining emissions come from aluminum, glass, paper and other light manufacturing.[2-5]

Decarbonizing the manufacturing sector will be challenging. Many industrial processes require high and sustained heat, which fossil fuels are well-suited to delivering. Some industrial processes, including cement-making, rely on chemical reactions that emit CO_2. Many industrial products are globally traded commodities, subject to significant loss of market share due to small increases in production costs.[6,7]

Artificial intelligence (AI) is showing promise in helping address the challenge of decarbonizing the manufacturing sector. This chapter discusses that potential and explores opportunities for further work.

A. How Can AI Help Decarbonize Manufacturing?

Consider the following example: AI can play a central role in reducing costs and emissions for electric arc furnaces (EAFs)—a key technology for decarbonizing steelmaking. EAFs melt scrap metal using electricity instead of coal. Using recycled/circular feedstock, such as scrap, is a core idea that pervades the effort to decarbonize all types of manufacturing. This idea introduces a novel challenge: how to manage new sources of variability.

Virgin raw materials are stable. Mining operators control their operations, packaging and shipping raw ingredients that meet specific quality criteria. Steelmakers are accustomed to this stability. But every batch of scrap is different. One batch of scrap may contain too much of an alloy, another possibly too little of it. Modern steelmakers can adjust for this variation by enhancing the scrap with costly additives. The most common strategy is simple: plan for the “worst batch” scenario.

This strategy has led to a consistent, industry-wide overuse of additives. No matter what scrap metal comes in, unnecessary amounts of additives are added. The extent of this practice is such that the biggest portion of EAF steel’s carbon footprint is the upstream emissions from sourcing these additives.[8]

AI offers a better approach to this challenge: instead of over-designing for the “worst batch,” AI can help steelmakers “adapt to each batch” with predictions that have higher accuracy than traditional software systems (Figure 5-1). The idea is to use AI to recommend optimal production settings, adapting to the variability in each batch.

Manufacturing remains a challenging segment of the economy to decarbonize and will require significant long-term hardware research and investments. Many governments are sponsoring capital-expenditure-heavy projects to adopt recycled feedstock, switch to greener sources of fuel, and make clever use of industrial heat.[9,10]

AI provides a complementary benefit that is (1) available today and (2) can be applied to existing manufacturing infrastructure. In many cases, AI can be applied today without any capital equipment change-out—it is ultimately just an operational change. As a result, AI can be orders of magnitude faster and cheaper to adopt than deeper decarbonization pathways that require significant capital expenditures.

Figure 5-1. *Factories are increasingly digitalizing their operations.*

B. What Are Common Applications of AI In Manufacturing?

i. Decarbonizing the process of making things

The steelmaking example highlights one way AI can reduce a manufacturer's emissions. There are many more. Here are a few proven ways AI can help reduce emissions across many sectors:

- Adapt to volatility faster. Manufacturing plants are designed to minimize variation and consistently produce high-quality goods. The idea of using data to control quality variation dates to Walter A. Shewhart, who established the field of statistical process control at Bell Laboratories in the 1920s.[11] AI extends the notion of statistical process control, enabling manufacturers to adapt to issues more quickly—any amount of time avoided making low-quality goods reduces scrap and minimizes a plant's waste and energy usage.
- Adapt to volatility better. Without AI, reducing the time wasted making low-quality commodities may be difficult because existing statistical methods may not be accurate enough to explain the root cause of production issues. AI-based production can pinpoint the specific root cause of an issue in real-time during production. AI's precision and ability to handle large numbers of potential root-cause factors is what drives this capability.
- Avoid past mistakes and enable expertise retention. Over three quarters of manufacturing firms are concerned about their aging workforces.[12] A primary component of their concern is losing the expertise that their skilled workers have amassed at specific manufacturing sites (e.g., the exact setting for a temperature for a particular product type). These sorts of insights are rarely recorded in an accessible manner, but skilled engineers and operators leave their marks in historical production data. Thus, while the experienced operator may know what to do in any scenario, a novice may leverage AI to sift through prior production runs and extract insights that resemble an issue at hand. AI can map challenges happening today to historical periods, filtering out interventions that did not work and focusing on those that did. In this way, AI can help new talent perform more efficiently, reducing waste and energy consumption during onboarding and beyond.

- Improve yield. Production at scale is never 100% efficient: while 10 grams of ingredients may yield 10 grams of a final product in the laboratory, 10 tonnes of ingredients may yield only 9 tonnes of final product at scale. Scaling production introduces inefficiencies caused by the challenge of operating large-scale machinery and prioritizing production speed.[13] AI can help minimize this yield loss. By analyzing historical production data, AI can identify unexpected points in production where complex operational changes may lead to improved yields. AI is uniquely suited to learning the idiosyncrasies of large-scale manufacturing facilities and can provide specific recommendations on how to improve production yield for each site individually.

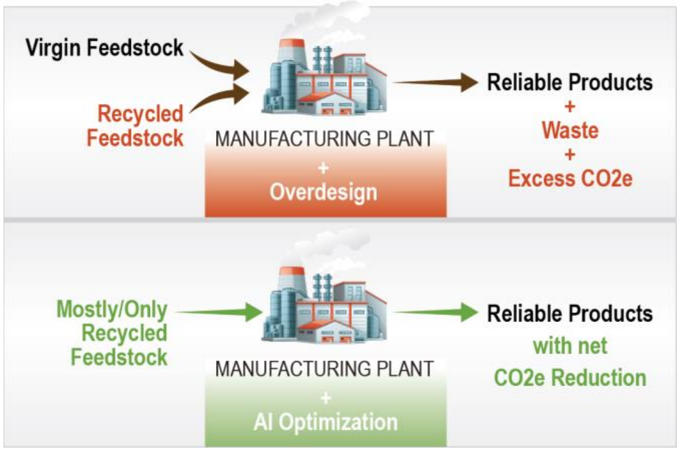

Figure 5-2. AI enables manufacturers to adapt to recycled feedstock. Factories typically address the increased variability of recycled feedstock by planning for the "worst case" scenario; this leads to unnecessary waste and excess emissions. Instead, factories can use AI to optimize operations and produce equally reliable products with net CO2e reductions.

- Enable recycling and circularity. Having traditionally relied on high-quality, low-variability raw ingredients, many industrial sectors are embracing recycled feedstock to reduce their carbon footprint, as well as increasing use of prior components and parts. Both could be considered increased circularity, potentially helping with cost, as well as carbon intensity. However, recycled and circular feedstocks typically exhibit low quality and certainly have high variability. This is the example from the steelmaking case study, with direct parallels in the chemicals, aluminum, glass, and paper sectors, among others. Embracing recycled feedstock not only reduces emissions during manufacturing, but also relieves demand on mining virgin ingredients in the first place. This aligns with the materials-efficiency objective highlighted in the sixth assessment report[14] of the Intergovernmental Panel on Climate Change (IPCC).

- Minimize energy consumption. Manufacturing facilities are not designed to minimize energy consumption; they are designed for safety. This means plants operate with conservative safety margins factored into all parts of production. This presents an opportunity for energy improvements while maintaining safety standards. This topic is a focus of the fifth assessment report[15] of the IPCC and serves as an optimization target for AI as well. Digital control systems which automatically operate much of the machinery at modern manufacturing sites, can be orchestrated using AI to adapt to operating conditions to safely reduce energy consumption. Reinforcement learning techniques can explore energy efficiencies in a gradual and safe way, exploiting operating set points that provide the biggest energy savings while operating with the safety margins that matter. Applications like these can provide net energy emissions reductions for plants with no hardware changes needed.

- Adopt alternative energy sources. In some sectors, such as scrap-based steelmaking, production is shifting to using clean electricity, which provides a pathway to shifting towards green production. In other cases, however, the switch may not be so simple. In direct steelmaking, manufacturers are shifting towards hydrogen, biomass, and carbon capture. In cement, the use of alternative fuels at the kiln is steadily increasing, including hydrogen and biomass, as well as carbon capture. Adopting alternative energy sources, however, comes with its own new source of volatility. Alternative cement fuels can negatively impact clinker quality, forcing cement mills to continue using hydrocarbon-based fuels for stability.[16] AI can help adapt to this new source of variability, enabling an increased, if not full conversion, to newer greener sources of fuels during production.

Box 5-1

CASE STUDY: ALLOY ADDITIVE REDUCTION IN STEELMAKING

In 2022, a Brazilian steel manufacturer using AI achieved 8% reduction in alloy additive consumption. This reduction came with a commensurate $3/metric ton cost savings and a 7.5% reduction in CO_2e/metric ton.[17]

This company achieved these results by

- Acquiring recycled scrap metal for their production
- Measuring the chemical composition of each batch of scrap
- Leveraging AI recommendations during melting to add as little (if any) additives as possible
- Predicting the risk of producing each batch of steel, trading off potential quality issues with emissions
- Reducing the quality variation of their final product.

Adopting AI as part of a plant's operating workflow, manufacturers can progressively target high-opportunity use cases within their production.

- Adopt smaller and quicker batch manufacturing. Batch production, which encapsulates much of the steel and chemicals sectors, embodies a tradeoff between size and speed. Larger batches offer more opportunity to correct for mistakes and adapt to production issues, while smaller and quicker batches use less energy and offer production flexibility. Reducing the cycle time—the amount of time it takes to make a batch from start to finish—is a common challenge, compounded by the switching between different product types between batches. AI can help analyze patterns in high-dimensional historical production data and recommend operational set points as production shifts quickly from batch to batch. Reducing cycle time comes with direct emissions reduction along with energy minimization, and typically requires no hardware changes to the plant.

ii. Decarbonizing supply chains and adopting dematerialization strategies

- Optimize manufacturing schedules. The production and storage of commodities are driven by market demands. Factories optimize their production schedules to minimize order wait-time while reducing switching costs between product types or grades. Inefficiencies in scheduling lead to superfluous production being stored on-site (leading to unnecessary emissions associated with moving large volumes of material) and switching costs (leading to unnecessary emissions due to keeping equipment running without producing any goods). AI can help with this scheduling process by optimizing complex production schedules to minimize such transitions and it can do so at greater speeds and accuracy than manual approaches. AI can also help forecast market demands, enabling manufacturers to prepare for anticipated market demand ahead of time.[18]
- Minimize logistics overhead. Manufacturers and shipping companies collaborate to deliver billions of tonnes of material across the globe. Handling and routing such large amounts of material with precision is a complex operational task. Shipments that are kept in storage and/or unnecessarily shuffled around during this process lead to energy waste. Poorly planned shipping routes can add to the indirect emissions that come with transporting goods to their final destinations. AI can help with this process in two ways. First, AI can optimize shipping operations, such as terminals and ports, to minimize container movement while correctly loading and unloading shipments from one mode of transport to another. Second, AI can help with forecasting both weather conditions and market demand, enabling logistics companies to plan and reduce operational inefficiencies.[19]
- Evaluate and adopt dematerialization strategies. The 6th IPCC Assessment Report highlights material efficiency as a key strategy in reducing the carbon footprint of manufacturing. This strategy involves increasing circularity of materials used during production, while consuming the smallest amount of new ingredients possible. It also involves designing and manufacturing of stronger, lighter, and better materials to reduce how much is needed for downstream applications. AI can assist with both objectives by targeting production practices that reduce waste—increasing stability with recycled feedstock—and precisely matching product specifications to production.[20] AI can also be used to design materials for easier disassembly and recycling. However, material efficiency is not tracked the same way as energy efficiency, which poses a systematic challenge in this endeavor.[21]

iii. Decarbonizing the impact of maintaining industrial equipment

- Monitor processes. Industrial facilities are typically designed to operate for long stretches of time, ranging from chemical plants that operate with one day of downtime per week, to steel blast furnaces that can operate continuously for years at a time. Any unexpected issues or downtime cause unnecessary and often preventable additional emissions. Aluminum smelters can sometimes unexpectedly fail in a way that releases perfluorocarbons—a potent GHG. AI forecasting models can predict when this is about to happen, enabling operators an opportunity to proactively avoid such scenarios.[22] Similarly, silicon levels in tapped iron of blast furnaces can indicate an unexpected cooling of the furnace—but only when it is too late to act. AI can forecast silicon levels in a blast furnace, enabling operators to pre-emptively avoid any furnace cooldowns that would cause avoidable emissions.[23]

- Plan for maintenance. Scheduling maintenance for batch production is reasonably straightforward since downtime between batches can be used to service equipment. However, continuous-process machinery requires regular maintenance that causes a reduction in capacity, if not direct downtime for the plant. Like cleaning a filter that clogs over time, these maintenance procedures are typically conducted on a regular basis—regardless of the state of the equipment. However, as manufacturing plants adopt increasing variable feed- and fuel-stock, continuous-process machinery can degrade at wildly differing rates. AI can be used to forecast the optimal time to service machinery, thus reducing downtime and the resulting unnecessary emissions that come from winding a plant down and up again.[24]

Figure 5-3. *Factories comprise thousands of interconnected sensors.*

- Manage alerts at scale. Highly instrumented production sites have thousands of sensors that raise alerts if their measurements are out of expected ranges. These alerts can sometimes refer to mild warnings that operators can ignore if they know the underlying cause is temporary (e.g., a particularly cold or hot day). Other alerts can be critical and require initiating costly plant shutdowns and other safety protocols. Handling such alerts, when hundreds may be going off at a time, is a challenging task for manufacturing operators. AI can contextualize these alerts to help manage them at scale. AI software can automatically detect patterns of common alerts that may be used to reconfigure underlying sensor limits. AI can also highlight very unusual alerts and raise additional awareness in the rare cases they occur. These techniques are already being applied in cybersecurity,[25] and can help manufacturing operators detect and minimize emissions with better accuracy and speed.

C. Barriers

Several barriers prevent the widespread adoption of AI in the decarbonization of manufacturing. They include the following:

- Lack of incentive to decarbonize. A threshold issue is the incentive of manufacturers to decarbonize, which can involve expense, market risk, adoption of unfamiliar technologies and disruption of longstanding ways of doing business. Regulatory requirements or clear market rewards are the two reasons why most factories and logistics companies pursue decarbonization, but such requirements or rewards are often lacking. In the absence of incentives to decarbonize, AI tools that could help with this process will rarely be considered or adopted.
- Lack of investment in digitalization. Manufacturing companies are often—culturally and operationally—anchored to the pre-digital era of the industrial revolution. While large manufacturing companies are at various stages of embracing digitalization across their production and supply chains, small- to medium-sized businesses may need to first invest in digitizing their operations. This process may involve installing sensors, connecting them to databases, and maintaining an information technology foundation to support connecting all parts of the business.
- Low digital literacy. Digitalization requires manufacturers to develop, hire or outsource personnel with expertise. Developing such talent in-house involves training internal domain experts with data literacy, storage, and manipulation skills. Hiring for digital talent often involves recruiting data scientists and data engineers to enhance existing staff in their work in this field. Some manufacturers may prefer to outsource such activities to consulting groups and other companies that provide such services.
- Need for coordination across large organizations. Adopting AI in day-to-day workflows requires buy-in from many stakeholders. Manufacturing companies execute complex workflows that can involve up to dozens of departments. Team members must be given sufficient resources and time to build trust in AI-based strategies, which in turn should have clear deployment ownership. Results should be quantified and shared among stakeholders to further incentivize adoption.
- Availability of recycled feedstock. Not every geography and economic market may have access to the same levels or quality of recycled feedstock. Individual recycling is an important challenge in recycling plastic products.26 Commercial recycling of commodities, such as steel, is well established in the United States, Europe, and Japan; similar workflows and markets are developing in South America, China, and India. Companies that lack consistent access to recycled feedstock may hesitate to adopt workflows, with or without AI, that rely on such sources.

D. Risks

The adoption of AI in manufacturing also comes with a variety of risks.

- Increased emissions due to lack of AI maintenance. Factories and logistics change over time. Any AI-based system that operates on real-time data must be carefully maintained and updated. Static AI solutions carry the risk of quickly producing inaccurate analyses, predictions and optimizations, which in turn can lead factories to carry out actions that increase their emissions. Factories that fail to adopt the workflows necessary to update and maintain AI systems raise the risk working with inaccurate AI systems over time.
- Industrial accidents due to improper use. Factories can be dangerous places. Industrial accidents can harm workers and neighboring communities. If properly used, AI can reduce risks at factories, but the opposite could occur with improper use. If AI is tested improperly or implemented incorrectly or if humans are not kept in the loop, the risk of industrial accidents could increase. In adopting AI-based solutions, companies must develop new safety procedures with additional training to mitigate the risk of negative human health and safety outcomes.
- Use of AI in processes that increase emissions. As a general-purpose technology, AI can also be used to reduce costs or speed deployment of industrial processes that increase GHG emissions. Regulatory pressure and market dynamics, along with other incentives, are ways to minimize this risk.

E. Recommendations

1. *Private companies should engage with governments, non-profits and academia to develop, release and maintain AI-ready datasets that pertain to industrial operations. This effort should leverage best practices for data sharing and hosting. Private companies should encourage those interested in leveraging their data to explore high-impact AI applications.*
2. *Private companies should develop clear processes to accelerate the adoption of digitalization within their organizations, from streamlining vendor evaluation to incentivizing internal adoption of AI in high impact use cases.*
3. *Technical societies should develop educational assets and programs to increase digital and AI literacy within industrial workforces. These initiatives should scale across the workforce, from operators up to executives. Emphasis should be on developing a foundational skill set that will enable the manufacturing sector to adopt AI-based solutions.*
4. *Governments and standards organizations should incentivize market demand for AI-optimized products that exhibit increased material circularity and lower carbon footprints. Governments should offer financial incentives to adopt such goods.*
5. *Governments and academia should develop and deploy education opportunities at the intersection of AI and manufacturing as part of computer science and engineering programs.*
6. *Governments should incentivize the market of recycled feed and fuel stock to increase their supply and reduce their costs. This reduces a barrier for adopting AI to increase material circularity.*

F. References

1 Peter John Turnbull Morris. *From classical to modern chemistry: The instrumental revolution*. (Royal Society of Chemistry, Great Britain, 2002).

2 Intergovernmental Panel on Climate Change (IPCC) Working Group III. *Climate Change 2022: Mitigation of Climate Change - Summary for Policymakers (Sixth Assessment Report);* https://www.ipcc.ch/report/sixth-assessment-report-working-group-3/ (2022).

3 United Nations Economic Commission for Europe (UNECE). *COP27: UN report shows pathways to carbon-neutrality in "energy intensive" steel, chemicals and cement industries* UNECE, https://unece.org/climate-change/press/cop27-un-report-shows-pathways-carbon-neutrality-energy-intensive-steel (2022).

4 The Economist. *The truth about recycling;* https://www.economist.com/technology-quarterly/2007/06/09/the-truth-about-recycling (2007).

5 RC Ziegler. *Environmental Impacts of Virgin and Recycled Steel and Aluminum;* US Environmental Protection Agency (EPA), https://nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=9101LWZP.txt (1976).

6 David Sandalow *et al. ICEF Industrial heat decarbonization roadmap;* Innovation for Cool Earth Forum (ICEF), https://www.icef.go.jp/pdf/summary/roadmap/icef2019_roadmap.pdf (2019).

7 Caleb M Woodall *et al.* Technology options and policy design to facilitate decarbonization of chemical manufacturing. *Joule* (2022). https://doi.org/10.1016/j.joule.2022.10.006.

8 Steel Manufacturers Association & CRU International Limited. *Emissions Analysis: Executive Summary;* https://steelnet.org/steelmaking-emissions-report-2022/ (2022).

9 New Energy and Industrial Technology Development Organization (NEDO) Evaluation Department. *NEDO Project Success Stories;* NEDO, Kanagawa, Japan, https://www.nedo.go.jp/content/100899120.pdf (2023).

10 US Department of Energy (DOE). *DOE Industrial Decarbonization Roadmap* US DOE, https://www.energy.gov/industrial-technologies/doe-industrial-decarbonization-roadmap (Accessed September 2023).

11 Richard E. Barlow & Telba Z. Irony. Foundations of Statistical Quality Control. *Lecture Notes-Monograph Series* **17**, 99-112 (1992). https://www.jstor.org/stable/4355628.

12 The Manufacturing Institute. *The Aging of the Manufacturing Workforce;* https://www.themanufacturinginstitute.org/research/the-aging-of-the-manufacturing-workforce/ (2019).

13 Jonathan Worstell. *Scaling chemical processes: practical guides in chemical engineering*. (Butterworth-Heinemann, 2016; https://doi.org/10.1016/C2015-0-01809-3).

14 International Panel on Climate Change (IPCC). *Sixth Assessment Report;* https://www.ipcc.ch/assessment-report/ar6/ (2021).

15 International Panel on Climate Change (IPCC). *Fifth Assessment Report;* https://www.ipcc.ch/assessment-report/ar5/ (2014).

16 Azad Rahman *et al.* Impact of Alternative Fuels on the Cement Manufacturing Plant Performance: An Overview. *Procedia Engineering* **56**, 393-400 (2013). https://doi.org/10.1016/j.proeng.2013.03.138.

17 Pamir Ozbay & Carter Almquist. Adopting Machine-Learning-Based Workflows for Reducing Production Risk and Cost in *AISTech 2023 Iron & Steel Technology Conference*, Detroit, MI. 2086-2100, https://www.proceedings.com/69204.html, (2023).

18 Pietro De Giovanni. Smart Supply Chains with vendor managed inventory, coordination, and environmental performance. *European Journal of Operational Research* **292**, 515-531 (2021). https://doi.org/10.1016/j.ejor.2020.10.049.

19 Reza Toorajipour *et al.* Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research* **122**, 502-517 (2021). https://doi.org/10.1016/j.jbusres.2020.09.009.

20 Lara Waltersmann *et al.* Artificial Intelligence Applications for Increasing Resource Efficiency in Manufacturing Companies—A Comprehensive Review. *Sustainability* **13**, 6689 (2021). https://doi.org/10.3390/su13126689.

21 Sasha Shahbazi *et al.* Material efficiency in manufacturing: swedish evidence on potential, barriers and strategies. *Journal of Cleaner Production* **127**, 438-450 (2016). https://doi.org/10.1016/j.jclepro.2016.03.143.

22 Ron Kremser *et al.* Anode Effect Prediction in Hall-Héroult Cells Using Time Series Characteristics. *Applied Sciences* **10**, 9050 (2020). https://doi.org/10.3390/app10249050.

23 Wandercleiton Cardoso, Renzo di Felice & Raphael Colombo Baptista. Artificial Neural Network for Predicting Silicon Content in the Hot Metal Produced in a Blast Furnace Fueled by Metallurgical Coke. *Materials Research* **25** (2022). https://doi.org/10.1590/1980-5373-MR-2021-0439

24 Alexandros Bousdekis *et al.* A Review of Data-Driven Decision-Making Methods for Industry 4.0 Maintenance Applications. *Electronics* **10**, 828 (2021). https://doi.org/10.3390/electronics10070828.

25 Tao Ban *et al.* Combat Security Alert Fatigue with AI-Assisted Techniques in *Proceedings of the 14th Cyber Security Experimentation and Test Workshop*, Virtual, CA, USA. 9–16, https://doi.org/10.1145/3474718.3474723, (2021).

26 Renee Cho. *Recycling in the U.S. Is Broken. How Do We Fix It?;* Columbia Climate School State of the Planet, https://news.climate.columbia.edu/2020/03/13/fix-recycling-america/ (2020).