

Commentary

24/7 carbon-free electricity matching accelerates adoption of advanced clean energy technologies

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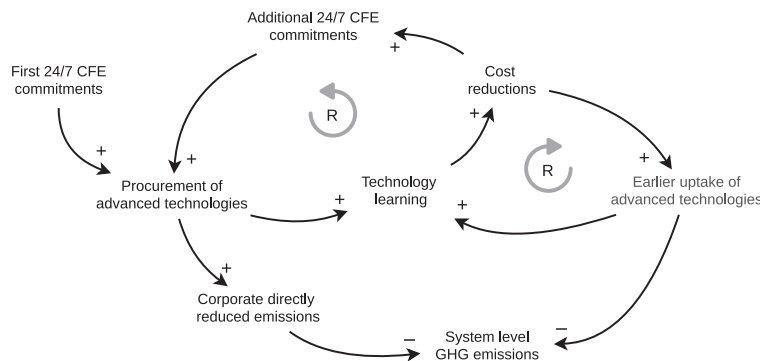
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Tom Brown leads a group of energy system modelers at the Technische Universität Berlin, where he holds the professorship for digital transformation in energy systems. His group researches future pathways for the energy system, with a particular focus on revealing the trade-offs between energy resources, network expansion, flexibility, and public acceptance of new infrastructure. He is a supporter of openness in research and is one of the lead developers of the widely used open-source software PyPSA. Tom holds a PhD from Queen Mary, University of London, and a BA and MMath from the University of Cambridge.

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Devon Swezey is senior manager for global energy and climate at Google, where he leads global clean energy advocacy. He is an author of numerous Google publications on 24/7 carbon-free electricity, including Google's 24/7 carbon-free energy (CFE) policy roadmap and paper on the corporate role in accelerating advanced clean electricity technologies. Devon earned a MA in international economics from the Johns Hopkins School of Advanced International Studies and a BA in international relations from Stanford University.

Big challenges ahead

Tackling climate change requires not only a massive scale-up of available energy technologies like wind, solar, and batteries, but also an accelerated research, development, demonstration, and widespread deployment of advanced technologies that are not yet commercialized at scale.^{1,2} Among them are clean firm generation technologies, such as next-generation geothermal power, advanced nuclear generators, Allam-cycle gas generators with carbon capture and storage (CCS), as well as long-duration energy storage (LDES) technologies, which can bridge multi-day gaps in clean power supply that cannot be filled by wind, solar photovoltaics (PV), or batteries.

Barriers to commercialization

Bringing new technologies to market on a large scale and in time, however, is fraught with challenges. New technologies often face a “valley of death” on the path to successful commercial deployment. Early-stage investments typically comprise governmental research and development (R&D) grants and venture capital, insufficient in both magnitude and duration to support new energy technologies.³ On the other hand, mature technologies such as wind and solar attract steady, de-risked capital from institutional investors. Achieving commercial viability requires companies to construct larger plants at scale and reduce manufacturing costs, which involves overcoming financial, engineering, and supply-chain issues unique to first-of-a-kind (FOAK) projects. Technology innovators often lack the resources to scale from demonstration plants to commercial-scale projects, frequently requiring a consortium of stakeholders that adds complexity and risk, complicating financing.³ Even after FOAK projects succeed, scaling further remains challenging, as repeated deployments are essential for achieving economies of scale. However, investors often hesitate until proven success is seen across multiple projects. Government support can be critical here, though it can also be temporary and even unpredictable, as when Germany ended subsidies for electric cars abruptly in 2023, or in Spain, where the withdrawal of renewable energy support led numerous investors to initiate success-

ful international arbitration proceedings against the state.⁴ Tight public budgets can also be a limiting factor. For example, in the EU, new fiscal rules may limit member states’ capacity to invest in green technologies.⁵

Overall, the road from the first demonstration plant to commercial uptake can be complicated, risky, and expensive—and it is challenging to secure the capital to fund it.

Bridging the valley of death

Consider how solar became a global industry and a truly disruptive technology. Bell Labs developed the first silicon PV cell in 1954, which made modern solar power possible. After more than 20 years of further development, in 1975, the levelized cost of electricity for solar PV was above \$10,000/MWh in today’s money. A historical trajectory for solar development involved Japan’s niche markets for consumer electronics in the 1980s and Germany’s feed-in tariff in 2004, which created a “demand pull” leading to massive industrialization of solar PV manufacturing in China and rapid cost reduction through technological learning.⁶ If we fast-forward to the 2020s, for projects with low-cost financing that tap high-quality resources, solar PV has now the cheapest levelized cost of electricity in history, with new utility-scale solar projects costing \$30–\$55/MWh in Europe, the US, and China.⁷

However, it took six decades for solar to become economically viable. The urgency of climate change mitigation demands that we accelerate this process for advanced clean energy technologies. A crucial question here: who will invest in these technologies when they are expensive at the beginning? These investments can bring wider social benefits. New technologies, such as Allam-cycle generators and iron-air battery storage, are also likely to experience cost reductions through evolving R&D processes, learning by doing, and iterative upscaling. In this way, even though initial investments come with a price premium and certain risks, they can result in cost reductions and an earlier rollout of advanced clean energy technologies. This produces indirect effects that result in greenhouse gas savings beyond the direct reductions

associated with initial investments. The key is initial investments to start this process.

In this commentary, we illustrate in the following sections how initial commitments to 24/7 carbon-free energy (CFE) matching can unlock these effects.

The significance of 24/7 CFE matching

Many public and private energy buyers support the global effort to decarbonize electricity systems by purchasing clean energy. Traditionally, this support has consisted of buying certificates or signing power purchase agreements for renewable energy that is matched to consumption on an annual basis. 24/7 CFE is a new approach that aims to eliminate all carbon emissions by aligning electricity demand with CFE supply on an *hourly* basis and on the same local grid where demand occurs. 24/7 CFE commitments were announced by large technology companies such as Google, Microsoft, and Iron Mountain, as well as by utilities, and the US federal government.⁸ The Climate Group has recently launched the 24/7 carbon-free coalition to encourage companies to move toward 24/7 CFE, initially comprising six companies from diverse industries—including information technology, pharmaceuticals, telecommunications, and cement—and spanning multiple geographic regions.⁹

Motivated by these commitments, several quantitative studies have been conducted on the means, costs, and system-level impacts of hourly CFE matching.^{10,11} There are three key findings that emerge from these studies.

- (1) 24/7 CFE commitments reduce participating buyers’ emissions as well as emissions from the electricity grids where they operate.
- (2) 24/7 CFE comes at a cost premium for participating consumers if only mature technologies, such as solar PV, wind, and battery storage, are used for CFE sourcing.
- (3) The cost premium can be substantially reduced if participating buyers incorporate a broad range of advanced energy technologies into their procurement strategies, such as long-duration energy storage and clean firm generators.

An illustrative example

We demonstrate the three findings above in an example depicted in Figure 1. Here, we display a situation in which a fraction of electricity demand in Germany voluntarily commits to matching their electricity demand with carbon-free electricity around the clock. Figure 1A illustrates how, as the CFE target is tightened, participating consumers reduce the emission rate ($\text{gCO}_2/\text{kWh}^{-1}$) attributed to their electricity consumption. Once demand and supply are perfectly aligned on an hourly basis, i.e., 100% 24/7 CFE matching is achieved, participating consumers reach an emission rate of zero. This goal requires a large portfolio of wind, solar PV, and batteries, as shown in Figure 1B. It is indeed difficult to match every kWh of electricity consumption with renewable electricity during times of dark wind lulls. As a result, achieving 24/7 CFE matching, including the most difficult 2% of times, adds a high cost premium for consumers in part due to the need to build large capacities relative to the demand of participating buyers (“Tech-1, CFE 100%”). Finding (3) above is also clearly visible in Figure 1C: the power capacity required for 24/7 CFE matching and associated costs are substantially reduced when LDES technology or clean firm generation technologies are added.

The main takeaway from this illustrative example is that 24/7 CFE matching creates an economic incentive to incorporate advanced energy technologies into procurement strategies and reduce the cost premium associated with 24/7 CFE matching. This, in turn, creates an early market for new technologies. For example, if 5% of commercial and industrial (C&I) consumers in Germany—representing approximately 1,900 MW of load—adopt a 24/7 CFE matching strategy, this would create a market for approximately 1,500 MW of advanced clean firm generators and about 23 GWh of LDES (assuming all technology options are deployed, Tech-3, CFE 100%). In a similar vein to how feed-in tariffs and renewable portfolio standards created a demand pull for wind and solar technologies in the past, 24/7 CFE commitments can drive the deployment and accelerate innovation of advanced clean energy technologies.

Technology learning

The early deployment of advanced energy technologies can help them drive down along the “experience curve”—a concept encapsulating a set of mechanisms by which technology costs decline as cumulative capacity is deployed: evolving R&D process, learning-by-doing, incremental upscaling, economies of scale, financial innovation, and experience, for example.

In this section, we analyze the expected technological learning for the two energy technologies selected as stand-ins for advanced clean firm generators and LDES: the Allam-cycle generator with CCS and iron-air battery storage, respectively. The Allam-cycle generator is a novel Allam-Fetvedt cycle that uses the oxy-combustion of carbonaceous fuels and a high-pressure supercritical CO_2 working fluid in a recuperated cycle that, by design, captures nearly all emissions. The iron-air battery is a multi-day energy-storage technology that uses a principle of reversible rusting to store and release energy. In practice, a wider range of long-duration storage and clean firm generation are being commercialized and are candidates for procurement under 24/7 CFE matching, including advanced nuclear fission, enhanced and closed loop geothermal energy, bio-energy with CCS, and combustion of carbon-free fuels like hydrogen, and a range of potentially low-cost electrochemical, chemical, thermal, and mechanical storage technologies.

The mathematical model of learning is based on empirical evidence in which the specific investment costs C of a technology decrease by a constant factor with each doubling of experience E . The functional dependency is given by:

$$C(E) = \bar{C}_0 \cdot \left(\frac{E}{\bar{E}_0}\right)^{-\alpha} \text{ where } \alpha = \log_2\left(\frac{1}{1-LR}\right) \quad (\text{Equation 1})$$

where the constants \bar{C}_0 (€/kW) and \bar{E}_0 (MW) are fixed starting points representing the initial costs and experience levels, respectively. The learning rate LR (%) is a parameter that determines the rate at which costs decrease with experience. If $LR = 20\%$, the costs are reduced by

20% for each doubling of cumulative experience. The observed learning rates for energy technologies range from near zero (nuclear, hydropower) to 21% (lithium-ion batteries)¹²; it has been shown that small, modular energy technologies have higher learning rates.¹³ Here, we use cumulative capacity E (MW) of a technology as a proxy for experience, which is calculated as the sum of the installed capacities of all projects that have been completed by a certain point in time. We collect information on existing and planned projects for each technology and use this as a starting point for the experience of the technology. 24/7 CFE matching contributes to the technology’s experience, the additional capacity procured by participating consumers, which is proportional to the participation rate (i.e., the share of C&I electricity demand that is matched with carbon-free electricity on an hourly basis).

The resulting investment costs $C(E)$ (€/kW) are shown in Figure 2 for Allam-cycle technology (top panel) and iron-air battery storage (bottom panel). The first 1% of participation (around 380 MW load in the German market) reduces costs for Allam-cycle generators by 12% and iron-air storage by 16%. The technology learning scales significantly from there: at 10% participation, Allam-cycle generators and iron-air storage costs are reduced by 38% and 44%, respectively. The learning effect has a diminishing return, due to the logarithmic term α in Equation 1. In other words, the first projects have the most significant impact on technology learning, and the effect diminishes as technology experience grows.

The learning model is subject to uncertainty in the initial costs and experience levels, as well as the learning rate. Our Monte Carlo simulation captures this uncertainty by sampling the initial costs and experience levels based on probability distributions derived from public information about planned projects. Figure 2 displays the Monte Carlo simulation results as violin plots. Even though both technologies have a wide range of cost outcomes, the main observation is robust to uncertainty: the early deployment of advanced clean energy technologies due to 24/7 CFE commitments substantially reduces technology costs, making them more attractive for other actors and

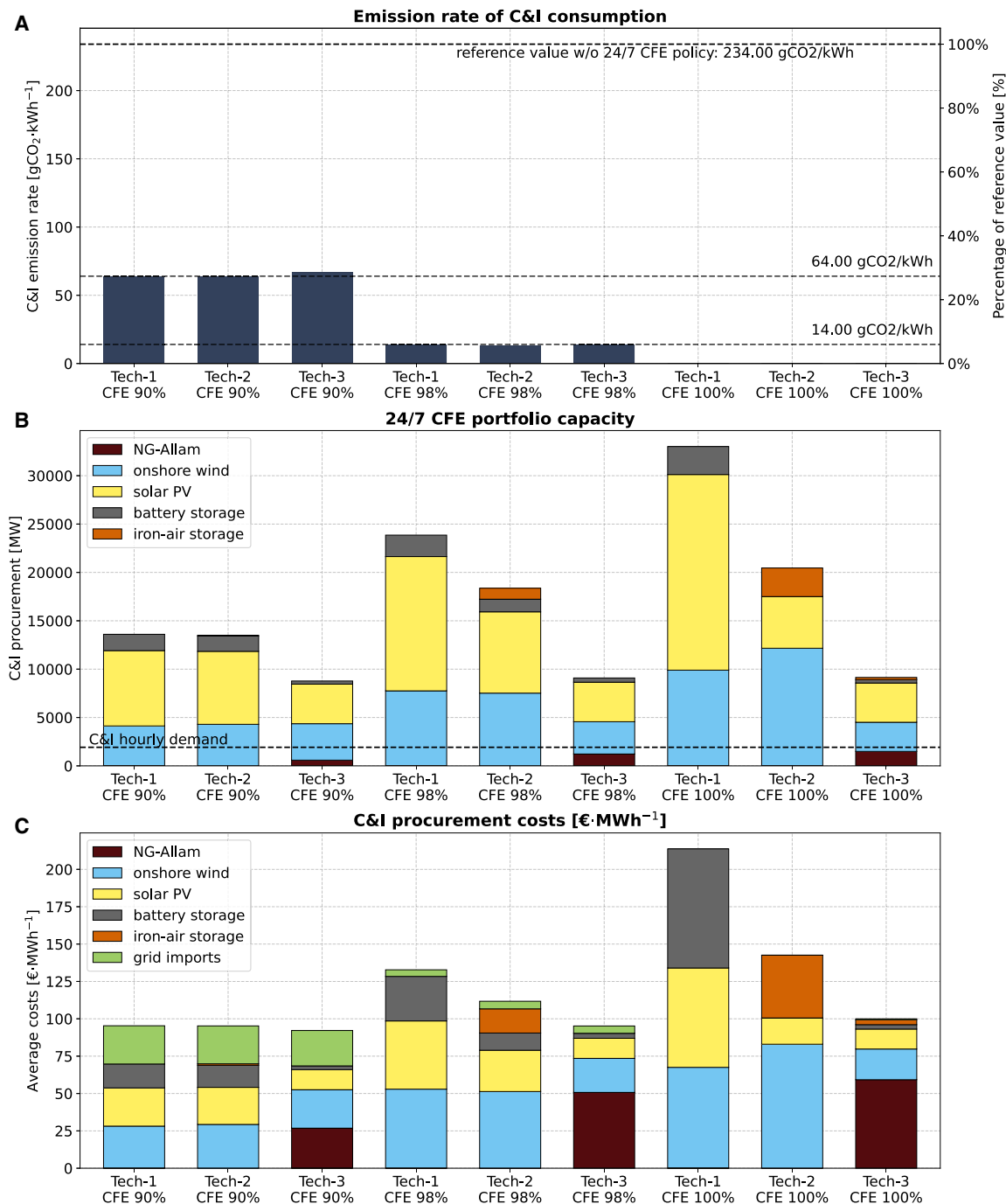


Figure 1. Illustrative modeling of 24/7 CFE matching

(A) Average emissions rate of participating consumers.

(B) Portfolio capacity procured by participating consumers.

(C) Procurement cost by scenario.

Here, we assume Germany in 2025 as an example location and a participation rate of C&I consumers in 24/7 CFE matching strategy at 5% (ca. 1,900 MW load). CFE scores of 90%, 98%, and 100% correspond to the share of time when the electricity consumed by the participating consumers is carbon free. Technology palette 1 (“Tech-1”) comprises technologies commercially available today: onshore wind, utility scale solar PV, and battery storage; “Tech-2” includes all above plus long-duration energy storage (here: the iron-air battery as a stand-in technology); and “Tech-3” includes all above plus a clean firm generator (here: the Allam-cycle generator with CCS as a stand-in technology). The 24/7 CFE procurement framework is based on a methodologies paper by Google LLC.¹⁸ Simulations were carried out using the 24/7 CFE model by Riepin and Brown.¹¹ Technology assumptions are provided in the [supplemental information](#).

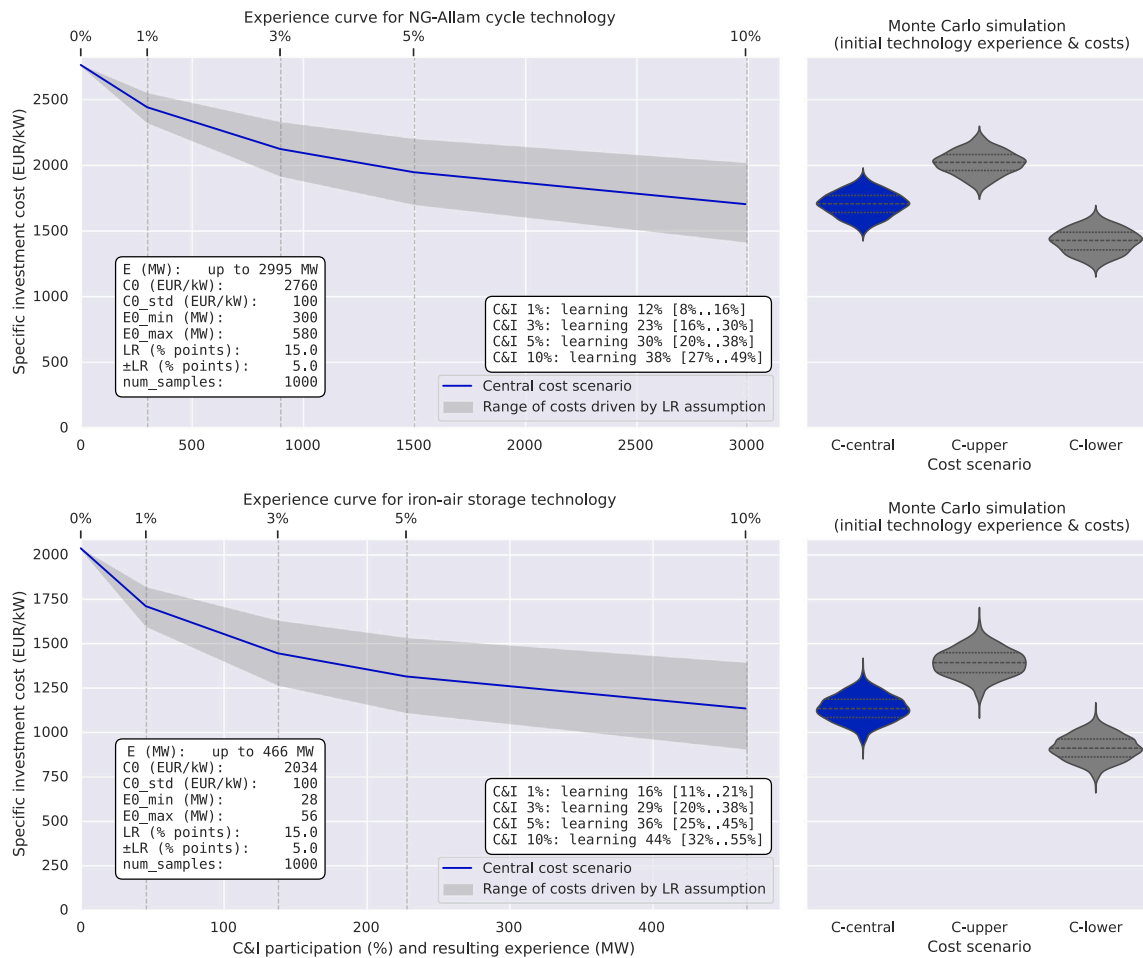


Figure 2. Technology learning curves for the NG-Allam cycle and iron-air battery storage

The learning curves are based on the experience model with the technology investments based on 24/7 CFE model with varying C&I participation level [0%..10%] and learning rates of $15 \pm 5\%$ resembling a wide range of possible outcomes for modular energy technologies.¹² For the Monte Carlo analysis calibration, the initial costs (C0) are sampled from a normal distribution with a mean based on technology cost assumptions for 2025 and a standard deviation of 100 €/kW. Initial experience levels (E0) are sampled from a uniform distribution, with bounds derived from public information about planned projects. For the NG-Allam case (top panel), initial experience lies between cases when one of two projects planned by 2025 is completed and when both projects are completed; for the iron-air case (bottom panel), the distribution bounds are formed by assuming that 50%–100% of the projects announced to operate by 2025 are realized on time (more information about these projects is provided in [supplemental information](#)).

accelerating the point where the technologies become cost-competitive in the rest of the electricity system.

Beyond directly reduced emissions

An illustration of the broader system impact is shown in [Figure 3](#), where we model the German electricity system in 2030 from a system planner's perspective. Here, we minimize the total system costs, including investment costs and operational costs of power generation and storage assets, while adhering to a set of operational constraints. For this case, we assume no voluntary commitments to CFE matching, meaning that

power capacity investments are made solely on the basis of economic considerations. The four scenarios represent different levels of CAPEX for iron-air battery storage, starting from the baseline scenario with 2,034 €/kW, and reducing the cost by 25% in each step. While we use a toy model representation of the German electricity system as an example, the system dynamics observed in simulations are generalizable to other markets and technologies. The same principles applied in multiple markets would indeed allow a wider palette of advanced technologies to be supported.

The results indicate that iron-air batteries need to cost around 1,525 €/kW to become economically competitive in the broader electricity system, which represents a 25% reduction from the baseline. The learning model for iron-air storage shows that this level would require a quadrupling of iron-air capacity expected by 2025 (with a conservative assumption of $LR \sim 12\%$, see [Figure 2](#)). In other words, assuming that the first movers do not benefit from the learning effect, an investment of approx. €340 million ($168 \text{ [MW]} \cdot 2034 \text{ [€/kW]} \cdot 1^3 \text{ [MW/kW]}$) can bring iron-air battery storage to the point of economic break-even by 2030,

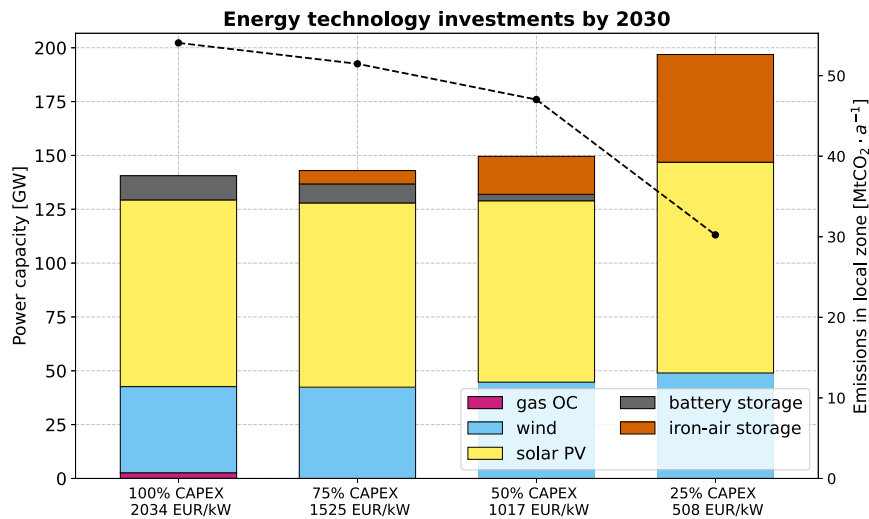


Figure 3. Power capacity investments and emissions in a toy model representation of German 2030 electricity system as a function of CAPEX for iron-air storage

Technology assumptions are provided in supplemental information. Price for EU ETS allowances is assumed to be 100 €/tCO₂. The configuration file in a public GitHub repository lists other background system assumptions.¹⁷

unlocking a wide range of societal benefits. To put this number into perspective, Germany paid approximately €1 billion for redispatch measures in 2023; the costs of the Nord Stream 2 project is estimated at €9.5 billion. The unlocked benefits include reduced system emissions—as shown in Figure 3, iron-air storage substitutes fossil peakers (gas open-cycle generators) reducing emissions in the electricity system by 3 MtCO₂ annually, already for a 25% reduction in iron-air storage costs. There are other advantages of long-duration storage technology deployment beyond the focus of this analysis, such as reduced curtailment of wind and solar generation, reduced need for additional transmission infrastructure, and increased energy security.

Such learning effects can be achieved if a handful of companies and governments (an aggregate electricity demand of approximately 1,200 MW—only 3% of German C&I electricity demand) target 24/7 CFE procurement and include advanced energy technologies in their portfolios (see Figure 2). The required investment can be distributed among a wide range of actors since companies from various sectors and regions can join the movement and contribute to technology learning. Early adoption of advanced technologies will also lead to technology learning and cost reductions

for other actors. It spins a “virtuous circle of innovation,” as we describe next.

Note that this section presented a toy model exercise in the spirit of “modeling for insight” instead of “modeling for numbers.”¹⁴ The back-of-the-envelope nature of this calculation does not aim at quantifying the learning effects of advanced energy technologies and their economical break-even points precisely. It is rather a model experiment to illustrate that a relatively small number of electricity buyers who commit to 24/7 CFE can create a demand pull for advanced technologies sufficient for kickstarting learning effects and making new technologies more accessible and affordable for everyone.

A virtuous circle of innovation

24/7 CFE matching accelerates electricity system decarbonization through three channels: (1) directly reducing emissions during hours when procured CFE is matched with electricity consumption, (2) inducing learning effects that make 24/7 matching more attractive for other companies, and (3) enabling advanced energy technologies to become cost-competitive and widely adopted across the broader electricity system.

- (1) The first channel comprises two mechanisms for directly reduced emissions. First, “profile” mechanism

refers to participating buyers procuring CFE resources that match their demand patterns. When some consumers align their demand with CFE supply on an hourly basis, the rest of the electricity system requires less dispatchable generation to firm intermittent renewable supply. The utilization of fossil-based generators, such as gas-fired power plants, is therefore reduced since participating consumers rely on procured CFE resources to cover their demand at all times. This reduces emissions associated with electricity consumption of participating buyers, as shown in Figure 1. Second, a “volume” mechanism relates to the impact of excess CFE, i.e., clean electricity generated by 24/7 CFE portfolio that exceeds demand in a given hour can be sold to the grid to replace emitting grid generators. Both mechanisms are explained in detail by Xu et al.¹⁰ and Riepin and Brown.¹¹

- (2) A second, indirect channel is the learning caused by early commitments to 24/7 CFE that facilitate innovation and create the early market for advanced technologies, as shown in Figure 2. This reduces the price premium for 24/7 CFE procurement goals, encouraging more companies to work toward them. This in turn further lowers system emissions via the two mechanisms in (1).
- (3) Finally, as advanced technologies are deployed repeatedly, they become economically competitive and are adopted more rapidly across the broader electricity system, thereby unlocking greenhouse gas savings beyond the directly reduced emissions associated the corporate portfolios in (1) and (2), as shown in Figure 3. This channel is significant as the benefits extend beyond voluntary commitments to clean energy matching, affecting numerous actors in various regions and jurisdictions.

A graphical abstract illustrates the nature of the system dynamics that result

from initial commitments to 24/7 CFE. It is a self-reinforcing cycle where early commitments create a market for advanced clean energy technologies, thereby reducing the costs of hourly CFE matching and making it more attractive for other companies to join the movement. A second self-reinforcing cycle emerges when new technologies are adopted early in the electricity system, which further reduces system-level emissions and drives down costs for all actors in the system. The result is a “virtuous circle” that spurs innovation, financeability, and widespread availability of advanced energy technologies, thereby accelerating decarbonization of electricity systems.

This virtuous circle of innovation can be activated by a handful of companies and governments committed to timely action. The early movers might be motivated to participate in 24/7 CFE through several incentives. First, corporate leadership campaigns can create strong incentives for action. Just as the RE100 campaign focused companies on 100% annual matching and celebrated them for working toward it,¹⁵ the 24/7 Carbon-Free Coalition can increase commitments in the 24/7 CFE space. Additionally, companies may be motivated by the research-based evidence of the positive impacts of 24/7 CFE procurement on electricity decarbonization, including through spillover effects of advanced technology commercialization. Finally, increasing public and regulatory scrutiny on corporate sustainability claims and a trend toward greater accuracy in electricity carbon accounting—such as potential updates of the Greenhouse Gas Protocol Scope 2 Guidance to require more granular accounting—may encourage companies to move toward 24/7 CFE matching.

Takeaways

Early markets for advanced clean energy technologies can spur substantial technological learning, leading to cost reductions and unlocking greenhouse gas savings far beyond the reduction of emissions directly associated with initial investments. Similarly to the feed-in tariffs and renewable portfolio standards that created a demand pull for wind and solar PV in the past, commitments to 24/7 CFE matching and other

advanced market commitments¹⁶ by private sector stakeholders can accelerate the development of FOAK and early commercial projects of innovative energy technologies. A proactive private sector contribution can complement governmental support and reduce pressure on tight fiscal budgets. The virtuous system dynamics we describe can be activated by a handful of companies and governments committed to timely action, thereby fostering rapid innovation and making climate solutions more accessible and affordable for everyone.

RESOURCE AVAILABILITY

Lead contact

Requests for further information and resources should be directed to and will be fulfilled by the lead contact, Iegor Riepin (iegor.riepin@tu-berlin.de).

Materials availability

This study did not generate new unique materials.

Data and code availability

The code to reproduce the illustrative experiments is available at GitHub under open licenses.¹⁷

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AUTHOR CONTRIBUTIONS

Conceptualization, I.R., J.D.J., D.S., and T.B.; methodology, I.R.; formal analysis, I.R., writing – original draft, I.R.; writing – reviewing and editing, J.D.J., D.S., and T.B.; visualization, I.R.; validation, T.B.; supervision, T.B.

DECLARATION OF INTERESTS

D.S. is senior manager of Global Energy and Climate at Google LLC. Google has a goal to run on 24/7 carbon-free energy on every grid where they operate by 2030. J.D.J. is part owner of DeSolve, LLC, which provides techno-economic analysis and decision support for clean energy technology ventures and investors. Clients within the last 12 months include Cloverleaf Infrastructure Partners, and a list of previous clients is available at <https://www.linkedin.com/in/jessedjenkins>. J.D.J. serves on the advisory boards of Eavor Technologies Inc., a closed-loop geothermal technology company; Rondo Energy, a provider of high-temperature thermal energy storage and industrial decarbonization solutions; and Dig Energy, a

developer of low-cost drilling solutions for ground-source heat pumps, and has an equity interest in each company. J.D.J. also serves as a technical advisor to MUUS Climate Partners and Energy Impact Partners, both investors in early-stage climate technology companies.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES

During the preparation of this work, I.R. utilized ChatGPT-4 for minor improvements in visualizations (specifically, for matplotlib code). After using this tool, I.R. reviewed and edited the content as necessary and takes full responsibility for its final version. No text in the manuscript was generated using AI-assisted technologies.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at <https://doi.org/10.1016/j.joule.2024.101808>.

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