Modeling and Implementation of the U.S. Hydrogen Production Tax Credit

by

Michael A. Giovanniello

B.S. Mathematics and Chinese, The College of William and Mary, 2020

Submitted to the Institute for Data, Systems, and Society
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE IN TECHNOLOGY AND POLICY

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

May 2024

Authored by: Michael A. Giovanniello
Institute for Data, Systems, and Society
May 10, 2024

Certified by: Dharik Mallapragada
Visiting Scientist, MIT Energy Initiative, Thesis Supervisor

Certified by: Ruaridh Macdonald
Research Scientist, MIT Energy Initiative, Thesis Supervisor

Accepted by: Frank R. Field III
Senior Research Engineer, Sociotechnical Systems Research
Interim Director, Technology and Policy Program

Modeling and Implementation of the U.S. Hydrogen Production Tax Credit

by

Michael A. Giovanniello

Submitted to the Institute for Data, Systems, and Society
on May 10, 2024 in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE IN TECHNOLOGY AND POLICY

ABSTRACT

Low-carbon hydrogen (H2) could contribute to achieving long-term climate goals by supporting the decarbonization of several hard-to-abate industries. The U.S. Inflation Reduction Act includes a tiered hydrogen production tax credit (PTC) awarded for producing H2 below certain emissions thresholds. One pathway for producing PTC-eligible H2 is water electrolysis supplied with low-carbon electricity. But assessing the systems-level emissions associated with electrolytic H2 is challenging, not only because instantaneous power flows from a particular producer cannot be directly associated with a particular user, but also because of the risk that electrolyzers might divert clean electricity away from the grid. Following the passage of the IRA, there has been a vigorous debate focusing primarily on the time-matching requirements — that is, the period over which electricity use must match production from contracted generators — for grid-connected H2 production to receive the PTC.

Applying a macro-energy systems model to case studies of Texas and Florida, we show that divergent results in the literature, which presented a conundrum for regulators trying to pick between policy options, are explained by different interpretations of the proposed "additionality" requirement. Specifically, the emissions associated with H2 production under different "time-matching" requirements are conditional on how additionality is modeled. We further show that the interaction of these qualifying time-matching requirements with other energy system policies could reduce the merits of more stringent time-matching requirements. For instance, if a region has a relatively high renewable portfolio standards (RPSs) to enable grid decarbonization, we show that less stringent (and therefore less costly) time-matching requirements are sufficient to avoid any increases in system-level emissions.

Building on this analysis, we explore how uncertainty in inter-annual variable renewable energy (VRE) generation complicates the implementation of stringent PTC requirements. We confirm that a system design that accounts for inter-annual VRE uncertainty comes at a cost premium — a reality ignored by the existing literature. In addition, we show that inter-annual VRE uncertainty will necessitate the formation of markets for hourly electricity attribution certificates (EACs) to make up for inevitable shortfalls in supply of contracted VRE electricity supply under an hourly time-matching requirement.

We recommend that the Treasury adopt a phased and regionally differentiated approach to implementing the PTC — regions without RPS policies could transition to an hourly time-matching requirement in the mid-term (e.g., by 2030), whereas regions with sufficient RPS policies could continue with looser requirements. In addition to PTC implementation,

these results are relevant to the broader field of Scope 2 emissions accounting for voluntary (e.g. corporate net-zero goals) and regulatory purposes. As more private enterprises, such as data centers owners, pursue voluntary measures to reduce their electricity-related emissions, our work provides a foundation for further research into clean energy procurement standards (voluntary or mandated) that support power sector decarbonization.

Thesis supervisor: Dharik Mallapragada
Title: Visiting Scientist, MIT Energy Initiative

Thesis supervisor: Ruaridh Macdonald
Title: Research Scientist, MIT Energy Initiative

Acknowledgements

I would like to dedicate this thesis to my family — Lea, Anthony, and Dominick Giovanniello. My mother Lea, a life-long steward of the environment, instilled in me a sense of responsibility for the planet and people that motivates this thesis. My father Anthony, a life-long public servant, taught me that policy and governance are powerful channels for well-intentioned people to make a difference. And my brother Dom, the favorite child, sets an example that I continue to aspire to.

I would like to thank my advisor, Dharik Mallapragada, for mentoring me to become a better thinker and researcher, as well Tim Schittekatte, for teaching me how electricity markets and policy work.

I owe more than I could ever repay to the Technology and Policy Program at MIT and the 1693 Scholars Programs at The College of William and Mary for the gift of an excellent and funded education. Thank you Barb, Frank, Noel, and Elena. And to my TPP family — Graham, Peter, Abby, Ben, Johnattan, Lauren, Luc, and Nirmal — I cannot wait to see where you all end up, but I hope it is with me in Boston.

Finally, I would like to thank Professor Dan Cristol, Kim Van Deusen, Professor XiaoYu Wu, and Professor Dan Maliniak for their mentorship and help along the way.

Table of Contents

List of Figures

List of Tables

Chapter 1: Introduction

Ultimately, the success of industrial policy depends on its implementation, and that is something that remains to be determined... If these initiatives are not implemented well, the United States will waste resources and time—and it does not have the luxury of wasting either... But done right, these new measures could make the United States a more competitive and greener country, helping it lead the world for decades to come.

— John M. Deutch and Ernest J. Moniz (2022)

Following the passage of the Inflation Reduction Act (IRA) in September 2022, Ernest Moniz, former Secretary of Energy, and John Deutch, former CIA Director, argued in Foreign Affairs [1] that the success of the U.S.'s efforts to combat climate change and revamp American industry hinge on effective implementation. The alternative is "wasting time and resources" as humanity marches towards catastrophic levels of climate change.

Their article foreshadowed a fierce debate over one of the IRA's key provisions — an uncapped subsidy for producing low-carbon hydrogen that is estimated to cost $385-756 billion [2]. Congress wrote the hydrogen production tax credit (PTC), also known as the 45V tax credit, into law in August 2022, but left key details related to implementation up to the Department of Treasury, which was tasked with finalizing the rules by August 2023 [3]. It wasn't until December 22, 2023, that the Treasury announced their proposed rules, delayed by fierce disagreement between industry, civil society, and academia over how strictly to implement the credit.

Proponents of strict requirements argued that lax standards would fund emissions intensive hydrogen projects, deviating from the legal intent of the IRA and undermining the U.S.'s climate commitments. Opponents of strict requirement argued that they would increase the technical and economic barriers to developing low-carbon hydrogen projects, which will slow the growth of low-carbon hydrogen industry and in turn hamper the decarbonization of other critical industries.

My lab and I entered this debate curious how macro-energy systems modeling could help identify the tradeoffs between strict and loose regulation. We observed that high-profile papers on the topic, which rely on macro-energy systems optimization models, were reaching conflicting conclusions about the emissions levels associated with different qualifying standards. This disagreement made it difficult for regulators to assess the policy options they were presented with.

This thesis describes my efforts to resolve this debate and the resulting insights into how the PTC should be implemented. Chapter 2 introduces the policy itself and salient questions related to its implementation. Chapter 3 describes how my lab and I resolved conflicting results between two high-profile papers regarding the emissions risks of different policy options by interrogating their different modeling approaches. In an article published in Nature Energy (Giovanniello et al., 2024), we called on the Treasury to adopt a phased approach to implementing the PTC — start with lax requirements in the near term, followed by a phase-in of strict requirements as electrolyzer demand grows and subsequent phase-out of strict requirement as the grid is deeply decarbonized. We also identified how policies that mandate the deployment of renewables minimize the emissions risks associated with looser requirements, which is a result with implications for the broader topic of low-carbon electricity accounting for specific loads (e.g., data centers). Chapter 4 describes my ongoing research into how the uncertainty of inter-annual renewables generation complicates the implementation of stringent PTC requirements.

This research is fundamentally at the intersection of technology and policy. I ask: how can the Treasury best implement the hydrogen PTC to scale the electrolyzer industry in service of the U.S.'s climate commitments? Throughout the research process, I also grappled with another issue of technology policy — the policy insights that we derive from macro-energy systems models are limited by our understanding of the complex technical, social, and policy context that these models aim to distill. Building a good model requires deeply investigating a complex system in order to identify its key features. The results, at best, map loosely to reality. Only by interrogating where the model does and does not reflect reality can we gain useful insights. This thesis serves as a reflection on the notion that effective modeling is as much about understanding the systems and contexts we want to model as it is a technical exercise.

Chapter 2: The Hydrogen Production Tax Credit

2.1 Background

Low-carbon hydrogen (H_2) is a promising pathway for decarbonizing a number of high-emitting and hard-to-abate industries, such as fertilizer and steel. Today, 98% of H_2 is produced using fossil fuels, which accounts for roughly 3% of global greenhouse gas emissions [4]. Low-carbon H_2 *can* be made using clean electricity via electrolysis, a process where electricity is used to split water (H_2O) into hydrogen (H_2) and oxygen (O). Policies aimed at economy-wide decarbonization, such as the Inflation Reduction Act (IRA) in the United States, emphasize electrifying end uses while decarbonizing the growing electric power supply [3]. In this context, electrolytic H_2 can play an important role in accomplishing economy-wide decarbonization, because it serves as a link between the growing clean electricity sector and industries that cannot be decarbonized via direct electrification.

The hydrogen production tax credit (PTC) was designed to kickstart the U.S.'s clean H_2 industry. It is an uncapped subsidy that is awarded per unit of H_2 that is produced below certain emissions thresholds. The maximum award is \$3 per kilogram for projects that begin construction before January 1, 2033 for a period of 10 years. This per kg subsidy is roughly **three times** the cost of producing H_2 using traditional fossil-fuel methods. The statute is technology neutral, but the electrolyzer industry is expected to be a major beneficiary.

Table 1: ***PTC subsidy tiers.*** *Subsidy is awarded per kilogram of H_2 that is produced within specific emissions intensity ranges.*

Lifecycle GHG Emissions ($kg\ CO_2eq/kgH_2$)	**PTC ($\$/kgH_2$) [3]**
2.5 - 4.0	0.6
1.5 - 2.5	0.75
0.45 - 1.5	1.0
0.0 - 0.45	3.0

Simply using grid-connected electricity to power electrolyzers, even in relatively high variable renewable energy (VRE) grids in the United States in 2021, such as California's, would result in greater emissions than H_2 produced from natural gas (NG) steam methane reforming (SMR) *without* carbon capture and storage (CCS) [5]. Thus, for an electrolytic H_2 producer to qualify for the PTC, they must demonstrate that their electricity is sourced from low-carbon generators. The simplest way to do so would be to connect the electrolyzer directly to a VRE resource. However, H_2 is expensive to transport, and the best land for siting VREs may not be not be where the H_2 would be consumed [6]. As a result, the most likely business model for producing electrolytic H_2 involves connecting the electrolyzer to the grid, then contracting with a low-carbon generator elsewhere to "match" the electrolyzer's electricity consumption. But this connection with the grid introduces several complex questions that makes implementing the PTC challenging.

1. What does it mean to "match" the electricity consumption of the electrolyzer to the generation of a contracted resource?

One approach, known as **annual time matching**, requires that the low-carbon electricity that is generated is at least equal to the electricity used over the course of a full year. Figure 1A illustrates how this would entail the contracted VRE resource overproducing relative to demand in some hours, and underproducing in others. When the contracted VRE is underproducing, the gap is made up by the grid, which means that the H_2 that is produces is as dirty as the marginal generator on the grid. Another approach, known as **hourly time matching**, requires that the electricity supplied by contracted generators is at least equal to the electricity consumption of the electrolyzer for *all hours* (Figure 1B). This guarantees low emissions, but it requires significantly more investment in VREs and other technologies like batteries and H_2 storage.

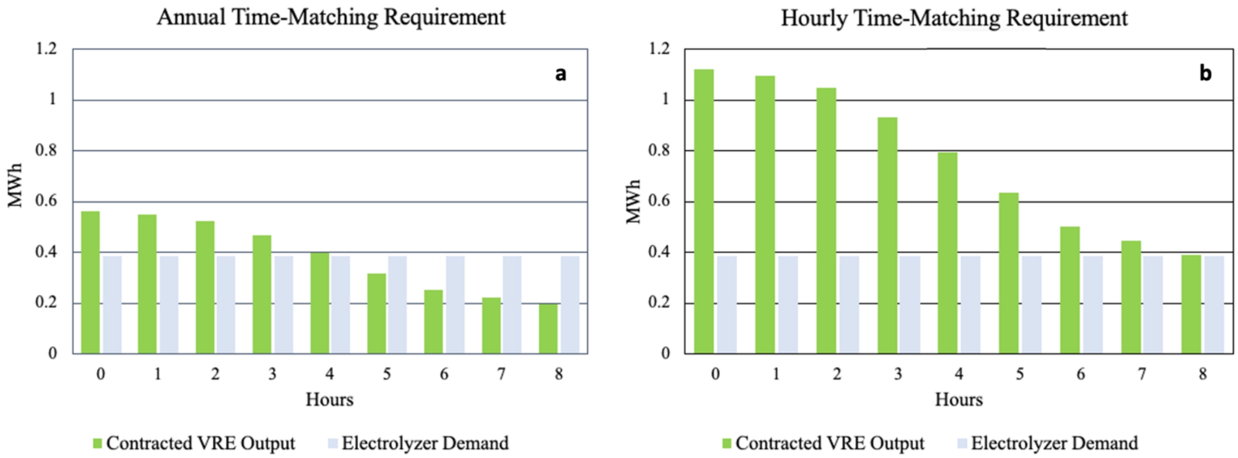


Figure 1: ***Simplified illustration of annual vs. hourly time matching.*** *Electricity demand and contracted VRE resource output under an annual (a) and hourly (b) time-matching requirement simplified such that the requirements are only enforced over eight hours. In the annual plot, aggregate electrolyzer demand is equal to aggregate output from the contracted VRE over the eight hours, which corresponds with over generation in some hours and under generation in other hours. In the hourly plot, contracted VRE output is greater than or equal to electrolyzer demand in each hour. To accomplish this, the VRE resources has to be sized at a higher capacity. Both subplots use the same VRE generation profile, but the capacity is sized to the minimum required to meet the relevant requirement. In practice, to meet the H_2 PTC hourly requirement a mix of VRE, batteries, and H_2 storage with flexible electrolyzer operation can be deployed.*

2. What kind of electricity generators should be allowed to count towards the time-matching requirement?

Low- or zero-carbon electricity must be used for electrolytic H_2 to qualify for the PTC. Many papers and reports have argued that an **additionality** standard should be applied to decide which generators are eligible [7], [8], [9], [10], which means that a generator would not have been built if not for the electrolyzer project. Using electricity from low-carbon generators that existed before the electrolyzer is problematic; the end result is more electricity demand without more low-carbon electricity generation, and therefore higher emissions at the system level. At a minimum, only generators built around the same time or after the electrolyzer begins operation should be eligible. But even the use of newly built generators can be problematic. In the context of a power sector that is rapidly adding VRE capacity, it is easy to imagine generators that were going to be built to serve the grid contracting with an electrolyzer project to get in on the lucrative tax credit. The result is, once again, more demand without more clean electricity generation. This risk of "diverting" clean electricity resources away from the grid is difficult to measure and manage, because we can only guess how much clean energy capacity would have been deployed in a world without the PTC.

3. How close should the contracted low-carbon generator be to the electrolyzer?

Just because a generator is placed on the same grid system as an electrolyzer does not mean the electrolyzer can access its electricity. The **deliverability** of electricity is constrained by the capacity of the electricity transmission system. For example, in Texas, clean electricity generated in the Northwestern part of the state cannot always be delivered to the state's major load centers because of transmission bottlenecks [11]. If the low-carbon generator contracted by an electrolyzer is on the other side of a transmission bottleneck, then the electricity demand of the electrolyzer will have to be met by the marginal generator in its area, while the electricity from the contracted resource is either curtailed or used in an area that is potentially saturated with VRE resources. Table 2 provides an overview of approaches to implementing PTC qualifying requirements related to electricity time matching, additionality, and deliverability.

*Table 2: **Overview of the approaches for implementing PTC qualifying requirements**. Qualifying requirements are defined across three dimensions (electricity time matching, additionality, and deliverability) and are ranked from least strict to strictest.*

	Least strict requirement	**Intermediate requirement**	**Strictest requirement**
Electricity time matching	Annual time matching (in effect in the U.S. until 2028 [3])	Monthly time matching (in effect in the EU until 2030 [12])	Hourly time matching (required in the EU by 2030 and in the U.S. by 2028)
Additionality	Electrolyzer can contract for electricity with existing generators	Only generators built after or at the same time as the electrolyzer begins operation are eligible	Generator would not have been built without electrolyzer project
Deliverability	No geographic constraints on electrolyzer and generator placement	Electrolyzer and generator must be located on same grid	Deliverability of clean electricity from generator to electrolyzer not affected by transmissions constraints

2.2 The Debate Over Implementation

The debate over PTC implementation intensified in February of 2023 when a coalition of environmental organizations and private companies released a joint letter to the White House, Treasury, and Department of Energy urging them to adopt the “Three Pillars” — a set of stringent PTC requirements relating to additionality, deliverability, and time matching [13]. Led by the Natural Resources Defense Council, the coalition called for: 1) use of only additional (i.e., newly built) clean electricity resources, 2) deliverability of electricity from those resources to the electrolyzers, and 3) an hourly electricity time-matching requirement. They cautioned regulators that “weak guidelines for grid-connected systems risk driving up emissions, in direct conflict with the IRA’s requirements,” and noted that the text of the 45V tax credit afforded “broad regulatory authority” for the Treasury to adopt the three pillars standard.

The three pillars elicited swift pushback from numerous companies and industry associations. In April of 2023, The Clean Hydrogen Future Coalition (CHFC), a hydrogen trade association comprised of fossil fuel companies, utilities, and clean energy companies — including Shell, BP, Exxon, Chevron, Duke Energy, NextEra, APEX Clean Energy, American Clean Power, etc. — publicly called for 1) no additionality requirement, 2) and “reasonable regional restrictions” for deliverability, and 2) annual time matching followed by monthly time matching [14]. They were joined in May of 2023 by the Fuel Cell and Hydrogen Energy Association (FCHEA) and 54 companies and organizations in the H_2 space arguing that additionality and hourly time matching would “significantly stifle the clean hydrogen market by adding unreasonable costs and delays for clean hydrogen producers, running counter to the IRA and undermining its economic, jobs, and environmental benefits” [15].

Amid a maelstrom of competing claims, the Treasury faced the difficult task of deciding which qualifying requirements for the PTC would fulfil the IRA’s statutory mandate to *scale* the *low-carbon* H_2 industry. In this context, academics can play an important role in equipping regulators with evidence to cut through the noise. But **the two high profile academic studies on the emissions impact of H_2 produced under different qualifying requirements were similarly in disagreement**. Zeyen et al. [16] found that annual matching generally leads to limited associated emissions, whereas hourly matching typically raises the cost of H_2 production compared to annual matching. In contrast, Ricks et al. [9] found that under annual matching, the emissions associated with H_2 production are significantly higher than acceptable thresholds, and therefore hourly matching is needed. These two conflicting results presented a conundrum for policy makers tasked with making imminent decisions about how to implement H_2 PTC policies.

Both Zeyen et al. and Ricks et al. apply power sector optimization models to assess the systems-level emissions impact induced by a specific grid-connected load that contracts with a specific grid-connected generation resource. This is a complex exercise because instantaneous power flows from a particular producer cannot be directly associated with a particular user. But characterizing the emissions impacts of individual loads is critical for informing the policy-making process. It is the basis for regulators to draft qualifying requirements that third parties (e.g., a H_2-producer or a corporation) need to fulfill for their activities or products to be "certified" as low-carbon and to reap financial and/or reputational benefits.

In the following section, I describe our efforts to understand and resolve this conflict in the literature. We start with the observation that the modeling assumptions adopted by Zeyen et al and Ricks et al. imply different understandings of what constitutes additionality. We use an open-source energy system model [17] to quantify the interaction between alternative interpretations of additionality (which we label "compete" and "non-compete") and time-matching requirements (annual and hourly) in terms of consequential emissions and the levelized cost of electrolytic H_2 production (LCOH). We find that the emissions impact of a time-matching requirement is conditional upon the applied additionality modeling framework and this observation partly explains the divergent findings of the above-mentioned papers. Furthermore, through modeling of different contextual policies, we demonstrate that the standard "compete" additionality framework in many contexts is likely to overestimate of the emissions impact of annual matching and/or underestimate those for hourly matching. We identify the critical role that policies that drive the deployment of VRE resources — such as state-level renewable portfolio standards (RPSs) or corporate power purchasing agreements (PPAs) — can play in minimizing the risk that H_2 production will lead to emissions increases under less strict time-matching requirements. In general, this study highlights that one cannot generalize emissions impacts of a selected time-matching requirement in isolation from how other qualification requirements are defined and other existing energy system-related policies that are in place.

Chapter 3: The Influence of Additionality and Time-Matching Requirements on the Emissions from Grid-Connected Hydrogen Production

This chapter investigates the modeling frameworks used by Zeyen et al and Ricks et al. to understand why they reach conflicting recommendations for PTC implementation. We identify key differences and ask: "how do these different modeling approaches map to reality?" We further consider four policy scenarios that give the Treasury insights into how PTC implementation may vary based on context. Through this analysis, we offer concrete policy proposal for the Treasury to consider regarding how strict to make the time-matching requirement.

3.1 Different Approaches to Modeling Additionality

At one extreme, any generation resource that is not operating in the system prior to installation of the electrolyzer can be considered "additional." This additionality definition, used by Ricks et al., can be modeled via two parallel runs with cost-optimal brownfield grid expansion under the same set of assumptions, including "initial grid" conditions (Figure 2A). The only difference between both runs is that one run excludes H_2 load ("baseline grid") while the other includes H_2 load that is constrained to meet certain temporal and/or spatial matching requirements ("counterfactual grid"). The consequential emissions from electrolytic H_2 production can be calculated as the difference in emissions between both grids. Under this modeling framework, in the counterfactual grid, the more low-carbon resources that are built out to satisfy H_2 demand, the fewer low-carbon resources might be built out merely because of their cost-effectiveness (due to the self-cannibalization effect of VRE resources). In that sense, H_2 demand "competes" with the decarbonization of other electrifying sectors without strict matching requirements (e.g., transport or heating).

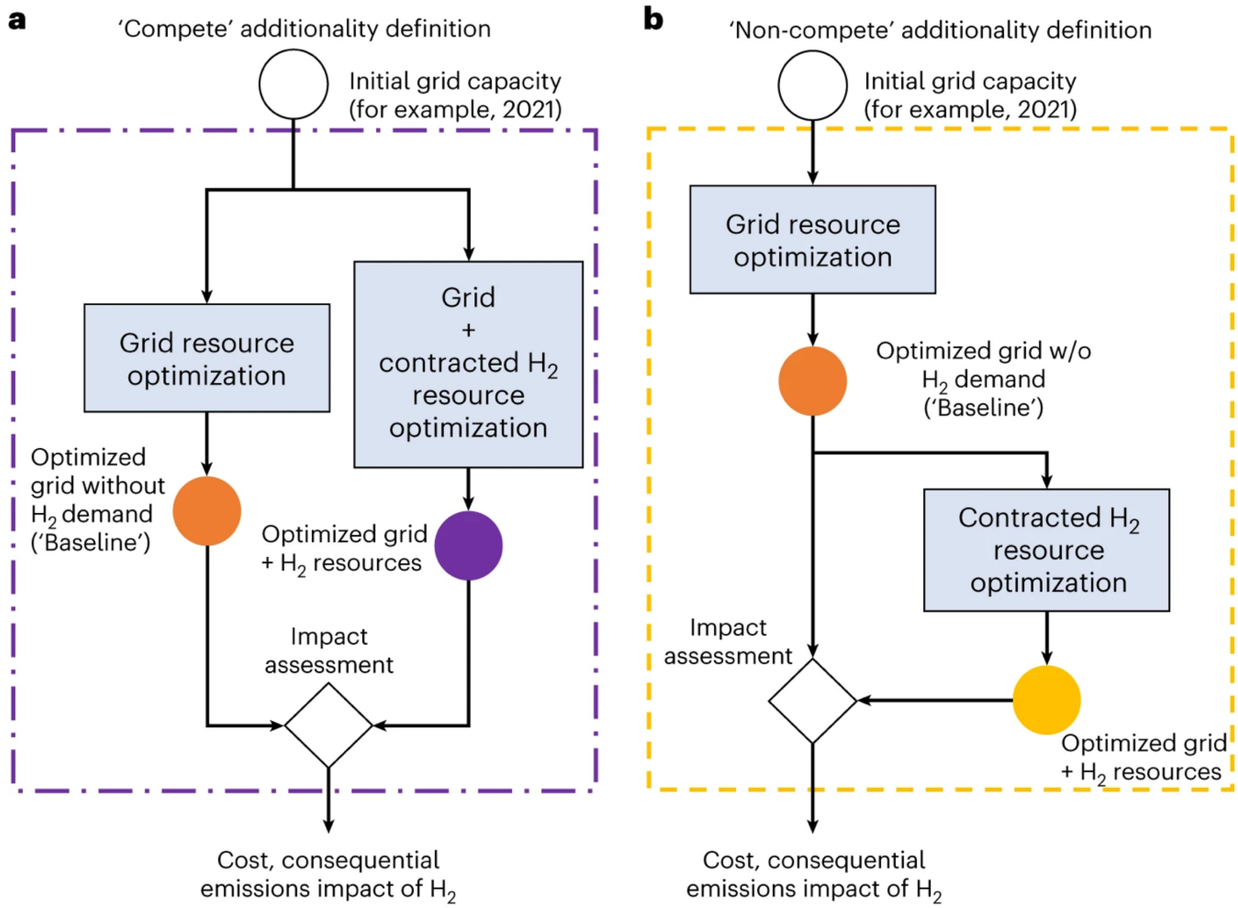


Figure 2: ***Modeling the emissions and cost impacts of additionality.*** *Approaches for evaluating the cost and consequential emissions impact of electrolytic H_2 production based on the two alternative definitions of additionality.* ***a****, The 'compete' definition (purple dotted box) mirrors the approach of Ricks et al. [9] and allows for competition among investment in resources contracted for H_2 production and other grid resource investments.* ***b,*** *The 'non-compete' definition of additionality (yellow dotted box) follows the approach of Zeyen et al. [16] where contracted H_2 resources are optimized after investments in non-H_2 related grid resources. Here contracted H_2 resources refer to battery storage, wind, solar generation, electrolyzers and H_2 storage resources to meet H_2 demand and satisfy the specified time-matching requirement. Note that the baseline grid in both additionality frameworks is the same, whereas the optimized grid with H_2 resources is different (as indicated by the different colors of the circles).*

At the other extreme, only generation resources that would not have been deployed in the absence of electricity demand for H_2 production can be considered additional. This additionality definition, applied by Zeyen et al, involves evaluating model outcomes in series rather than in parallel (Figure 2B). First, we solve the cost-optimal grid brownfield expansion excluding H_2 load to yield the "baseline grid". Subsequently, the counterfactual grid is obtained by running the cost-effective grid expansion to satisfy H_2 demand with the expanded baseline grid as a starting point. As H_2 demand for low-carbon resources is only satisfied after low-carbon resource needs for non-H2 demand or any other decarbonization policy is fulfilled, H_2 load does not compete with other drivers for investment in low-carbon electricity. This so-called “non-compete” framework implies a stricter definition for additionality, while the additionality definition according to the “compete” framework is easier to enforce in practice.

3.2 Four Critical Policy Scenarios

Besides analyzing alternative additionality frameworks, we also evaluate the impact of four policies on the system impacts of time-matching requirements under the “compete” additionality framework, where such policy interactions are relevant (

Third, we constrain the maximum annual capacity factor of the electrolyzer, so as to incentivize a producer meeting a fixed H2 demand under annual time-matching to forgo production during periods of high electricity prices. This policy would also reduce the emissions impact of H2 production in a fossil-fuel dominant power system, where periods of high electricity prices are correlated with periods of high marginal grid emissions intensity.

Table 3). First, to analyze the impact of the initial grid on the emissions and LCOH of alternative qualifying requirements, we evaluate scenarios where we impose minimum annual VRE generation requirements (60% and 80% of the non-H_2 electricity demand). Such an annual VRE generation requirement can be realized by two approaches in isolation or in combination: via renewable portfolio standard (RPS) policies [18], as is in place in 29 U.S. states as of June 2023 [19], or via decentralized procurement of VRE supply by several end-use customers, e.g., by the numerous pledges of corporates to become climate neutral [20]. When including a minimum VRE requirement under the “compete” framework, VRE for non-H_2 load is prioritized. This prioritization, by definition, is inherent in the “non-compete” framework.

Second, many grids are facing significant delays in connecting new generation to the transmission grid [21], [22], which was not considered in prior studies. We model this policy failure by adding a constraint that limits the capacity of VRE and battery storage that can be built out (see Methods).

Third, we constrain the maximum annual capacity factor of the electrolyzer, so as to incentivize a producer meeting a fixed H_2 demand under annual time-matching to forgo production during periods of high electricity prices. This policy would also reduce the emissions impact of H_2

production in a fossil-fuel dominant power system, where periods of high electricity prices are correlated with periods of high marginal grid emissions intensity.

Table 3: ***Summary of the four relevant energy policy scenarios****. Scenarios are selected based on their potential relevance for the emissions and cost associated with H_2 production under alternative time-matching and additionality requirements.*

	Standard case	**Policy scenario**
Minimum annual VRE generation requirement ("RPS")	None	60 and 80% VRE target for non- H_2 electricity demand (Eq. 5)
VRE + battery storage capacity buildout limit	Unconstrained	15 GW (Eq. 6)
Limiting the electrolyzer's annual capacity factor	Baseload and unconstrained flexible operation	Range of max. annual capacity factors (20%-80%) (Eq. 7)
Use of NG-based H_2 to meet H_2 demand	Only electrolytic H_2	Competition for H_2 production between electrolysis and NG-based H_2 with CCS

Fourth, while most studies on qualifying requirements focus exclusively on electrolytic H_2, other H_2 pathways like NG-based H_2 production with CCS (so-called blue H_2) are also receiving policy support. To understand how qualifying requirements impact competition between green and blue H_2, we evaluate scenarios with the option to also invest in blue H_2.

3.3 Methods

3.3.1 Model Formulation and Assumptions

Model overview

This study uses the Decision Optimization of Low-carbon Power and Hydrogen Networks model [17], an open-source energy systems capacity expansion model that co-optimizes investment and operation of electrical power and H_2 sectors while considering their spatially and temporally resolved interactions. The model minimizes the total system cost associated with the infrastructure of both commodities (electricity and H_2). This includes annualized capital costs for new capacity and fixed and variable operating costs for both existing and new generation, storage and transmission capacity and any costs for load shedding. The cost minimization is carried out subject to many system and technology-level constraints, including: ramping limits and temporally dependent resource availability limits for VRE generation and system-level constraints, which includes hourly energy supply–demand balance for H_2 and electricity at each location, and case-specific or hourly/annual time matching and energy share requirements. Further details of the model formulation and set-up can be found in [17]. Key modifications and additions to the model that were implemented for this analysis are reported in subsequent sections.

Region and time horizon of interest

Our analysis is based on two regional U.S. grids that are representative of low and high end of VRE generation share in U.S. as of 2021: grids managed by the Electric Reliability Council of Texas (ERCOT) and the Florida Reliability Coordinating Council (FRCC). The contributions of grid-connected VRE generation in ERCOT and FRCC grids as of 2021 were 26.5% (3.1% solar, 23.4% wind) and 3.0% (3.0% solar, 0% wind), respectively. Low VRE penetration grids are a common occurrence in the U.S. as of 2021—for example, Mid-Atlantic (2.4%), New England (6.1%) and East South Central (0.4%) [23]. Full results for FRCC are reported in Supplementary Figs. 19–27.

Power sector modelling assumptions

The data inputs and sources used to define the 2021 system for both ERCOT and FRCC studies are provided in the Supplementary Information. Unless otherwise stated, all costs have been converted to 2021 U.S. dollars. Relevant technology cost and performance assumptions are reported in Supplementary Tables 1 and 2. Across all scenarios, we allow the model to alter the power capacity mix via investment in solar, wind and Li-ion battery storage, both for non-H_2 and H_2 electricity demand and retirement of existing fossil fuel generation resources. In our analysis, we do not allow for retirements of existing nuclear plants, based on the assumption that it would be economically viable to continue running these plants based on the available credits for nuclear in the IRA. The parametrization of battery storage also considers a self-discharge rate of 0.002% per hour [24]. The model can independently vary the installed energy capacity and power capacity for Li-ion storage so long as the ratio of energy capacity to power capacity (that is, duration) is between 0.15 and 12 h.

Aggregated power generation capacity for all resources for ERCOT and FRCC are reported in Supplementary Table 5. Annual demand and generation information is reported in Supplementary Table 6. The electricity demand data was obtained from PowerGenome [25] and corresponds to demand for 2021 for the two regions.

Hourly resource availability data for onshore wind and solar photovoltaics for each region was generated by averaging hourly resource availability profiles for weather year 2012 from multiple sites, available from a previous study [26]. The site-level data for photovoltaics were simulated using site-level irradiation data from the National Solar Radiation Database in conjunction with the open-source model PVLIB. In the case of wind, the site-level resource data were simulated using site-level wind speed data from the National Renewable Energy Laboratory Wind Integration National Dataset Toolkit and power curve data based on the Gamesa G26/2500 wind turbine. Further details about the site-level data calculation are provided in the supporting information of a previous publication [26]. Supplementary Figure 3 shows the geographic areas used to compute average capacity factors for wind and solar generation in FRCC and ERCOT. The regional-level wind and solar availability profiles for FRCC were generated by averaging resource availability profiles over the entire FRCC service territory. In the case of ERCOT, we considered only sites in West Texas and the Panhandle, to account for the fact that this region has the highest quality VRE resources and, thus, is likely to dominate new resource deployment (and already dominates existing resource deployment). As a simplification, we do not impose additional constraints or costs on VRE deployment and thus do not capture the increasing marginal cost of adding wind and solar resources into the system used by other grid studies [9].

Supplementary Figure 1 visualizes the hourly demand profile and VRE resource profile for FRCC, which highlights how wind availability tends to be low during summer months when electricity demand is relatively high. Supplementary Figure 2 visualizes the VRE resource and demand data for ERCOT, with wind exhibiting less seasonal variation than in FRCC.

Fuel cost assumptions

The model runs were based on fuel price assumptions based on 2019 rather than 2021, as summarized in Supplementary Table 4, so as to not consider the short-term distortion in fuel prices resulting from exceptional events (COVID-19 pandemic, EU energy crisis and so on). Whereas the spot prices of natural gas through 2021 were much higher than 2019 values (as high as US$6 per one million British thermal units (MMBtu−1)), prices in 2023 have come down to levels seen in 2019. For example, according to the data from the U.S. Energy Information Administration [27], the average Henry hub spot price in January and February 2023 were US$3.27 MMBtu−1 and US$2.38 MMBtu−1, respectively.

We use modified fuel costs for natural gas technologies using CCS for H_2 production to implicitly account for the cost of CO_2 transportation and storage. The incremental CCS cost adder to the fuel cost is computed by multiplying the captured CO_2 per MMBtu of NG (Supplementary Table 3) with the assumed CO_2 transportation and storage cost), equal to US$11.6 tonne−1 per the assumption used by the National Energy Technology Laboratory in their techno-economic analysis of natural gas H_2 production technologies [28].

3.3.2 H_2 System Characterization and PTC Constraint Formulation

H_2 demand characterization and electrolyzer capacity modeling

Under both baseload and flexible electrolyzer operation in our analysis, electrolyzer capacity is sized to meet exogeneous H_2 demand, such that at any hour, only 95% of the installed capacity is available for generation. This is to account for planned outages related to maintenance. We evaluated the system outcomes for varying levels of hourly H_2 demand of 18.4 to 92.1 tonnes of

H_2 per hour (0.16 to 0.81 MT per year), which for typical electrolyzer specific power consumption (54.3 MWh tonne−1) ranges from 1 to 5 GW of hourly electric power consumption. For simplicity, when discussing results, we use labels such as '1 GW' to indicate an hourly H_2 demand level of 18.4 tonnes of H_2 per hour. Because the total amount of H_2 produced is fixed, the available PTC does not impact the operational behavior of the electrolyzer and therefore we do not consider it in the model but rather include it when estimating the levelized cost of H_2. Eq. 1 enforces that sum of electrolytic H_2 production (gen_t^{Ely}) plus production from natural gas reforming technologies, if available ($\sum_{g \in G} gen_{g,t}^{NG}$) plus net discharge of H_2 storage ($dischg_t^{H2} - chg_t^{H2}$), if available, must equal the exogeneous hourly H_2 demand (δ_t^{H2}) for all hours of the year.

$$gen_t^{Ely} + \sum_{h \in H_{NG}} gen_{h,t}^{NG} + dischg_t^{H2} - chg_t^{H2} = \delta_t^{H2} \qquad \forall t \in T \tag{1}$$

Supplementary Table 2 summarizes cost assumptions for electrolyzers and H_2 storage and natural gas H_2 production with CCS. The latter is only considered in the policy scenario evaluating competition between green and blue H_2 pathways.

Time-matching requirements modeling

As in [9] and [16], we model two time-matching requirements—hourly and annual. We compare the results for these time-matching requirements under two alternative frameworks for additionality, as defined earlier.

Annual time matching is implemented via a constraint that requires that the annual generation output from contracted wind and solar resources must equal the annual electricity consumption of the electrolyzer (Eq. 2). This constraint states that sum of annual VRE generation ($gen_{g,t}^{VRE}$) from the set of eligible VRE resources (TMR_g) throughout the year must be equal to annual electrolyzer electricity consumption, while accounting for energy storage losses. The latter is calculated as a product of the annual H_2 demand and power consumption per unit of H_2 produced (λ^{Ely}).

$$\sum_{g \in TMR_g} \sum_{t \in T} gen_{g,t}^{VRE} + \sum_{t \in T} \sum_{k \in TMR_b} \left(dischg_{k,t}^{bat} - chg_{k,t}^{bat}\right) = \lambda^{Ely} \sum_{t \in T} gen_t^{Ely} \tag{2}$$

Hourly time-matching requirement implemented via a constraint that requires the net hourly output of contracted resources (VRE generation and battery storage net discharge) to be at least equal to the hourly electricity consumption of the electrolyzer (Eq. 3). For every hour of the year, the electrolyzer power consumption, equal to product of its generation times the specific power consumption (λ^{Ely}), must be less than or equal to generation from the set of contracted VRE generation resources (TMR_g) + net injection from set of eligible battery storage (TMR_b). This ensures that new electrolyzer demand is accounted for by these additional resources at each hour. If there is no storage or natural gas reforming technologies, then the electrolyzer will be operating in baseload conditions resulting in $gen_t^{Ely} = \delta_t^{H2}$ by Eq. 1.

$$\sum_{g \in TMR_g} gen_{g,t}^{VRE} + \sum_{k \in TMR_b} \left(dischg_{k,t}^{bat} - chg_{k,t}^{bat} \right) \geq gen_t^{Ely} \lambda^{Ely} \; for \; all \; t \in T \quad (3)$$

To ensure battery storage charges using only eligible VRE generation resources, we only allow the contracted battery, if deployed, to charge in each hour up to the available generation from contracted VRE resources (Eq. 4). At each time step, the amount charged by the new battery resource (part of set TMR_b) cannot exceed maximum available generation from the set of contracted VRE resources (TMR_g), defined as the sum of the hourly capacity factor ($\alpha_{g,t}^{VRE}$) times the installed capacity (Cap_g^{VRE}). This ensures that the battery is charging only when procured VRE electricity is available.

$$chg_{k,t}^{bat} \leq \sum_{g \in TMR_g} \alpha_{g,t}^{VRE} \times Cap_g^{VRE} \;\; \forall \, t \in T \,, k \in TMR_b \quad (4)$$

The hourly time-matching requirement allows for the contracted resources to sell any excess electricity in a given hour (for example, an hour with high solar or wind availability) to the grid and earn revenues. These revenues can partly offset the capital cost associated with the contracted resources, and thereby reduce the cost of H_2 production. The option to sell electricity to the grid when economical is also available in the annual time-matching requirement case, so long as the sum of annual generation matches that of the electricity consumption of the electrolyzer.

Calculation of the 45V and 45Q tax credit impacts on annualized LCOH

The 45V production tax credit for producing low-carbon H_2 using electrolyzers is only available for the first ten years of project operation, and the 45Q tax credit for sequestrating CO_2 captured from SMR with CCS pathway is available only for the first 12 years of operation. H_2 production plants will probably be in operation longer than the window for receiving their respective tax credit—we assume 20 years for electrolyzers and 25 years for SMR facilities (Supplementary Table 2). The annualized impact of the tax credit on LCOH must account for the fact that the credit is available only for a portion of the project's full lifetime, that is, the full US\$3 kg−1 PTC will not reduce LCOH by US\$3 kg−1. We conducted an annualized cost calculation in which the respective credit is awarded for the eligible number of years then not awarded in the remaining years of operation. We assume a 4% discount rate and 2% inflation rate for these calculations. The net result is a PTC credit, and resulting reduction in LCOH, of US\$1.95 kg−1 and 45Q credit of US\$56.5 tonne−1 CO_2 sequestered.

3.3.3 Methods for Assessing Relevant Policy Scenarios

The four policy scenarios outlined previously are modeled by adding or altering constraints to the baseline model.

Minimum annual VRE generation requirement

The minimum annual VRE generation requirement, enforced via Eq. 5, ensures that annual generation from non-PPA resources must be at least equal to a specified fraction (κ) of annual sum of hourly electricity demand (δ_t^{elec}). Note that electricity demand does not include electricity consumed for H_2 production. In addition, generation from PPA VRE resources (i.e., belonging to set TMR_g) are not counted towards meeting this constraint. Allowing excess electricity sales from PPA VRE resources to be counted towards meeting the annual VRE generation requirement results in PPA VRE capacity deployment that is much in excess of H_2 production needs. This means that electricity rather than H_2 is the primary product of these contracted VRE resources. Since our focus was on H_2 production, we chose to disallow contracted VRE resources to participate in meeting the system-wide annual VRE generation requirement constraint. As the relative magnitude of "excess sales" (PPA VRE resources not used for H_2 production – "excess sales") is small relative to the total amount of VRE production in the system, we argue that this simplification does not have a substantial impact on the results.

$$\sum_{g \in VRE \setminus TMR_g} \sum_{t \in T} egen_g^{VRE} \geq \kappa \times \sum_{t \in T} \delta_t^{elec} \tag{5}$$

Maximum VRE+storage deployment limit

In cases where the VRE capacity deployment constraint is modelled, we set this limit at 15 GW for illustrative reasons. Average VRE additions in ERCOT for the ten-year period 2012–2021 was 2.7 GW per year [29]. Thus, 15 GW is roughly what might be expected to be installed in ERCOT over five years. Note that ERCOT has been one of the power systems where the interconnection queue issue has so far been relatively modest compared with other U.S. power systems (due to a proactive buildout of transmission).

The maximum VRE+ storage deployment is enforced by Eq. 6, which states that the total power capacity of new VRE and battery storage resources, both to meet contractual requirements for H_2 production and to serve non-H_2 demand, must be less than or equal to an exogenously specified value (Max_{Cap}). TMR_g and TMR_b refer to VRE and battery resources for H_2 production, respectively, and $Grid_g$ and $Grid_b$ refer to VRE and battery resources for non-H_2 demand.

$$\sum_{g \in TMR_g} Cap_g^{VRE} + \sum_{g \in Grid} Cap_g^{VRE} + \sum_{k \in TMR_b} Cap_k^{bat} + \sum_{k \in Grid_b} Cap_k^{bat} \leq Max_{Cap} \qquad (6)$$

Electrolyzer maximum annual capacity factor

The maximum annual capacity factor limit ($\alpha^{Ely,Max}$) is implemented by adding Eq. 7 to the model. The constraint effectively translates into a minimum electrolyzer capacity deployment constraint for an exogeneous annual H_2 demand. β^{ELY} refers to the availability factor for the electrolyzer, which denotes the fraction of installed capacity (Cap^{Ely}) that is available for production in any hour.

$$\frac{1}{8760} \sum_{t\ in\ T} \delta_t^{H2} \leq \alpha^{Ely,Max} \times \beta^{ELY} \times Cap^{Ely} \qquad (7)$$

3.3.4 Metrics of Interest

The emissions impact of H_2 production is evaluated using *consequential emissions intensity*, defined as the difference in power system emissions with and without H_2 demand divided by the annual quantity of H_2 produced. As noted by others [3], [4] this is an appropriate metric for assessing emissions intensity in modeling exercises; however, alternative metrics are needed for real world accounting, since the "counterfactual grid" used to calculate consequential emissions cannot be observed. Although the PTC focuses on lifecycle GHG emissions, as a simplification, our analysis only considers CO_2 emissions related to fossil fuel combustion for electricity generation since these will dominate overall emissions.

Aside from consequential emissions intensity, we evaluate the *levelized cost of H_2 (LCOH),* which approximates the cost to the H_2 producer who invests in the electrolyzer and H_2 storage, as well as the additional low-carbon electricity generation that is required for the H_2 to be eligible for the PTC under alternative time-matching and additionality requirements. The LCOH can also be thought of as a proxy for the minimum H_2 selling price that would lead to a zero profit for the H_2 producer over the lifetime of the investment in the electrolyzer. In practice, the H_2 producer may not directly invest in the VRE plus battery storage assets, but could instead choose to sign a power purchase agreement (PPA) that pays another developer who has invested in these assets. Here, we are trying to approximate the cost of the PPA by accounting for the difference between the cost of electricity grid consumption incurred by the H_2 producer and the revenues from sales of electricity from the VRE plus battery storage assets.

The LCOH includes: the capital cost of added VRE and battery storage (after the 30% ITC under the IRAs), the cost of electricity purchases from the grid for H_2 production, revenue from electricity sales to the grid from the procured VRE resources (accounting for battery charging/discharging), and electrolyzer and H_2 storage fixed costs. Revenues and costs for electricity purchases and sales to the grid are accounted for based on the shadow price of electricity supply-demand balance constraint enforced for each hour of the year in the model. In each case, we report the LCOH with and without including the applicable H_2 PTC.

3.3.5 Comparison with Other Studies

Table 4 provides a high-level overview of the key assumptions in this study and two other recent papers with significant overlap on the research questions of interest. We do not consider transmission constraints and spatial matching requirements. In a nutshell, the major reason behind the different results presented in the aforementioned two papers is that in the Ricks et al.'s modeling, low-carbon generation built in the baseline grid (orange circle in Figure 2A) to serve the non-H_2 load can be "shifted" in the counterfactual grid (purple circle in Figure 2A) to serve the H_2 power demand. Also, under this modeling approach, we allow higher-carbon generators that are present in the initial grid (white circle in Figure 2A) to be retired in the baseline grid but retained in the counterfactual grid to serve the non-H_2 load. Such dynamics, play a much larger role under annual time-matching than under hourly matching. In Zeyen et al. this shifting is proscribed, so that the annual time matching largely succeeds in driving the desired additionality vis-à-vis the baseline grid, and thus does not lead to high levels of consequential emissions.

Table 4: ***Comparison of key assumptions and context between this thesis and two other recent papers with a significant overlap on the research questions of interest.*** *[a]The authors in [16] assume a fixed H_2 demand of 28 TWh of H_2 per annum. [b]Our model starts with an initial grid resembling generation mix in 2021 and uses 2022 technology cost and performance assumptions to evaluate near-term evolution of the grid mix in both regions (Supplementary Table 1).*

	Ricks et al. [9]	Zeyen et al. [10]	This thesis
Additionality definition evaluated?	"Compete"	"Non-compete"	"Compete" and "Non-compete'
Inter-regional transmission constraints?	Yes	Yes	No
Region and time horizon of interest	Western U.S. — 2030	Germany, Netherlands, — 2025/2030	Texas (ERCOT), Florida (FRCC) — 2025-2030[b]
Exogeneous H_2 demand characterization	No demand enforced, both in quantity and profile	Constant hourly H_2 demand (3.2 GW[a])	Constant hourly H_2 demand 1 and 5 GW
Energy storage options evaluated	Li-ion	Li-ion, tank-based gaseous H_2 storage and other lower cost forms of H_2 storage	Li-ion, tank-based gaseous H_2 storage
Operation of the electrolyzer	Flexible	Flexible	Baseload and flexible
Time-matching requirements analyzed	• Annual matching • Hourly matching without excess sales • Hourly matching with excess sales • Weekly matching	• Annual matching • Hourly matching without excess sales • Hourly matching with 20% excess sales • Monthly matching	• Annual matching • Hourly matching with excess sales

Note that our assumptions for exogeneous H_2 demand and energy storage options are aligned with Zeyen et al. but differ from the assumptions of Ricks et al. For instance, we assume a constant hourly H_2 demand, which is what would be expected from typical industrial applications that are likely to be major consumers of electrolysis-based H_2 [30]. This implies that irrespective of electrolyzer operating mode, the combination of electrolyzer output plus net discharge of H_2 storage, where available, must meet a constant H_2 load for each hour of the year. We model cases with and without H_2 storage investments, corresponding to scenarios with *baseload* and *flexible* electrolyzer operation, respectively. Baseload operation may be appealing to maximize capital utilization and minimize degradation. Under *flexible operation*, exogenous, time-invariant H_2 demand must be met, as in the baseload case, but electrolyzer size and operation, along with the size of H_2 storage, are decision variables (see Eq. 1). In contrast, Ricks et al. do not enforce an exogeneous H_2 demand, nor in quantity or in profile and also do not model investment in H_2 storage. As the H_2 demand is not fixed exogenously in their model, the electrolyzer can operate flexibly depending on relative difference between marginal cost and exogeneous H_2 revenue. Finally, even though Ricks et al. and Zeyen et al. model additional time-matching requirement options, for clarity, we model only the two most debated options– hourly and annual time-matching requirements.

3.4 Results

The results are reported in two subsections. First, we describe how different additionality assumptions impact 1) the resource mix of the grid and H_2 project, 2) system-level consequential emissions, and 3) the levelized cost of hydrogen (LCOH). Then, we describe how the cost and emissions outlooks from the additionality framework analysis are impacted by the four relevant policy scenarios.

3.4.1 Impact of Different Interpretations of Additionality

Figure 3 shows that the contracted resource mix for H_2 production under annual time-matching requirements is more sensitive to the additionality definition than under hourly requirements. In general, wind plays a greater role under an hourly time-matching requirement than under an annual requirement for both additionality frameworks in the ERCOT case study. Under the "compete" framework, solar generation is preferred to meet annual time-matching requirements, while under the "non-compete" framework, wind generation plays a greater role to meet the contractual requirement. This is a consequence of which generation resources are built out in the baseline grid expansion. Since baseline grid expansion in the ERCOT case study solely results in solar additions (Supplementary Figure 4), use of solar to serve H_2 load under the "non-compete" framework has diminished economic value as compared to the "compete" framework.

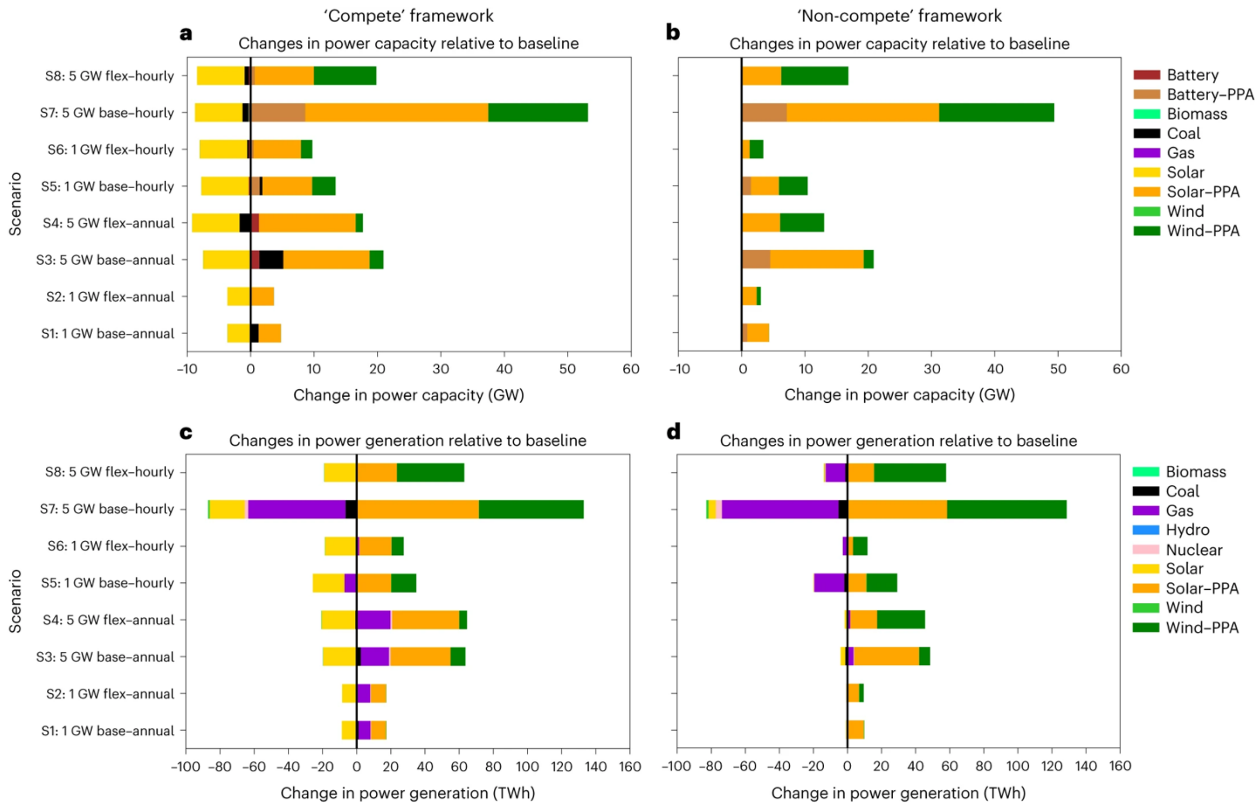


Figure 3: ***Power sector resource changes due to H_2 production.*** *a–d, Change in power generation and storage capacity (a,b) and annual power generation (c,d) resulting from electrolytic H_2 production under alternative H_2 demand scenarios, time-matching requirements and additionality frameworks. Results correspond to the case study based on the grid managed by ERCOT and are reported relative to the baseline scenario involving grid resource expansion without any H_2 demand. Power purchase agreement (PPA) refers to resources added specifically to meet time-matching requirements for H_2 production.*

Compared to annual time-matching, hourly time-matching leads to higher capacities of contracted resources for H_2 production under both additionality modeling frameworks. Consequently, **hourly matching generally leads to reductions in carbon-based generation**, especially NG, compared to the baseline grid scenario for both ERCOT (Figure 3C/D) and FRCC (Supplementary Figure 19). The increased capacity deployment is necessary to ensure that the VRE generation plus net-discharge of battery storage from contracted resources is at least equal to hourly electrolyzer power consumption (Eq. 3).

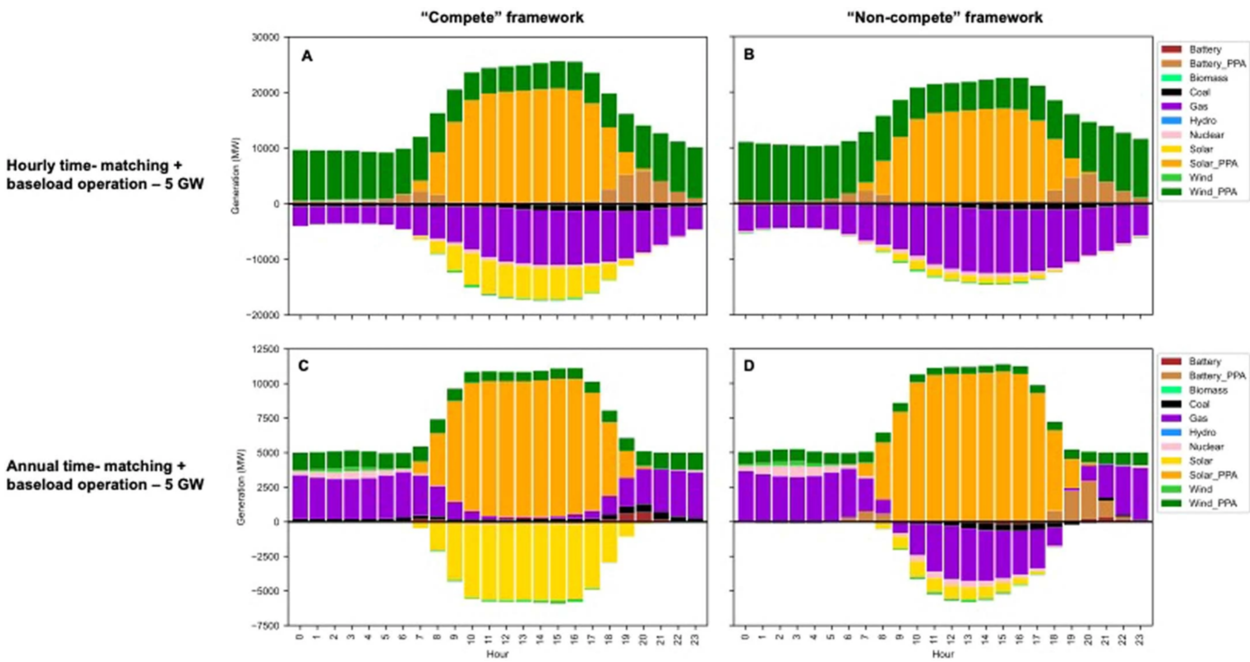


Figure 4. ***Difference in average hourly dispatch between grid with and without H_2 production.*** *Difference in average hourly dispatch in ERCOT between counterfactual and baseline grid under the 'compete' (1st column) and 'non-compete' definitions (2nd column) of additionality and annual (top row) and hourly time-matching requirements (bottom row): A and B: 5 GW of H_2 production with baseload electrolyzer operation and annual time-matching requirements. C and D: 5 GW of H_2 production with baseload electrolyzer operation and hourly time-matching requirements. Resources with suffix '_PPA' refer to resources added specifically to meet time-matching requirements for H_2 production.*

Extensive deployment also implies that these contracted resources will generate in excess of electrolyzer power demand at certain times. As such, more expensive generation on the margin is displaced (Figure 4A/B). The displaced generation includes VRE resources that would have been deployed in the baseline grid as well as NG and, to a limited extent, coal generation. Hourly time-matching generally leads to low or negative emissions under both additionality modeling frameworks. In the "compete" framework, competition with non-contracted grid resources results in less negative, or even positive, consequential emissions (Figure 5).

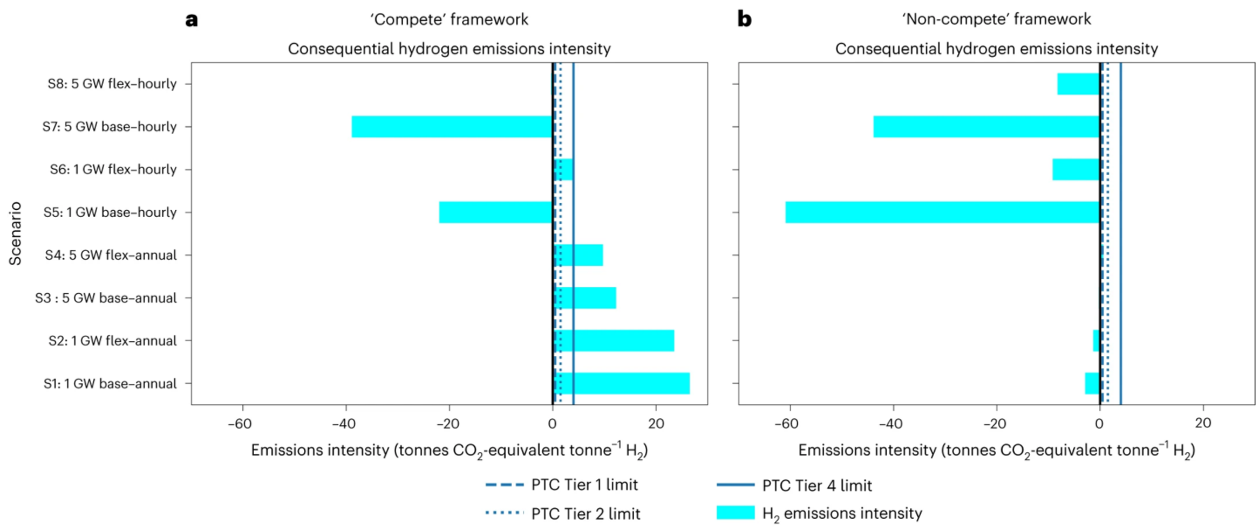


Figure 5: ***Emissions impacts under alternative additionality frameworks.*** *Consequential emissions intensity of H_2 production for alternative H_2 demand scenarios, electrolyzer operation modes and time-matching requirements under the 'Compete' (a) and 'Non-compete' (b) frameworks of additionality. Results correspond to the ERCOT case study and are reported relative to the baseline grid. Also shown are threshold emissions intensity values for the H_2 PTC in the IRA. H_2 that meets the Tier 1 limit is eligible for a credit of US\$3 kg−1, whereas H_2 that meets the Tier 2 or Tier 4 limits are eligible for credits of US\$1.0 kg−1 and US\$0.6 kg−1, respectively.*

In the annual time-matching cases and the "compete" framework, additional gas generation is needed to meet electricity demand for H_2 production during times of low solar availability (Figure 4C). In contrast, under the "non-compete" framework, increases in gas generation during low VRE availability hours are largely offset by decreases in gas and coal generation during hours with high solar availability (Figure 4D). This is explained by more VRE investment for non-H_2 electricity demand under the "non-compete" framework, which is the main driver of the diverging consequential emissions under annual matching when comparing both additionality frameworks (Figure 5). **In the "compete" framework with annual time-matching, the emissions under baseload operation are greater than the emissions of H_2 produced using NG without CCS** [11]. Flexible operation slightly mitigates this effect by limiting NG generation versus the baseline grid.

Flexible electrolyzer operation results in lower capacity deployment for both annual and hourly time-matching requirements under both additionality modeling frameworks (Figure 5). This is because flexible operation enables the shifting of electricity consumption for H_2 production to better match the availability of contracted VRE resources, while relying on relatively low-cost H_2 storage (Supplementary Table 2) to meet H_2 demand. It also avoids the need for expensive battery storage deployment to meet hourly time-matching requirements, instead deploying H_2 storage capacity (Supplementary Figure 7 and 8). As a consequence, under flexible operation, the volume of excess electricity sales is lower (Supplementary Figure 5 and 6), and less negative consequential emissions are observed with hourly time-matching (Figure 5). Interestingly, in the 1 GW H_2 demand scenario with hourly time-matching under the "compete" framework, the combined effect of flexible operation and competition with other grid resources results in positive consequential emissions in both ERCOT (Figure 5) and FRCC (Supplementary Figure 24). This is due to a greater reliance on solar compared to the corresponding baseload operation scenario and the lack of any contracted battery storage that results in greater reliance on NG to meet net load requirements (Supplementary Figures 5 and 6). Higher H_2 demand levels result in wind accounting for a greater share of contracted VRE capacity towards H_2 production, which decreases consequential emissions intensity.

In nearly all cases for ERCOT (Figure 6 and FRCC, Supplementary Figure 25), the **LCOH is greater under hourly versus annual time-matching requirements when disregarding the attribution of a PTC** (Figure 6). Under the hourly time-matching requirement with baseload electrolyzer operation, the LCOH after including the PTC remains greater than \$1/kg in all cases and thus not competitive with NG H_2 without CCS [11]. **Flexible electrolyzer operation reduces the LCOH compared to the corresponding baseload operation scenario when disregarding the PTC** (Figure 6), most notably under an hourly time-matching requirement. This is because the reduction in contracted power sector resources more than offsets increases in the fixed cost of the electrolyzer and H_2 storage. This result reaffirms other studies that note the importance of electrolyzer flexibility to minimize the cost of H_2 production and support grid decarbonization efforts [12].

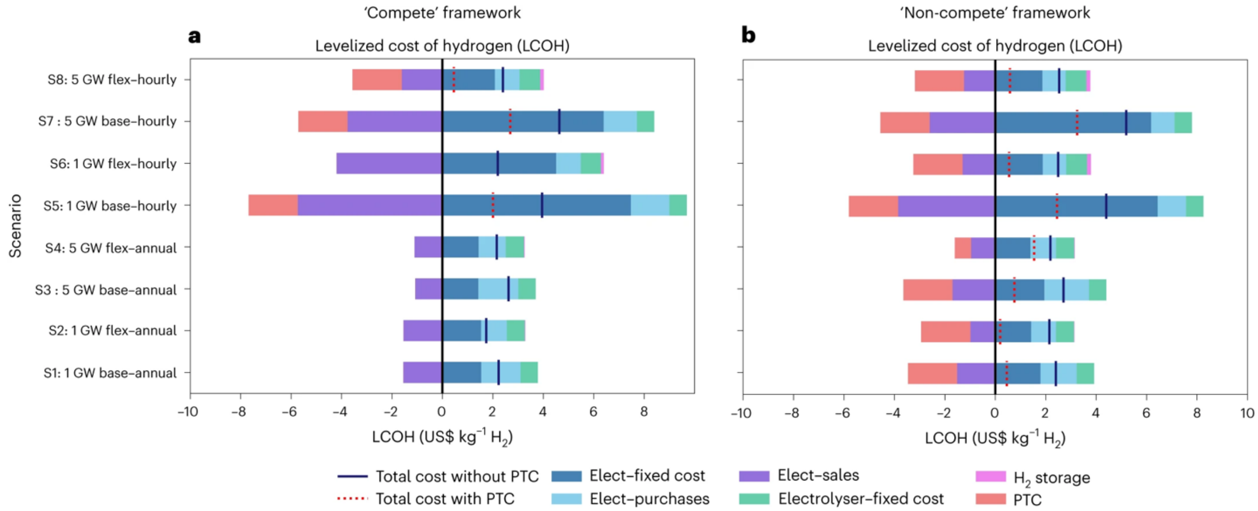


*Figure 6**: LCOH impacts under alternative additionality frameworks.** Levelized cost of H_2 (LCOH) for the ERCOT case study under scenarios with different H_2 demands, time-matching requirements, and electrolyzer operation modes under the 'Compete' (a) and 'Non-compete' (b) additionality frameworks. Levelized cost calculated per description provided in 3.3.4. Elec–sales, revenues earned from selling excess electricity to the grid using contracted power sector resources; elec–purchases, cost of grid electricity purchased to operate the electrolyzer; electrolyzer–fixed cost, annualized capital and fixed operating and maintenance (FOM) cost of the electrolyzer; elec–fixed cost, annualized capital and FOM cost of contracted power sector resources, after accounting for investment tax credit (30%); H_2 storage, capital and FOM cost of gaseous H_2 storage system, which includes the capital cost of the compressor and tank. The total cost with PTC shows the LCOH after accounting for PTC based on consequential emissions for each case.*

LCOH without PTC attribution is generally greater under the "non-compete" framework than the "compete" framework. This is because the value of excess electricity sales, defined as the difference between absolute value of *elec-sales* and *elec-purchases* in Figure 6, is generally smaller in the "non-compete" vs "compete" framework (Supplementary Tables 7 and 8). This is due to two effects. First, in the "compete" framework, H_2 is inherently prioritized and contracts the most valuable VRE portfolio relative to resources built out for non-H_2 load. Second, wholesale electricity prices under the "non-compete" framework are more depressed due to greater amounts of VRE generation in the baseline grid. However, when attributing the PTC that corresponds to the consequential emissions found in our modeling, the "non-compete" cases generally have much lower LCOH than the "compete" cases, especially under annual time-matching.

3.4.2 Impact of Relevant Energy Policies

In this subsection we describe the results of our four policy scenarios. We report the most relevant modeling runs, rather than discussing all results under alternative H_2 demand scenarios, time-matching requirements, and additionality frameworks.

The first two policy scenarios — a minimum annual VRE requirement (e.g., an RPS) and a lack of an adequate interconnection policy for VRE deployment — test the robustness of the previously described additionality modeling results. Their results provide insights into how the emissions associated with different time-matching requirements may vary based on regional conditions. The final two policy scenarios —an operating constraint on electrolyzers and competition with blue H_2 — assess additional policy levers and technology tradeoffs.

Imposing an annual VRE generation requirement for non-H_2 electricity demand

Here we introduce a minimum annual VRE requirement in serving non-H_2 load that is above the level that is optimal with regards to the objective function. Such a requirement can be interpreted as an RPS policy or an aggregation of voluntary VRE procurement commitments of grid users. This policy scenario is most relevant under annual time matching and the "compete" additionality framework due t the high emissions associated with H_2 production in the base case (Figure 5).

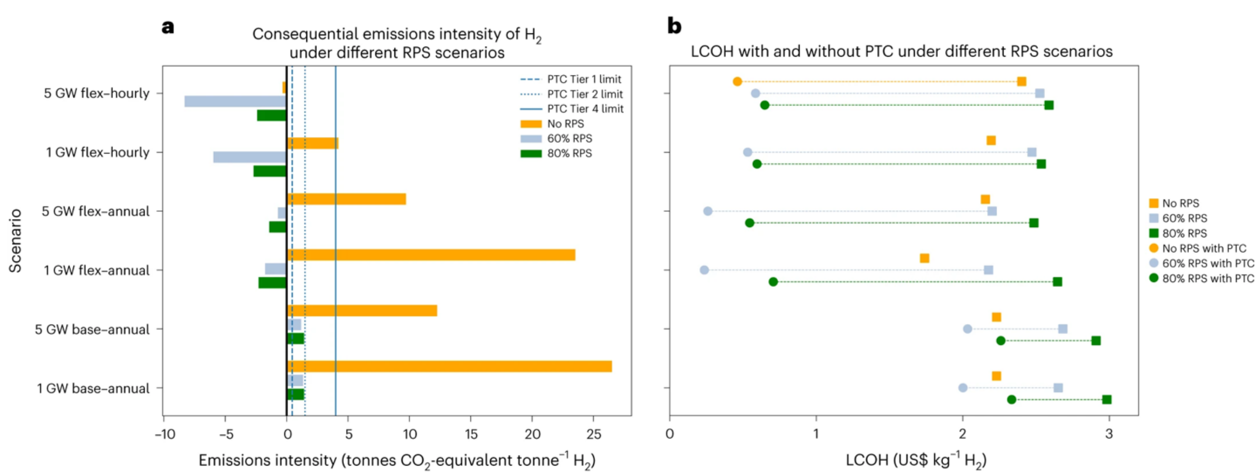


Figure 7. ***Emissions and cost under binding renewable electricity targets.*** *a,b, Consequential emissions intensity of H_2 production (a) and levelized cost of H_2 with and without the PTC (b) under VRE requirements (no RPS, 60% RPS and 80% RPS) for scenarios with different H_2 demand levels, time-matching requirements and electrolyzer operation modes under the 'compete' additionality framework. Results correspond to the ERCOT case study. For the levelized cost of H_2, the awarded PTC subsidy is based on the consequential emissions intensity of H_2 for each scenario. Additional results for the annual VRE requirement scenarios are reported in Supplementary Figs. 12–14.*

The key finding (Figure 7A) is that **enforcing a minimum VRE requirement of 60% under the 'compete' framework is sufficient to reduce the consequential emissions associated with both annual and hourly time matching below the most stringent PTC threshold**, when flexible operation is considered. In short, the consequential emissions under the 'compete' framework with the RPS mirror those under the 'non-compete' framework without RPS (Figure 5). This is because the RPS effectively reduces competition between the VREs built for non-H_2 load and those contracted for H_2 production, thereby making the latter 'strictly additional'.

Under an hourly time-matching requirement, a RPS of 80% results in less negative consequential emissions than the 60% RPS due to the declining value of excess electricity sales from the VRE resources available for H_2 production. Moreover, under an 80% RPS, the emissions intensity associated with H_2 production under hourly or annual time-matching requirements becomes relatively similar. This finding suggests that in very high VRE grids, at least with regards to consequential emissions, the choice of an hourly or annual time-matching requirement has limited impact.

Figure 7B shows that a RPS increases LCOH, not accounting for PTC attribution, similarly to the trend seen under the 'non-compete' framework as compared with the 'compete' framework in Figure 6. The competition between VRE deployments for H_2 production and the RPS results in a lower value of electricity sales to the grid and thus a higher LCOH. The impact is smaller for hourly matching, which may be due to the increased availability of energy storage (Supplementary Fig. 14) that enables electrolyzers to reduce their electricity purchase costs. Nevertheless, the relatively larger LCOH increases for annual time matching with a RPS policy are more than offset by the eligible PTC under this scenario.

Introducing a constraint on the VRE + battery storage buildout

In this policy scenario, we introduce a constraint on the maximum buildout of VRE + battery storage. This policy scenario is most relevant under hourly time-matching under which larger VRE capacities are deployed to serve H_2 load compared to annual time matching. Figure 8 shows the results for the "compete" framework and relatively high H_2 demand (5 GW) that can be served by operating the electrolyzer flexibly. Under a 1 GW H_2 demand and flexible electrolyzer operation, the VRE capacity constraint is not binding and hence not shown.

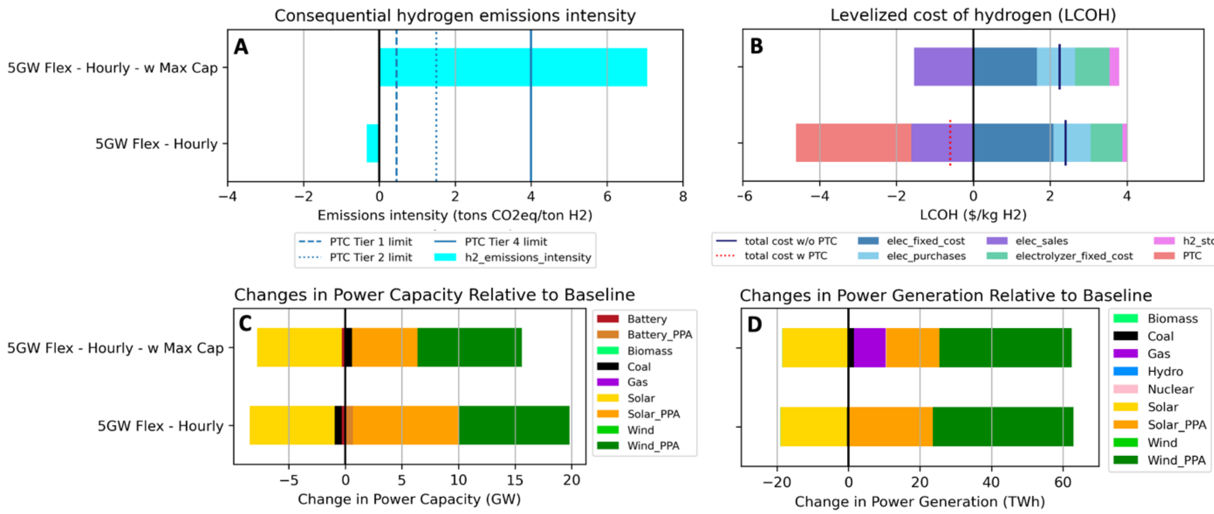


Figure 8. ***Impact of limits on the capacity of renewables plus storage deployment.*** *a-d, Consequential emissions intensity of H_2 production (a), levelized cost of H_2 (b), power system capacity change (c) and power system generation change (d) under an hourly time-matching requirement with 5 GW of hydrogen demand and flexible electrolyzer operation with unconstrained VRE plus storage capacity deployment and a 15 GW limit under the 'compete' modelling framework. Note that 15 GW VRE plus storage deployment limit is not binding for the 1 GW electrolyzer demand. Results correspond to the ERCOT case study and are reported relative to the baseline grid involving grid resource expansion without any H_2 demand. See the caption of Figure 5 for details on the consequential emissions subplot (a) and the caption of Figure 6 for details on the LCOH subplot (b). Additional results for the VRE deployment scenarios are reported in Supplementary Figs. 17 and 18. An explanation for the 15 GW VRE and storage limit is provided in 3.3.4.*

A limit on the buildout of VRE and battery storage, which represents interconnection or supply chain challenges, leads to equal or lower-than-cost-optimal VRE capacity levels. Figure 8 highlights that this effect is most impactful under hourly time matching under which higher VRE capacity is deployed to serve H_2 load. **Such a buildout limit results in substantially greater consequential emissions associated with hourly matching** under the 'compete' additionality framework (Figure 8A). For 5 GW of H_2 demand, a 15 GW deployment limit causes emissions to rise from being negative to being greater than 6 tonnes CO_2-equivalent per tonne of H_2, exceeding the least-stringent PTC threshold. This occurs because overbuilding VRE capacity relative to electrolyzer demand is not feasible under the buildout limit, which increases fossil fuel generation as compared with the baseline grid case (Figure 8D).

Surprisingly, Figure 8B shows that the introduced constraint has limited impact on LCOH when not considering attribution of the PTC, even though the objective function (system cost) increases by approximately 1.5%. When VRE + storage capacity additions are limited, the VRE mix deployed to contract with H_2 demand favors wind over solar (Figure 8C) to improve capacity utilization, which results in lower electricity-related fixed costs than seen in Figure 6. In addition, to further improve capacity utilization and minimize VRE curtailment, the capacity of electrolyzer and H_2 storage are increased (duration increases from 33 to 61 hours of H_2 demand), which increases their fixed costs and offsets the reduction in electricity-related fixed costs. However, because consequential emissions intensity increases with a VRE + storage capacity limit in place, substantially higher LCOH is seen when considering the PTC attribution.

Finally, it is worth noting that modeling the above VRE + storage deployment constraint with the same H_2 demand is not feasible under the "non-compete" framework. The H_2 demand cannot be fulfilled anymore, as insufficient VRE capacity is available to be built out. A large share of the grid-connected capacity has been utilized by VRE built out in the baseline run to cost-optimally serve non-H_2 load. A possible implication of this result is that under VRE + storage deployment constraints, an hourly time-matching requirement might lead to fewer electrolyzer projects in favor of other low-carbon H_2 production technologies like NG-based routes with CCS (see *Competition with NG-based H_2 production*).

Limiting the electrolyzer's annual capacity factor

In this policy scenario, the maximum annual capacity factor of the electrolyzer is incrementally reduced below levels that are optimal with regards to the objective function (i.e., overall system cost minimization). Setting such limits has been proposed as a lever for reducing emissions under an annual time-matching requirement [16] because they may discourage operation during hours with expensive electricity, which correlates with dirtier electricity. We focus on the case with annual time-matching and the "compete" additionality framework, which saw high electrolyzer capacity factors of 95-96% when assuming baseload operation (see Figure S7 and Figure S8).

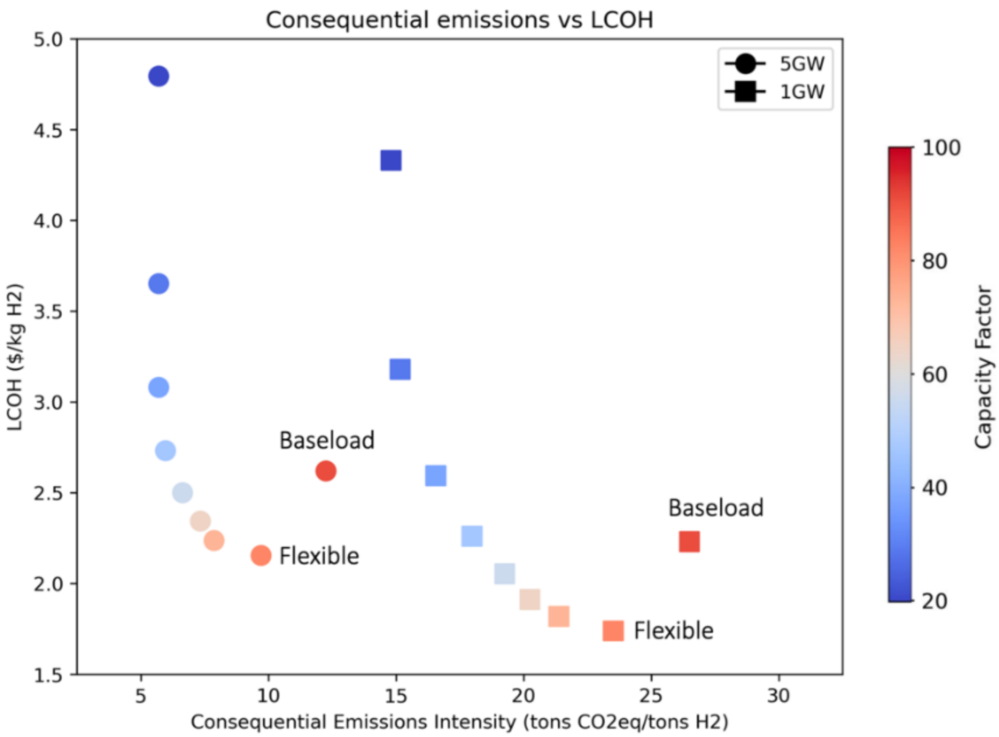


Figure 9. ***Cost vs. emissions tradeoff of limiting annual electrolyzer capacity factors.*** *Consequential emissions intensity vs the levelized cost of H_2 (LCOH) under baseload operation, flexible operation, and scenarios with different upper limits on annual electrolyzer capacity factor (20%, 30%, 40%, 50%, 60%, 70%, and 80%) under the "compete" framework and annual time-matching requirement. Capacity factor refers to the number of hours in a year that the electrolyzer is in operation. The color of each marker indicates the capacity factor at which the electrolyzer operates. The "Flexible" label indicates the scenarios with flexible electrolyzer operation and no capacity factor limit. The "Baseload" indicates the scenarios with baseload electrolyzer operation. Additional results for the electrolyzer capacity factor limit analysis are reported in Figure S9- Figure S11.*

Figure 9 illustrates that limiting the electrolyzer capacity factor results in a trade-off between emissions and cost. Constraining the electrolyzer capacity factor results in lower emissions under an annual time-matching requirement in the "compete" additionality framework, however, this reduction comes at the expense of increasing LCOH. As discussed in the previous section, none of the scenarios with annual time-matching under the "compete" modeling framework achieve even the least stringent PTC emissions threshold. This remains true even at the lowest capacity factor limits modeled here (20%). **Imposing modest capacity factor limits, for instance 80% or 70%, lead to relevant reductions in emissions at only a modest increase in the LCOH** (compared to the scenario where no capacity factor limit is in place — labeled "Flexible"). Reducing the capacity factor limit further conversely leads to very low reductions in emissions at significant increases in the LCOH.

Competition with NG-based H_2 production

In this policy scenario, we introduce competition between electrolytic and NG-based H_2 production to satisfy the exogenous H_2 demand under different scenarios using the "compete" additionality framework.

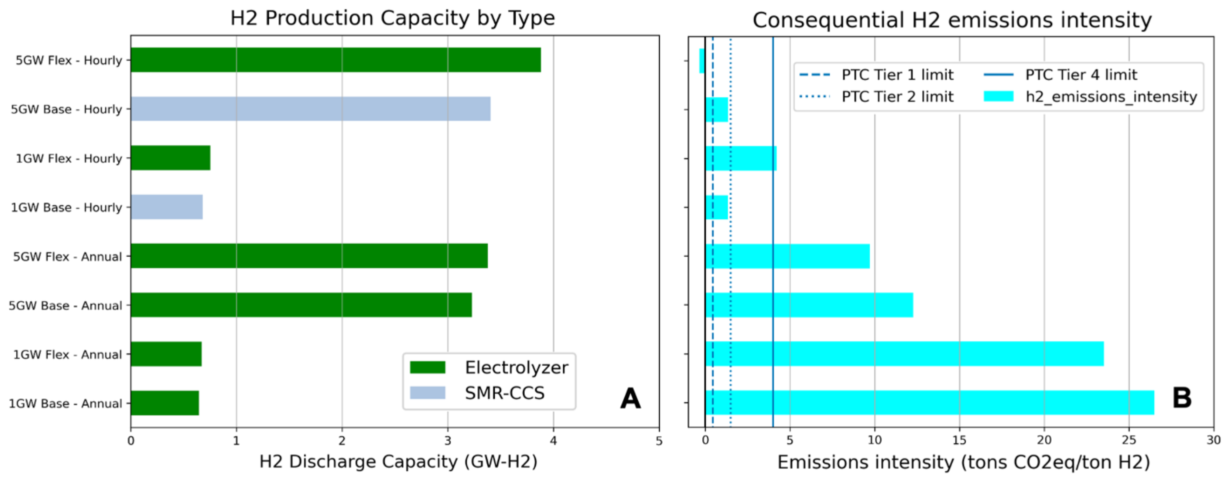


Figure 10. ***Impact of competition with NG-based H_2 production on H_2 production mix and emissions.*** *H_2 production capacity by resources type (available resources are electrolyzer, SMR, SMR with CCS, and ATR with CCS) (A) and consequential emissions (B) under different scenarios of time-matching requirements, exogeneous H_2 demand and electrolyzer operation modes. Results correspond to "compete" additionality framework runs for the ERCOT system SMR = Steam Methane Reforming. CCS = Carbon Capture and Storage. ATR = Autothermal Reforming. Consequential emissions results correspond to the ERCOT case study and are reported relative to the baseline grid involving grid resource expansion without any H_2 demand, as defined in Figure 2. Additional results for changes in power capacity and generation, absolute power and generation capacity, and electrolyzer capacity factors, and battery and H_2 storage are reported in Figure S15-Figure S16.*

Figure 10A shows that substitution of electrolyzers with SMR with CCS (blue H_2) only occurs in scenarios with an hourly time-matching requirement and when baseload electrolyzer operation is enforced. This reflects the LCOH results reported in Section 3.1.3, which shows that compared to the other scenarios, hourly time-matching with baseload electrolyzer operations leads to significantly higher LCOH (Figure 6). An important implication of these results is that, **with the PTC, electrolytic H_2 is competitive with NG-based H_2 production with CCS, even under the more stringent hourly time-matching requirement**, assuming that flexible electrolyzer operation is feasible. However, in a range of scenarios, green H_2 can be substituted by blue H_2, and this is most likely under hourly time-matching. Such scenarios include the cases when flexible operation is not optimal or feasible (e.g., more expensive H_2 storage, or higher than anticipated investment cost of electrolyzers) or when contracting VRE is more expensive than anticipated.

The latter could also include the scenario when VRE + battery storage deployment is constrained due to supply chain or interconnection issues, as highlighted earlier in Figure 8. Future analysis is required to better understand under what conditions overall higher energy system-wide emissions would result when green (i.e., electrolytic) H_2 would be substituted by blue H_2 due to the additional financing and/or grid connection capacity needs that hourly matching introduces.

3.5 Policy Interpretation

Two key results summarize our findings from the standard cases (Figures 3-6) across the two considered regions (ERCOT and FRCC). First, the consequential emissions of electrolytic H_2 are conditional upon how the additionality requirement is modeled. Under the "compete" framework, an hourly time-matching requirement is the only way to reach consequential emissions that are under the threshold needed to receive the highest PTC. In contrast, under the "non-compete" framework, an annual time-matching requirement is sufficient in all cases to meet the threshold needed to receive the highest PTC ($3/kg). The second key result is that independent of the additionality modeling framework, hourly time-matching requirements lead to a higher LCOH relative to annual requirements, excluding the attribution of a PTC, but this disparity can be largely reduced via flexible electrolyzer operation. Considering both electrolyzer operation modes, we find that the increase in LCOH from annual to hourly is $0.25- $2.49/kg, which is a greater range than the $0-1/kg increase between hourly time-matching and no time-matching requirements reported by Ricks et al.

Further, we investigated how four policy scenarios impact our results, with a focus on the results in the "compete" additionality framework where the impacts of time-matching requirements are the most striking.

Table 5. ***Summary of results of the four policy scenarios relative to the results under the "compete" additionality framework*** *(Figures 3-6).*

<table>
<tr><th></th><th>Time-matching requirement</th><th>Consequential emissions</th><th>LCOH</th></tr>
<tr><td>Limiting annual electrolyzer capacity factor</td><td rowspan="2">annual matching</td><td>decrease</td><td>increase</td></tr>
<tr><td>Minimum annual VRE generation requirement ("RPS")</td><td>significant decrease across all cases</td><td>increase under annual requirements</td></tr>
<tr><td>VRE +battery storage capacity buildout limit</td><td rowspan="2">hourly matching</td><td>significant increase when limit is binding</td><td>negligible impact</td></tr>
<tr><td>Use of SMR-CCS to meet H_2 demand</td><td>increase under hourly requirements with baseload operation; flexible operation cases unchanged</td><td>decrease under hourly requirements with baseload operation; flexible operation cases unchanged</td></tr>
</table>

In the first two policy scenarios in Table 5, the consequential emissions under annual matching are reduced relative to the standard case. Significantly, state RPS policies reduce the emissions associated with H_2 production under an annual requirement to below the PTC's most stringent threshold. In the other two policy scenarios, the consequential emissions under hourly time matching increase relative to the standard case in some implementations. In summary, these results show that the existing literature, which does not consider these relevant policy scenarios, in many contexts may overestimate emissions for annual matching and underestimate emissions for hourly matching. These results also suggest that the difference in the LCOH under annual and hourly matching will likely be smaller relative to the standard case.

Our results provide robust evidence for our original thesis: one cannot generalize emission impacts of a specific time-matching requirement in isolation from how other qualification requirements are defined and other existing policies. However, it leaves open an important question for policy makers: which time-matching requirement is the most appropriate to consider when determining eligibility for the PTC in the U.S.?

We call for a regionally differentiated and temporally phased approach. Regarding regional differentiation, we argue that hourly matching, which carries the additional costs and implementation challenges (described below), is not necessary for states with sufficient RPS policies. Our results show that in these states, an annual requirement is sufficient to avoid any increases in emissions associated with H_2 production. However, further analysis is required to determine what constitutes a “sufficient” RPS, which will likely relate not only to the final clean energy target itself, but also the timeline of incremental targets for reaching it.

For states without an RPS, we show that an annual requirement could lead significant emissions impacts. Therefore, we propose a phased approach. It can be argued that the near-term context, in which the relative demand for renewable electricity for electrolytic H_2 is small compared to the total additions of VREs, more closely resembles the “non-compete” additionality framework; we expect significant non- H_2 load related VREs to enter before seeing significantly large volumes of electrolytic H_2. As of May 2023, installed electrolyzer capacity in the United States amounted to 67 MW (579 MW under construction) [31], implying that 1 GW and 5 GW electricity-equivalent H_2 demand would represent roughly a 2X and 10X of installed and under-construction capacity. Moreover, in the near-term, demand for green H_2 is likely to originate from sectors where H_2 is already used today (e.g., ammonia production) and thus, be relatively small compared to the scale of electricity demand. For example, if 10% of U.S. H_2 consumption in 2021 (around 1 MT/year) were to immediately shift to consume electrolytic H_2, it would amount to around ~1% of U.S. electricity consumption as of 2021. At the same time, VRE deployments on the grid are likely to grow rapidly in the near term, as evident from their dominance in the existing interconnection queue in many U.S. regions [21], as well as due to dedicated VRE incentives, e.g., PTCs or investment tax credits (ITCs) in the IRA, state RPSs [19] and corporate procurements [20].

The above interpretation would imply that less stringent annual time-matching requirements may be reasonable in the near term to ensure minimal consequential emissions (Figure 5) while leading to lower LCOH outcomes (Figure 6). Requiring hourly time-matching in this decade may work against the policy objectives of the PTC to scale green H_2 production. While hourly time-matching with flexible operation can also achieve low consequential emissions and LCOH outcomes under the “non-compete” framework, its implementation would require much larger land area, onsite H_2 storage, and capital investments than under annual time matching that may serve as additional barriers. In the case that electrolytic H_2 would manage to secure the scarcely available connection capacity, we have shown that the consequential emissions of H_2 production under hourly matching can significantly exceed the lowest PTC tier (Figure 8). In addition, under hourly matching, the likelihood of substitution of green H_2 with blue H_2 is higher than under annual matching, again leading to potentially increased overall system-wide emissions (Supplementary Figure 28).

In contrast, in the near-term, lower implementation barriers and electrolyzer H_2 sales prices under annual matching would encourage the deployment of electrolyzers, allowing for technology scale up and associated reductions in capital costs. Realizing low prices for green H_2 would support long-term economy-wide decarbonization goals by potentially displacing fossil fuel based H_2 in industrial applications, as well as stimulating new demand for H_2 in end uses that are currently dominated by fossil fuels (e.g., heavy-duty transport). In the case of the new H_2 demand, additional investments will be needed to facilitate H_2 use (e.g., refueling infrastructure, new equipment), and having cheap H_2 in the short-term incentivizes its use. To mitigate risk of competition for VREs during peak periods, the introduction of an annual capacity factor limit for the electrolyzer can be a pragmatic policy to complement annual time-matching requirements. Slight decreases in the capacity factor (e.g., capacity factor ≤ 80%) lead to important decreases in emissions at the expense of only a limited increase in the LCOH (Supplementary Figure 29).

However, as demand for green H_2 grows, it is likely that the magnitude of VRE resources contracted for H_2 production will grow and increasingly compete with VRE resources that would be deployed for other reasons. In this case, the "compete" framework for additionality is more suitable to evaluate the consequential emissions impact of H_2 production. Therefore, in the medium-term (e.g., 2030 onwards), shifting to hourly time-matching requirements may be necessary to avoid the risk of high consequential emissions impacts. Moreover, a phased approach for implementing more stringent hourly time-matching may also benefit from capital cost declines for power sector resources (VRE, battery storage) and electrolyzers that would make the LCOH outcomes for hourly time-matching more compelling than values estimated here.

Finally, in the longer run, when grids are highly decarbonized (e.g., over 60% of non- H_2 load covered by low-carbon generation including VREs, nuclear, hydro), an hourly time-matching requirement may no longer be necessary. Annual matching under flexible operation can achieve negative consequential emissions and similar LCOH outcomes as hourly time matching, without incurring additional VRE and storage investment (Figure 7A). Collectively, these factors indicate that a phased approach on defining the qualifying requirements for the H_2 PTC may be the most pragmatic approach to minimize barriers to grid decarbonization while at the same time stimulating electrolytic H_2 use in difficult-to-decarbonize applications through the availability of low cost H_2 supply.

Chapter 4: The Impact of VRE Uncertainty on PTC Modeling and Implementation

4.1 Motivation: Treasury Proposes Strict Time-Matching Requirements

On December 22, 2023, four months after the August deadline set by lawmakers, the Treasury released a draft of the final PTC rules [26], followed by a 60-day period for public comment. The proposal adopted relatively strict versions of additionality, deliverability, and time matching, with modest flexibilities that are consistent with the policy recommendations outlined in Chapter 3, specifically a phase-in period for hourly time-matching.

Treasury's proposed 45V rules [32]

Additionality: Electrolyzers must procure electricity from "new clean power" resources (instead of "additionality, the draft rules use the term "incrementality"). Eligible resources must have begun operation no earlier than 36 months before the electrolyzer.

Deliverability: Electrolyzers and generators must be located within the same transmission zone, as defined by the DOE's National Transmission Needs Study [27]. This reduces the risk that electricity generated by the contracted VRE resource will not be deliverable due to transmission bottlenecks.

Time matching: Annual time matching until 2028, then hourly. Electrolyzers operating before the beginning of 2028 will only have to meet an annual time-matching requirement. However, all electrolyzers, including existing projects, must meet an hourly time-matching requirement by 2028. Current interpretation of the guidance is that grandfathering will not be allowed [28]. Compliance with the time-matching requirement is tracked via the purchase of energy attribute certificates (EACs), which means that new markets for hourly EACs (currently only annual are available) must be created by 2028.

Treasury is currently reviewing over 30,000 public comments before finalizing the rules [32], and while there has been no indication that that the additionality or hourly time matching provisions will be abandoned, there has been reporting that DOE is actively considering where exemptions may be reasonable [33].

4.1.1 Implementing Time Matching: Challenges and Possible Exceptions

Treasury's proposed rules raise a number of questions related to the feasibility, cost, and emissions of low-carbon electricity-based H_2 production in the U.S. Chief among them is the impact of VRE uncertainty in meeting a time-matching requirement. When relying on VRE resources for electricity supply to meet the time-matching requirement, H_2 producers will need to contend with the uncertainty in VRE availability across multiple time-scales. A number of papers and reports have used optimization models to estimate the resource mix, cost, and emissions associated with meeting such requirements [9], [10], [16]. But to the best of our knowledge, none of these studies consider the impact of uncertainty in inter-annual VRE availability. This is an important dimension for developers who have to make decisions about how to size their electrolyzer and storage systems, as well as how to structure their contracts for procuring low-carbon electricity and supplying low-carbon H_2 to their customers. It is also relevant for regulators, who have to decide what reasonable flexibilities should be granted to electrolyzer operators. As discussed in 3.4, the intra-annual variability and intermittency of VRE resources make time matching more challenging under an hourly requirement — we investigate whether inter-annual variability further complicates implementation of hourly requirement.

To understand the significance of inter-annual VRE uncertainty, recall from 3.3.5 that industrial applications that use H_2 typically require a near constant flow of H_2. Contracts between electrolyzer operators and their off-takers will likely call for a constant, dependable supply. Thus, electrolyzer operators face the challenge of taking a variable and intermittent supply of clean electricity and somehow delivering a steady supply of H_2, which will likely involve pairing the electrolyzer with storage technologies, i.e., H_2 storage and battery storage. Existing work focuses on finding the lowest cost combination of contracted VRE resources, electrolyzer, and storage technologies to meet H_2 demand over a single weather year for VRE production (e.g., Chapter 3 used 2012 VRE availability profiles). But this approach ignores uncertainty in VRE supply across years — **the cheapest resource mix for one year might not be the best mix when planning a multi-year project that will have to provide a steady supply of H_2 subject to uncertain VRE availability.**

Intuitively, an electrolyzer projected designed to be robust to handle VRE uncertainty will be more expensive, because more storage and/or VRE resources will be needed. This implies that the existing literature, which does not consider VRE uncertainty, likely underestimates the cost of time matching. We ask *what is the impact of inter-annual VRE uncertainty on an electrolyzer projects under hourly and annual time-matching requirement*? This question has particular significance in light of the result from the previous chapter that the emissions associated with different time-matching requirements are dependent on regional policies and grid contexts. Most significantly, binding policies for VRE deployment (e.g., state RPSs) can reduce the emissions under annual time matching to below the PTC emissions thresholds. In states where RPSs are driving VRE deployment for the grid, the more costly hourly requirement may not be necessary to avoid high emissions. If the literature is underestimating the cost of hourly time matching then regulators are less equipped to weigh the tradeoffs between the two time matching standards, which is relevant as they consider whether there are areas for reasonable exemptions to the hourly matching requirement.

Another critical question is *what happens in the event that an electrolyzer is unable to source low-carbon electricity due to adverse VRE conditions but is contractually obligated to produce hydrogen for the off-taker?* Recall that the time-matching requirement is tracked through EACs (energy attribute certificates). In practice, an electrolyzer operator would likely contract with a portfolio of VRE resource owners for the EACs associated with their generation. These contracts are not a guarantee that the sun will shine or that the wind will blow. In the event that the contracted resources cannot supply EACs — for example, because of a period of low VRE production or because the electrolyzer operator did contract with a sufficient mix of resource — the electrolyzer operator will need to procure them elsewhere. Currently, many regions have markets for what are called renewable energy credits (RECs), which are effectively annual EACs typically used to track compliance with the regional RPSs. But there are currently no markets for hourly RECs/EACs that electrolyzer operators could turn to in order to meet their hourly requirement if their contracted portfolio of additional VRE resources fails. This issue does not emerge in the existing literature, because VRE uncertainty is not accounted for in the modeling, and therefore we have little information on the extent to which electrolyzer operators might have to turn to real-time hourly REC/EAC markets.

The rest of the chapter focuses on addressing the above questions using the ERCOT case study introduced in Chapter 3.

4.2 Deterministic vs. Stochastic Modeling: Approaches to Modeling VRE Availability

Existing studies of the cost and emissions performance of time-matching requirements for H_2 production primarily use linear programming models, which optimize investment and dispatch decisions for the power and H_2 sectors from the perspective of a central planner [9], [10], [16] . All such studies, including our own [34], rely on so-called "deterministic" models, which only consider VRE output associated with a single weather scenario and assumes perfect foresight of resource availability. We anticipate three limitations with this approach (and identify additional limitations in the *Results* and *Policy Interpretation*). First, the solution of deterministic models may be highly sensitive to the selected VRE scenario — in turn, the cost and emissions performance of possible policy avenues may not be fully understood by deterministic studies. Second, the solutions may not reflect real world decision making. In reality, H_2 project developers do not have foresight into VRE availability and will instead prioritize a mix of resources that is robust across different scenarios, which may result in different decisions being made about the composition of H_2 systems and the VREs contracted to meet the PTC requirements. Third, deterministic models inflate the value of storage assets, because batteries are optimally dispatched with perfect foresight of VRE availability across only one year.

Alternatively, one can make design decisions regarding the power grid and electrolyzer project using a stochastic model, where the system design is co-optimized with operation over multiple VRE scenarios. In this way, the impact of inter-annual VRE uncertainty is accounted for in the design decisions. Mathematically, the stochastic model can be described as a two-stage stochastic program with investment decisions made in the first stage and operational decisions for each weather scenario made in the second stage [35].

Here, we build on the deterministic modeling approach described in the previous chapter to develop a stochastic model that assesses the impact of VRE uncertainty on PTC implementation. We first test the deterministic approach under multiple VRE scenarios and illustrate how that system sizing, cost, and emissions are highly variable across these scenarios. We then solve the same problem using the stochastic model and compare the stochastic solution to the set of deterministic solutions. Finally, we conduct and out-of-sample analysis in which the design variables from the deterministic and stochastic runs (i.e., the capacities of grid resources and the components of the and H_2 project) are fixed and the system is operated subject to VRE outputs associated with different set of VRE scenarios not considered by the models used for determining the design.

4.3 Methods

4.3.1 The Deterministic Model

The deterministic model introduced in Chapter 3 considers only VRE scenario when finding the optimal mix of grid and H_2 project resources to meet electricity and H_2 demand at the lowest cost. The deterministic formulation of the model in this analysis is exactly as the model described in the 3.3.1., with some modifications outlined in this section. The objective function is composed of two parts: (1) the annualized investment cost of new capacity and (2) the annual fixed and variable operating costs for both existing and new resources as well as costs for load shedding.

Eq. 8 provides a simplified writing of the objective function, where K is generators that have new capacity, T is the set of 8760 hours in a year, G is the set of all existing and new generators, and NSE is the cost associated with non-served energy for demand sources D, which are grid load and H_2 demand. Full details on the objective function and model formulation can be found at [17].

$$OBJ\ min \sum_{k \in K} cap_k * inv\_cost_k + \sum_{t \in T} \left(NSE(t)_{d \in D} + \sum_{g \in G} (fixed\_cost_g(t) + var\_cost_g(t)) \right) \tag{8}$$

4.3.2 The Stochastic model

The stochastic model considers multiple VRE availability scenarios and finds the optimal mix of grid and H_2 project resource capacities that minimizes the sum of investment costs and operational costs across all VRE scenarios. The objective function of the stochastic model is comprised of the investment cost for grid and H_2 resources and the expected value of operational costs for each VRE scenario, s, in the set of VRE scenarios, S, where the probability of a specific scenario is σ_s. We assume that all VRE scenarios have equal probability of occurring, although future analysis may want to explore a more sophisticated approach to VRE scenario probability. Eq. 9 is a simplified representation of the stochastic objective function, which illustrates how the model considers multiple VRE scenarios by considering the expected value of the fixed and variable operation cost component across those scenarios.

$$\text{OBJ min} \sum_{k \in K} cap_k * inv\_cost_k + \sum_{s \in S} \sigma_s * \sum_{t \in T} \left(NSE(s,t)_{d \in D} + \sum_{g \in G} (fixed\_cost_g(s,t) + var\_cost_g(s,t)) \right) \tag{9}$$

4.3.3 Additional Model Modifications

Unless otherwise specified, the stochastic model and deterministic model use the same assumptions as described in Chapter 3 — i.e., technology cost and performance, as well as power system characteristics (electricity demand, existing generators, value of lost load). Here, we report noteworthy changes made to the model for this study.

Clustering low-utilization coal and steam turbine generators

To increase the number of weather scenarios considered in the stochastic model while maintaining computational tractability with off-the-shelf LP solvers (e.g., Gurobi), we reduce the resolution of the characterization of the existing power generation fleet. Specifically, we combined all coal and steam turbines that either operated at <5% capacity factor in the baseline run from the previous analysis or had heat rates greater than 15 MMBTU/MWh into one cluster. This reduced the number of generators from 64 to 47, which enabled more scenarios to be considered in the stochastic model.

Adjusting the value of non-nerved H_2 demand

The value of non-served H_2 demand was changed from \$1,000,000/kgH_2 to \$54,300/tonneH_2. The original value resulted in H_2 demand being prioritized over grid load. The new value, which translates to \$1000/MWh of electrolyzer demand, means that grid load, which incurs a \$9,000\$/MWh cost of curtailment, is prioritized over H_2 load, but is still well above the cost of the most expensive electricity generator, meaning that H_2 demand will only be curtailed in the event of scarce electricity supply.

Constraining on excess electricity sales from PPA resources

A cap on the quantity of annual electricity sales from PPA resources to the grid is implemented under the hourly time-matching requirement to discourage resources that would have been built for the grid to be designated as PPA resources and thereby reduce model degeneracy. Eq. 10 describes how this constraint is implemented in the stochastic model, where the excess electricity sales limited is enforced for every individual VRE scenario. This constraint is adapted from a similar constraint included by Zeyen et al. [16]. Eq. 10 restricts the quantity of electricity sales from contracted VREs to the grid at 120% ($\beta = 0.2$) of annual electrolyzer demand, which translates into a 20% excess sales allowance. Practically, this constraint introduces a stronger operational relationship between PPA resources and electrolyzer by ensuring that majority of electricity generated by the VRE resources is contracted by the electrolyzer.

$$\sum_{t\in T}\left(\sum_{g\in VRE} egen_g^{VRE}(t) + batt_{disch}(t) - batt_{charge}(t)\right) \leq (1+\beta)\sum_{t\in T}\delta_t^{elec} \qquad \forall s \in S \tag{10}$$

4.3.4 Out-of-sample analysis

The out-of-sample analysis takes the solutions generated by the stochastic and deterministic model results (the *design* model) and tests their performance using VRE outputs for other (*out-of-sample model)* weather scenarios. The purpose is to assess the robustness of solutions generated by the stochastic and deterministic model, as well as gain insights into possible contract designs for procurement of hourly renewable electricity and need for real-time hourly EAC markets. The cost-optimal system design for the power grid and H_2 production and storage obtained by the *design* model are fixed in the *out-of-sample dispatch* model where the operation of this system is optimized using an *out-of-sample* VRE scenario than was used to generate the design solution.

Without some level of flexibility in the hourly-time matching constraint, the out-of-sample dispatch model may be infeasible. To quantify maintain model feasibility and quantify how much flexibility is required, a slack term, TMR_{slack}, is introduced into the hourly time-matching requirement constraint (see Eq. 11, which is a modification of Eq. 3) for the out-of-sample cases. This slack term enables the electrolyzer to operate without perfect matching from contracted resources. Without this slack term, the model would be infeasible whenever contracted VRE resources are unable to meet the time-matching requirement. Utilization of TMR_{slack} is penalized at \$500/MWh in the objective function, which is lower than the cost of not serving the grid (\$9000/MWh) but well above the cost of the most expensive electricity generator. This ensures that the slack variable is only used when electricity from the PPA resources is scarce, but that the time matching constraint will not take priority over the grid during grid scarcity events.

$$\sum_{g \in TMR_g} gen_{g,t}^{VRE} + \sum_{k \in TMR_b} \left(dischg_{k,t}^{bat} - chg_{k,t}^{bat}\right) + TMR_{slack} \geq gen_t^{Ely} \lambda^{Ely}, \qquad \forall t \in T \tag{11}$$

4.3.5 Demand and PTC Time Matching Scenarios

We assess the deterministic and stochastic models considering 1 GW of hourly H_2 demand (18.418 tons of H_2 per hour) for all scenarios to be met solely via electrolyzer-based H_2 production either directly or indirectly via H_2 storage. Flexible electrolyzer operation is allowed in all scenarios (see 3.3.2), which our previous analysis confirmed is the most economic operating mode and is likely to be the preferred approach in practice (Figure 6). An annual and hourly time-matching requirement is considered when comparing the stochastic solution to the set of deterministic solutions. For the out-of-sample analysis, we focus on the impact of the more stringent hourly-time-matching requirement givens the Treasury's proposal to enforce hourly matching by 2028.

4.3.6 VRE Data and Scenario Selection

Both the deterministic and stochastic model use hourly VRE availability profiles from ERCOT as inputs. The deterministic model considers one year of hourly VRE generation (8760 hours), whereas the stochastic model considers nine years of hourly data (9 * 8760 hours) for each technology (wind, solar). To construct these profiles, we use the ERCOT's Hourly Wind and Solar Generation Profiles dataset [36] which provides solar and wind generation profiles for existing and planned plants from 1980 to 2021. Existing plants are defined as VRE plants that were operational as of 2020. Planned plants are VRE plants that had received approval for or were under construction as of 2020. The ERCOT dataset uses spatially granular historical weather data to estimate hourly generation from both types of resources for all years in the dataset — e.g., a planned resource will still have an hourly generation profile available for 1980 that is based on the technical parameters of that plant and the weather conditions in 1980. To construct the VRE profiles input into our single-region model of ERCOT, we aggregate by existing or planned resources, sum the hourly generation within both groups, and divide the aggregated hourly generation by the total capacity of each group. The result is four time series (existing/planned x wind/solar) of hourly capacity factors for the years 1980-2021 (Figure 11).

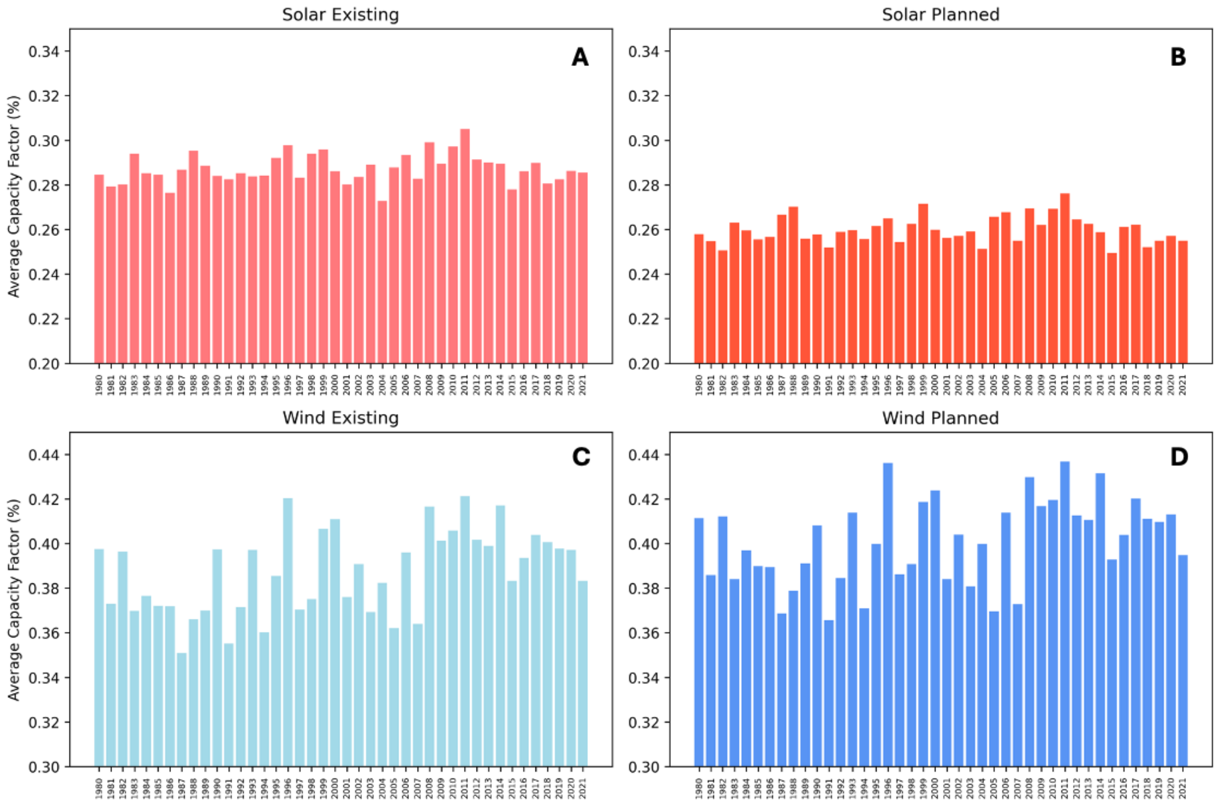


Figure 11. ***Annual capacity factors of solar and wind resources in ERCOT (1980-2021).*** *Capacity factors are reported for solar (A, B) and wind (C, D) resources that are either existing (A, C) or planned (B, C) as of 2021. Note that the y-axes do not extend to zero, which is done to make it easier to observe variation among years.*

Rather than solving the stochastic model over all 41 weather scenarios, which be computationally intractable using commercial solvers, we perform scenario reduction via k-means clustering to identify a set of representative scenarios from the data. The data is sorted into 10 clusters, and we take the closest timeseries to each centroid to constitute a set of 10 representative VRE scenarios. As seen in Chapter 3, wind is favored to meet an hourly time-matching requirement, so we select representative VRE years based on wind. Solar scenarios correspond to the 10 years selected from the k-means clustering for wind. Due to computational constraints, the stochastic model was only able to consider nine VRE scenarios, so the year with the median annual wind capacity factor was dropped from the set of 10 representative VRE scenarios identified by the k-means clustering. These nine representative VRE scenarios correspond to the years 1980, 1985, 1990, 1991, 2005, 2008, 2015, 2017, and 2020, whose hourly capacity factor distribution for new wind and solar resources is highlighted in Figure 12A and B, respectively.

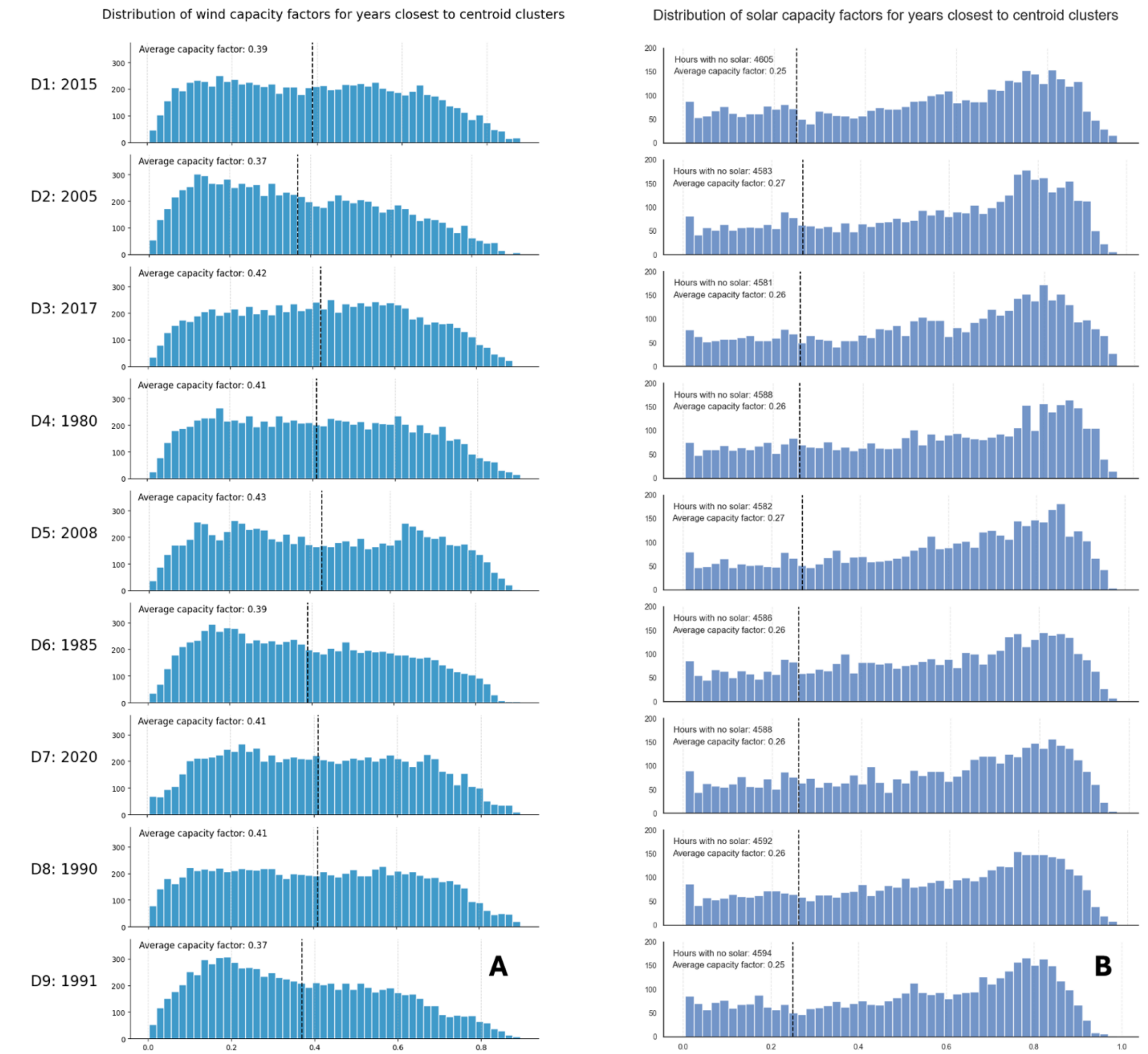


Figure 12. ***Distribution of hourly wind and solar capacity factors for the nine design cases.*** *Data corresponds to planned wind resources (A) and planned solar resource (B) from the nine VRE years selected via k-means clustering from the 41 ERCOT VRE scenarios. Design scenarios are label "DX" followed by the year of ERCOT's VRE data that they correspond to. Vertical lines indicate the average capacity factor. To make it easier to see the distribution of hours with non-zero capacity factors for solar, hours with capacity factors of less than 0.005 are not shown in the chart, but the number of such hours is reported as "Hours with no solar" in the top left of each subplot.*

The 10 out-of-sample VRE scenarios were selected by randomly sampling from the 32 VRE scenarios that are not used for the design cases. The selected years were 1982, 1989, 1993, 1998, 1999, 2000, 2003, 2006, 2012, and 2018 whose hourly capacity factor distribution for new wind and solar resources is highlighted in Figure 13A and B, respectively.

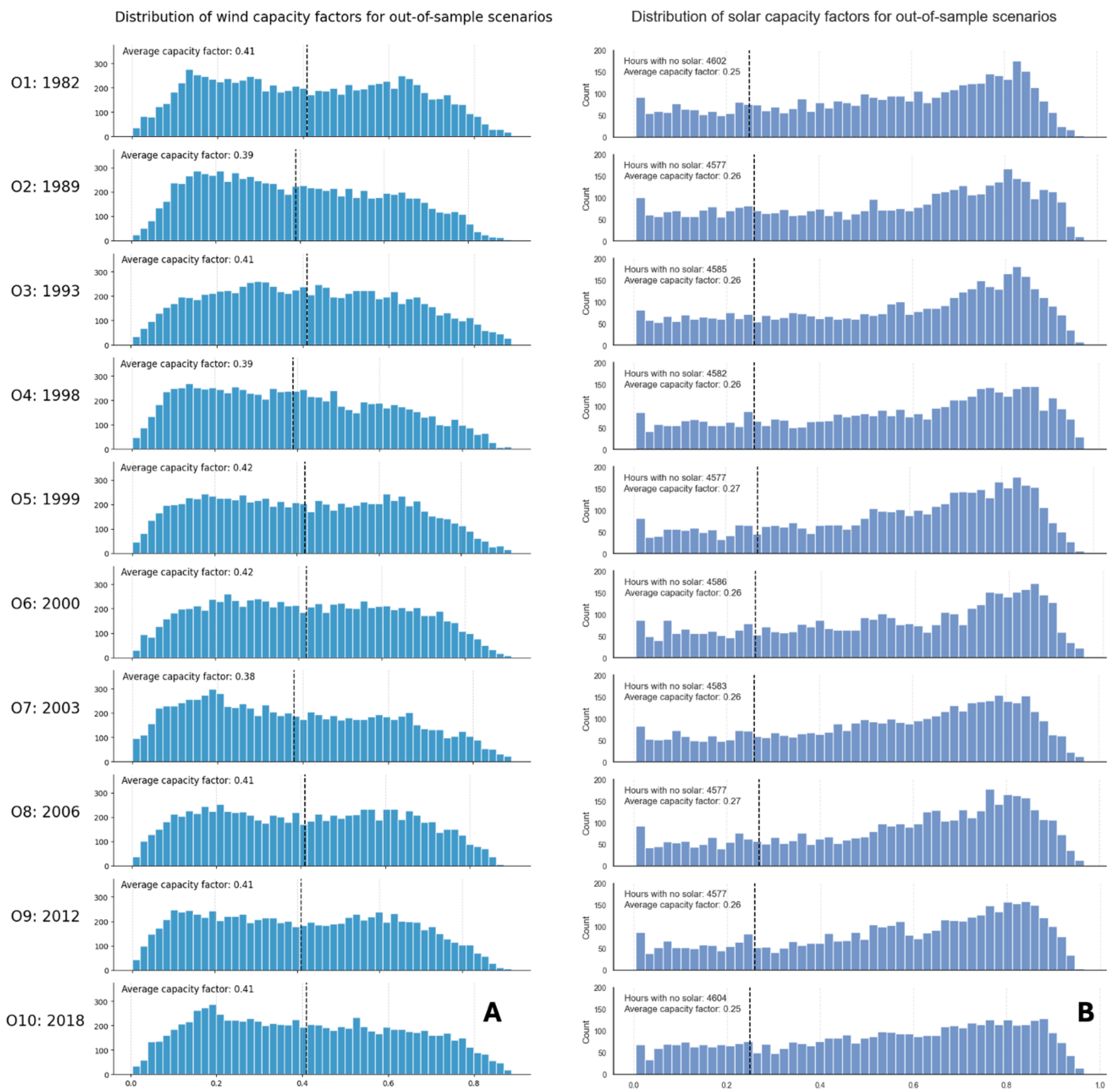


Figure 13. ***Distribution of hourly wind and solar capacity factors for the 10 out-of-sample scenarios.*** *Data corresponds to planned wind resources (A) and planned solar resource (B) from the 10 VRE years randomly selected from 41 ERCOT VRE scenarios, excluding the years used for the design cases. Out-of-sample scenarios are label "OX" followed by the year of ERCOT's VRE data that they correspond to. See caption of Figure 12 for further details.*

4.3.7 Metrics of Interest

The deterministic and stochastic models are compared in terms of the relevant metrics of interested used in the analysis in Chapter 3. These include: a) installed power generation capacity by technology type, b) installed electrolyzer capacity, c) installed energy storage capacity by type, and d) total generation by resource type, and e) levelized cost of H_2 (LCOH).

For the out-of-sample analysis, we also consider several new metrics. First, the *share of unmatched electrolyzer demand* is the sum of the utilization of the TMR_{slack} variable throughout the year divided by annual electrolyzer power demand. This metric reveals the share of the total electrolyzer demand that was not matched with electricity injected into the grid by contracted VRE resources. Since the model is heavily penalized for using TMR_{slack}, at $500/MWh, the *share of unmatched electrolyzer demand* represents the minimum possible utilization of non-contracted grid electricity. Second, we track the number of hours in a year for which the TMR_{slack} variable is used, which indicates how often electrolyzer operators might turn to an hourly EAC market to procure EACs in real-time meet the hourly time-matching requirement. Third, we assess *non-served electricity* (NSE) for the grid, which indicates the fraction of non-H_2 power demand that is curtailed over the year. Fourth, we assess *average annual electricity prices*, which are influenced by NSE and directly impact the LCOH associated with electrolytic H_2 production. This is calculated based on the hourly electricity price timeseries produced by the model (i.e., the dual variable or shadow price of the system-wide electricity supply-demand balance, see [17] for details). Finally, we calculate *impact of lost PTC on LCOH*. This metric is calculated by summing the total quantity of H_2 produced during hours in which the hourly time-matching requirement is not fully met — i.e., TMR_{slack} is utilized — dividing by the total quantity of H_2 produced over the year, and then multiplying by the annualized PTC value ($1.95/kg$H_2$, see 3.3.2).

4.4 Results

Here, we report the results from the stochastic and deterministic design cases, followed by the results from the out-of-sample analysis. The stochastic case, labeled "Stochastic," refers to solution of the stochastic model that simultaneously considers nine VRE scenarios. The deterministic cases, in which each of those nine VRE scenarios that comprise the stochastic model are modeled deterministically, are labeled "D1 – 9." We also report the average of the nine deterministic cases, labeled "Deterministic Average."

4.4.1 Stochastic vs. Deterministic Model with H_2 Demand: Design Outcomes

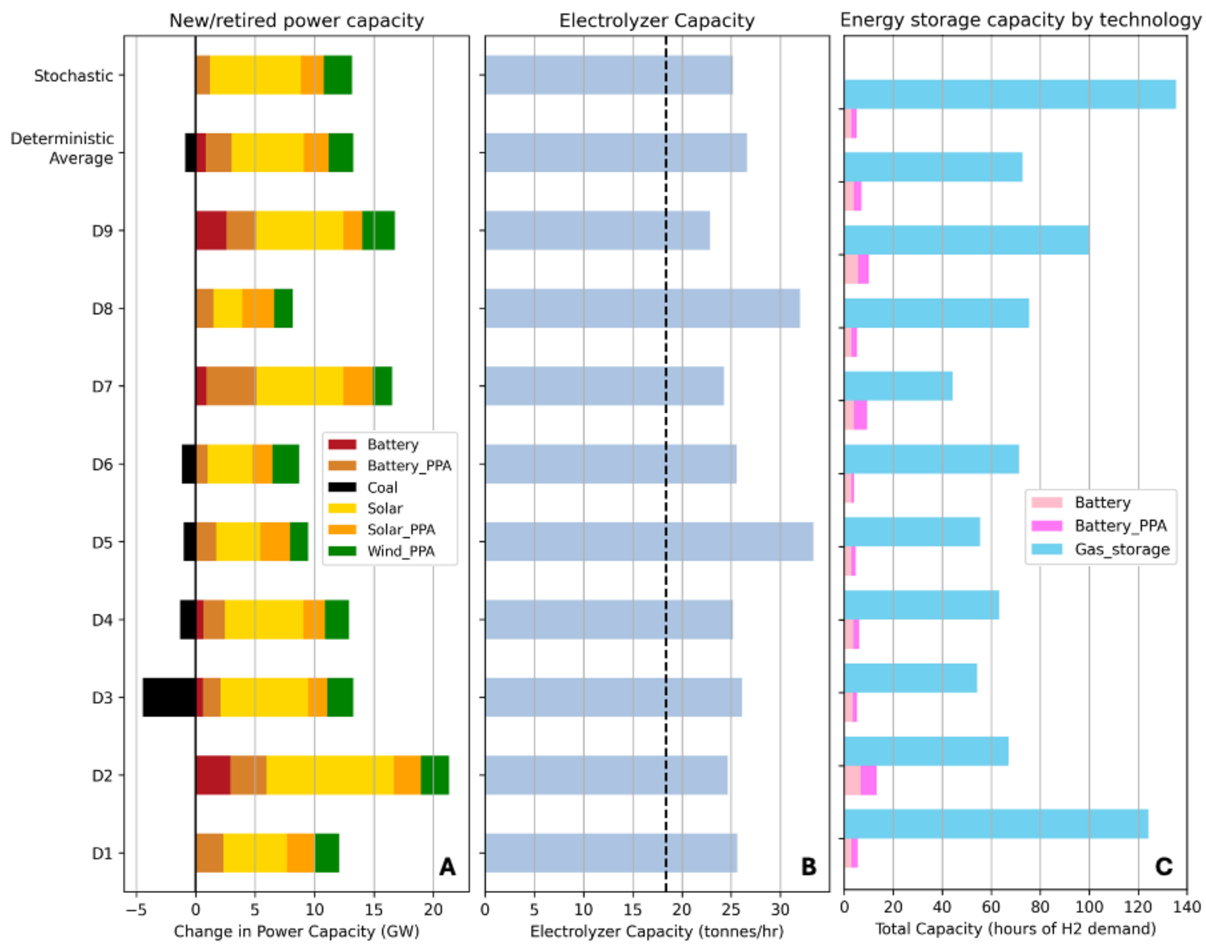


Figure 14. ***System design of the stochastic and deterministic cases under an hourly time-matching requirement.*** *New/retired generator capacity relative to the initial grid state (A), electrolyzer capacity (B) and energy storage capacity by storage technology (C) for the stochastic case, average of the nine deterministic cases, and individual deterministic design cases. Power purchase agreement (PPA) refers to resources added specifically to meet time-matching requirements for H_2 production. Stochastic model (labeled "Stochastic") co-optimizes design over 9 VRE scenarios, while deterministic model is solved for each of the nine VRE scenarios (labeled "DX"). The average of the*

nine deterministic cases is reported as "Deterministic Average." For batteries, energy storage capacity in terms of hours of H_2 demand is calculated by dividing the battery energy capacity (in GWh) by the electricity required for the electrolyzer to produce one hour of H_2 demand (i.e., 1GWh / 18.412 tonnesH_2) — e.g., a 2GWh battery is storage is equivalent to two hours of H_2 demand.

Figure 14 compares key components of the system design from the stochastic and deterministic models under an hourly time-matching requirement. Our first key observation is that **the design of the power sector and H_2 project under the deterministic model are highly sensitive to the underlying VRE scenario**. In particular, the grid changes in solar, batteries, and coal capacity, as well as the capacity of H_2 storage (Figure 14A/C), vary significantly across VRE scenarios, whereas electrolyzer capacity is relatively stable besides two outliers (Figure 14B). Generation by resource type is similarly variable across the design cases, with the largest absolute swings in natural gas, grid solar, and grid wind generation (Figure 15).

Second, we note that **the design obtained by simply averaging the design across all the deterministic cases is notably different than the optimal design obtained from the stochastic model (**Figure 14). On average, the deterministic cases build more battery capacity and less grid solar (Figure 14A, highlighted by the stacked bar corresponding to the deterministic average), as well as much less H_2 storage than the stochastic model — 137 versus 72 hours of H_2 demand (Figure 14C). This suggests that H_2 storage is preferred over battery storage for meeting the time-matching requirement when accounting for VRE uncertainty. There is also retirement of coal capacity in several deterministic cases, averaging ~1 GW across all deterministic cases, whereas no coal is retired under the stochastic model.

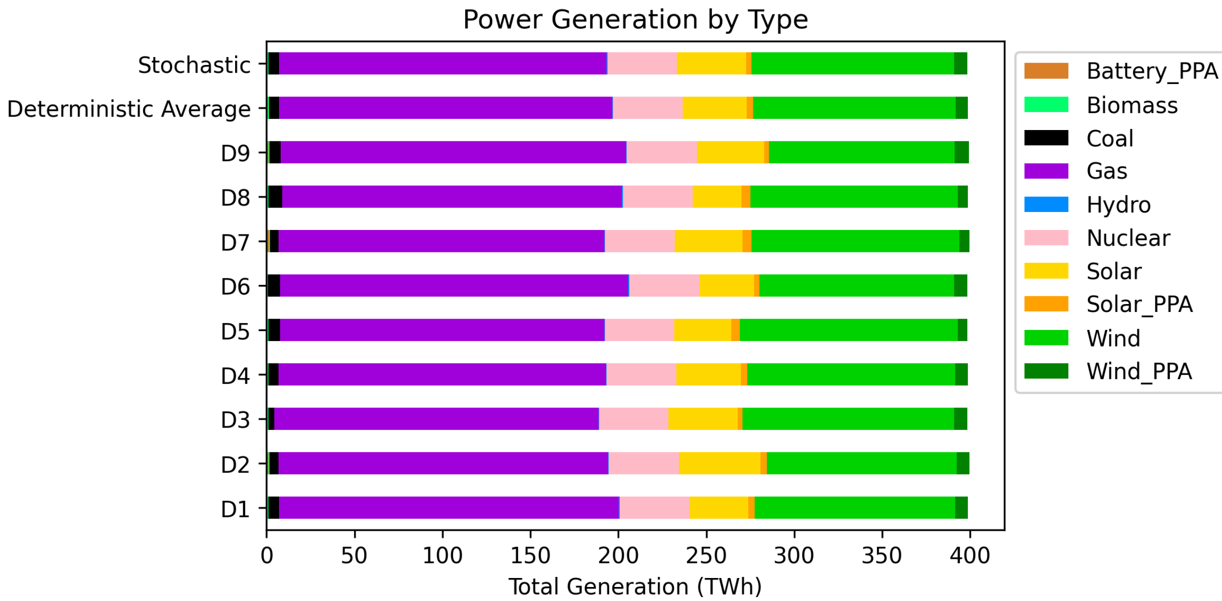


Figure 15: ***Total annual power generation of stochastic and deterministic cases under an hourly time-matching requirement****. Stochastic model (labeled "Stochastic") co-optimizes design over 9 VRE scenarios, while deterministic model is solved for each of the nine VRE scenarios (labeled "DX"). The generation values for the stochastic case correspond to the average generation under the nine VRE scenarios, which are considered simultaneously by the model. The average of the nine deterministic cases is reported as "Deterministic Average." Power purchase agreement (PPA) refers to resources added specifically to meet time-matching requirements for H_2 production.*

Interestingly, these differences in capacity between the stochastic case and average of the deterministic cases do not correspond with notable differences in generation by type (Figure 15). This underscores how the stochastic model is sized with reliability in mind. Even though average generation by type is similar to the deterministic average, the underlying resource mix is different (e.g., more coal) to guarantee reliability across multiple VRE scenarios. Later in this section, we describe the relationship between grid reliability and LCOH in the out-of-sample analysis, which relates directly to the power sector capacity mix. Figure 14 also highlights that the electrolyzer installed capacity is similar across the stochastic and deterministic model outcomes, barring a few outliers. This finding is likely due to the relatively high capital cost of the electrolyzer compared to VRE resources that make it necessary to have relatively high capacity utilization (77.0 and 73.3% for the stochastic and average of the deterministic cases, respectively) irrespective of the VRE resource quality.

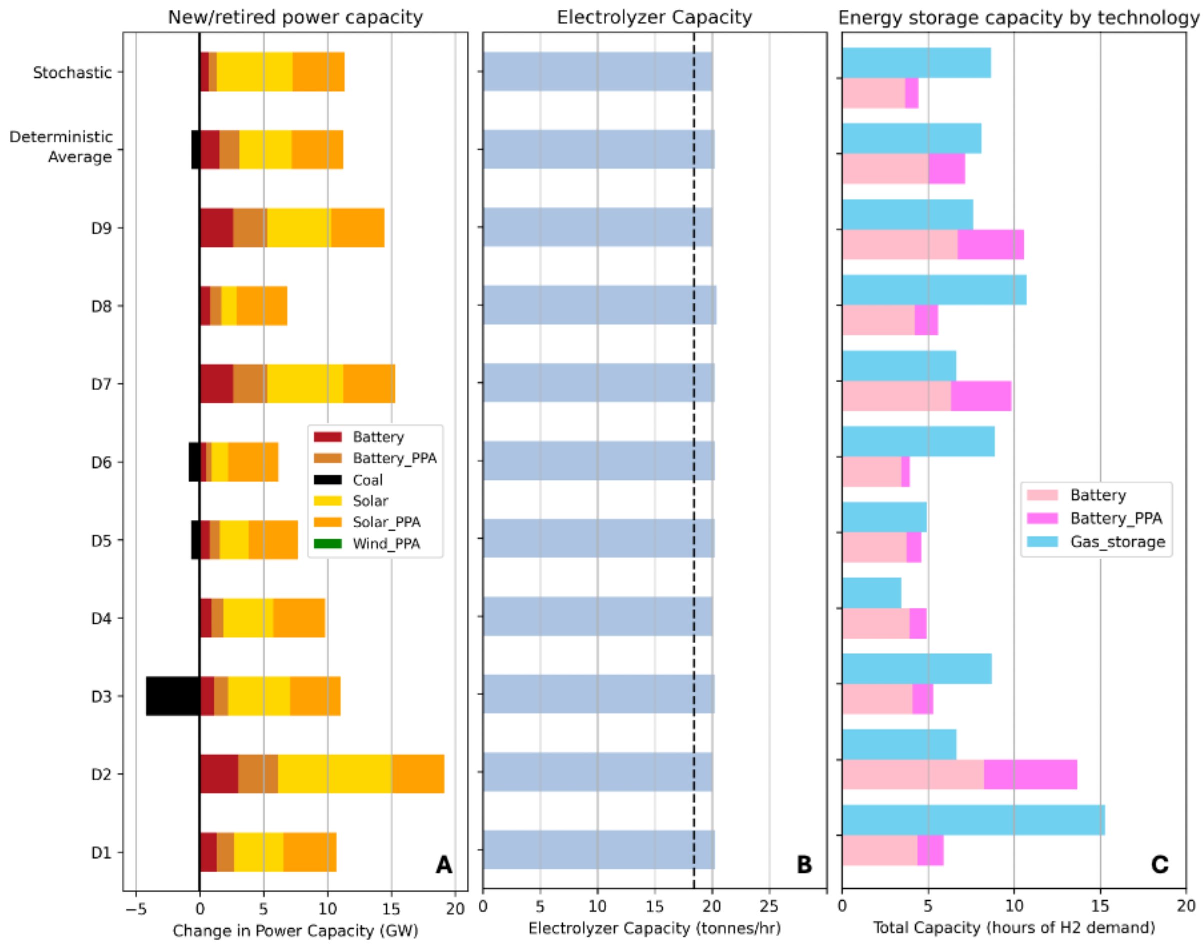


Figure 16. ***System design of stochastic and deterministic cases under an annual time-matching requirement.*** *New/retired generator capacity relative to the initial grid state (A), electrolyzer capacity (B) and energy storage capacity by storage technology (C) for the stochastic case, average of the nine deterministic cases, and individual deterministic design cases. See caption of Figure 14 for further details.*

Figure 16 shows how the differences in system design between the stochastic and deterministic models — i.e., system design under the deterministic model is highly sensitive to the underlying VRE scenario and the stochastic solution differs from the average of the deterministic solutions — are similarly exhibited under an annual time-matching requirement. However, there is less variability in the mix of PPA VREs, since only solar is used to meet the annual time-matching requirement (see a discussion of this in 3.4.1). Furthermore, there is no variability in electrolyzer capacity and less variability in H_2 storage capacity compared to the hourly requirement, which suggests that VRE uncertainty is more consequential when designing the electrolyzer project subject to the more stringent hourly time-matching requirement.

4.4.2 Performance of the Stochastic and Deterministic Solutions Under Out-of-Sample VRE Scenarios

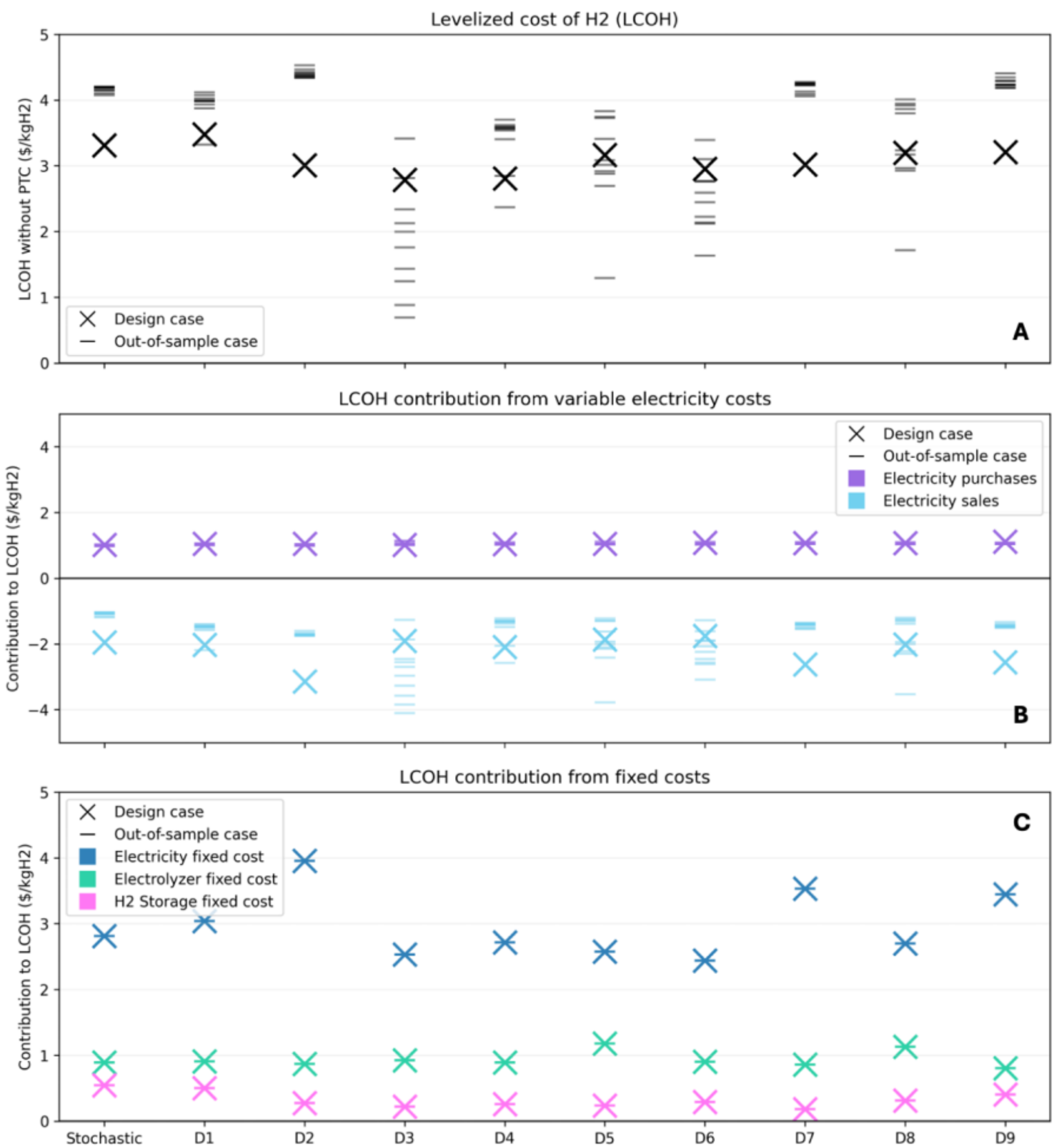


Figure 17. ***LCOH breakdown for design and out-of-sample cases under the deterministic and stochastic models****. Levelized cost of H_2 (A), contribution of variable electricity costs (i.e., electricity sales by the contracted PPA resources and electricity purchases by the electrolyzer)to LCOH (B), and contribution of fixed costs (investment and fixed operation and maintenance costs of contracted electricity PPA resources, the electrolyzer, and H_2 storage) to LCOH (C) for the stochastic model ("Stochastic") and nine deterministic models ("D1-D9") under an hourly time-matching requirement for the design cases ("X") and out-of-sample cases ("—").*

Figure 17Figure 17A shows LCOH obtained from the stochastic model and nine deterministic model runs under hourly time matching for both the design case out-of-sample cases. Recall that LCOH considers the fixed cost of the electrolyzer, H_2 storage, and contracted VRE resources, as well as the variable costs associated with operating those resources and from buying and selling grid electricity (3.3.4). We focus on the hourly time-matching requirement for the out-of-sample analysis given the greater variability in design outcomes for deterministic and stochastic models as compared to the annual time-matching requirement scenario. Furthermore, hourly time matching is currently the standard that the U.S. and E.U. have decided to implement by the end of the decade (2028 and 2030, respectively)

For the design cases, LCOH under the stochastic model is (slightly) more expensive than all but one deterministic model case, which is to be expected because the optimization has to accommodate greater range of variability for VRE resources**.** The fixed cost of contracted electricity resources and the variable cost of electricity sales are the primary factors contributing to LCOH variation across the design cases (Figure 17B/C). However, these two LCOH components have countervailing impacts on overall LCOH — the more you spend on electricity resources the more revenue you earn from electricity sales. Consequently, although there is relatively high variation within these costs categories (e.g., 2.5-4 \$/kg H_2 for fixed electricity costs), overall LCOH does not vary dramatically across design cases (2.8-3.5 \$/kg H_2). Attribution of the full PTC, which reduces annualized LCOH by 1.95 \$/kg H_2, brings most deterministic cases below or within \$0.25/kg H_2 of the \$1/kg H_2 threshold [11] necessary to be cost competitive with fossil-fuel based H_2 production, whereas the LCOH with PTC of the stochastic solution is 1.39 \$/kg H_2.

Regarding out-of-sample performance, LCOH is more variable for designs obtained from the deterministic model and exhibits less variability from the designs obtained via the stochastic model. Figure 17B illustrates how the LCOH variability under out-of-sample scenarios is driven by variability in the revenues earned by electricity sales from the contracted electricity resources. While lower LCOH sounds appealing, these instances of lower LCOH in the out-of-sample deterministic cases are often accompanied with non-served energy on the power grid that leads to high electricity prices and thus high electricity sales revenue. In other words, the low LCOH outcomes in the out-of-sample cases are symptomatic of a myopic design of power grid that leads to non-served energy, rather than a well-functioning H_2 project. When the grid fails to meet demand, which occurs more often in the out-of-sample cases for designs using the deterministic model (see Figure 18), the price of electricity is set to the *value of lost load*, which has historically been set at $9,000/MWh in ERCOT [37]. VREs that are contracted by the electrolyzer can earn high revenues for selling electricity if they are available during these scarcity events. Since the electricity sales revenues of contracted VREs is part of the LCOH calculation, these high-price grid scarcity events result in lower LCOH. This phenomenon is well-illustrated by scenario *D3*, in which LCOH is typically lower for *out-of-sample* cases than the design case (Figure 17A). Figure 18 illustrates the relationship between non-served electricity demand for the grid and high electricity prices, as observed in the out-of-sample analysis of the designs from the stochastic and deterministic model. *D3*, for example, on average experiences nine times as non-served grid electricity as the other cases (0.0081% vs 0.00087%), corresponding with average an electricity price that is nearly double that of the other cases (47.8 vs. 24.1 $/MWh). In this sense, the LCOH of out-of-sample deterministic cases “benefit” from a poorly designed, and consequently overburdened, power sector.

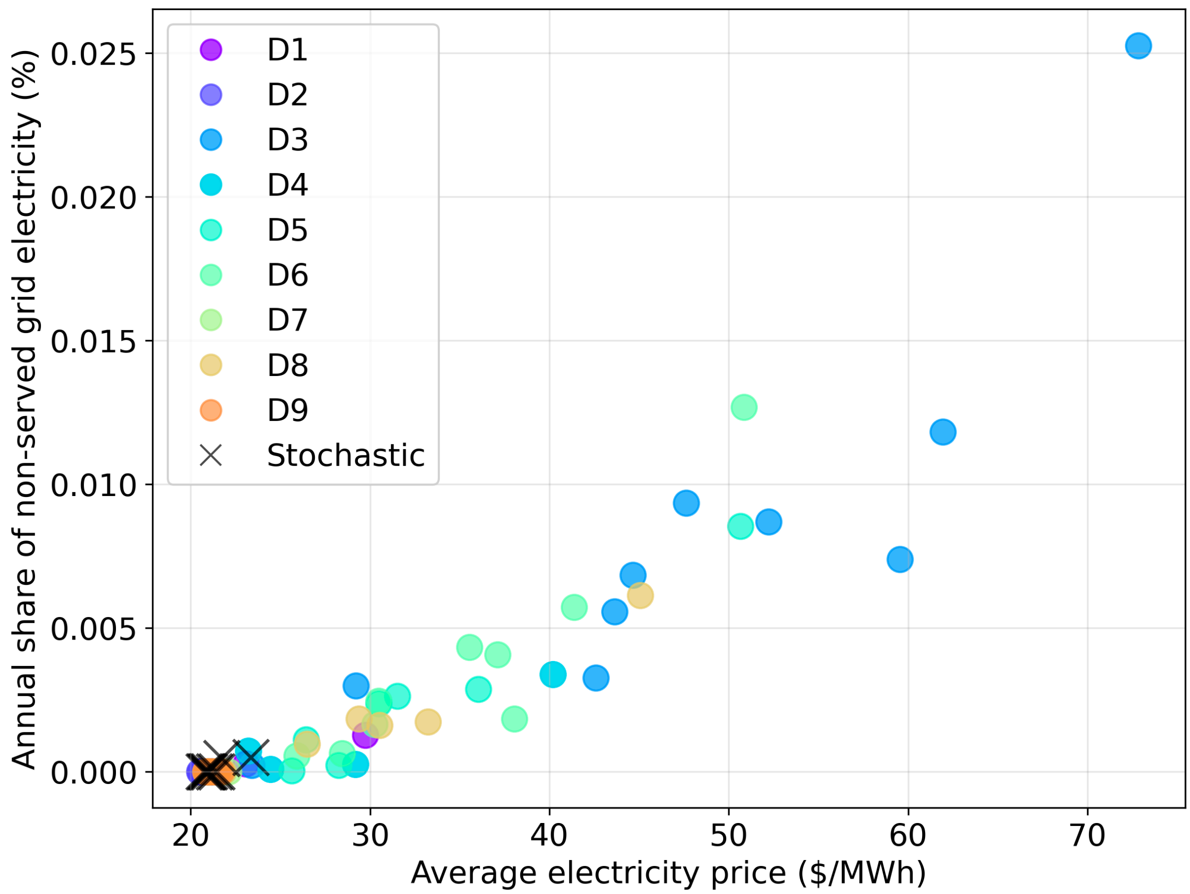


Figure 18. ***Average electricity price vs. share of non-served grid energy for out-of-sample cases.*** *Each point represents an out-of-sample case corresponding to one of the nine design scenarios (differentiated by color) under an hourly time-matching requirement.*

Instances of non-served electricity demand not only impact electricity prices and LCOH; they are symptomatic of a grid that is struggling to maintain reliable operation when subject to different VRE scenarios. **The out-of-sample deterministic cases experience more non-served grid energy than the out-of-sample stochastic cases.** This calls into question how the cost and emissions estimates found from deterministic modeling exercises may be skewed by unrealistic grid choices made in the deterministic model. Recall, for example, how the deterministic design cases had more retirement of carbon-intensive coal generators than the stochastic design case (Figure 14) and lesser reliance on H_2 storage.

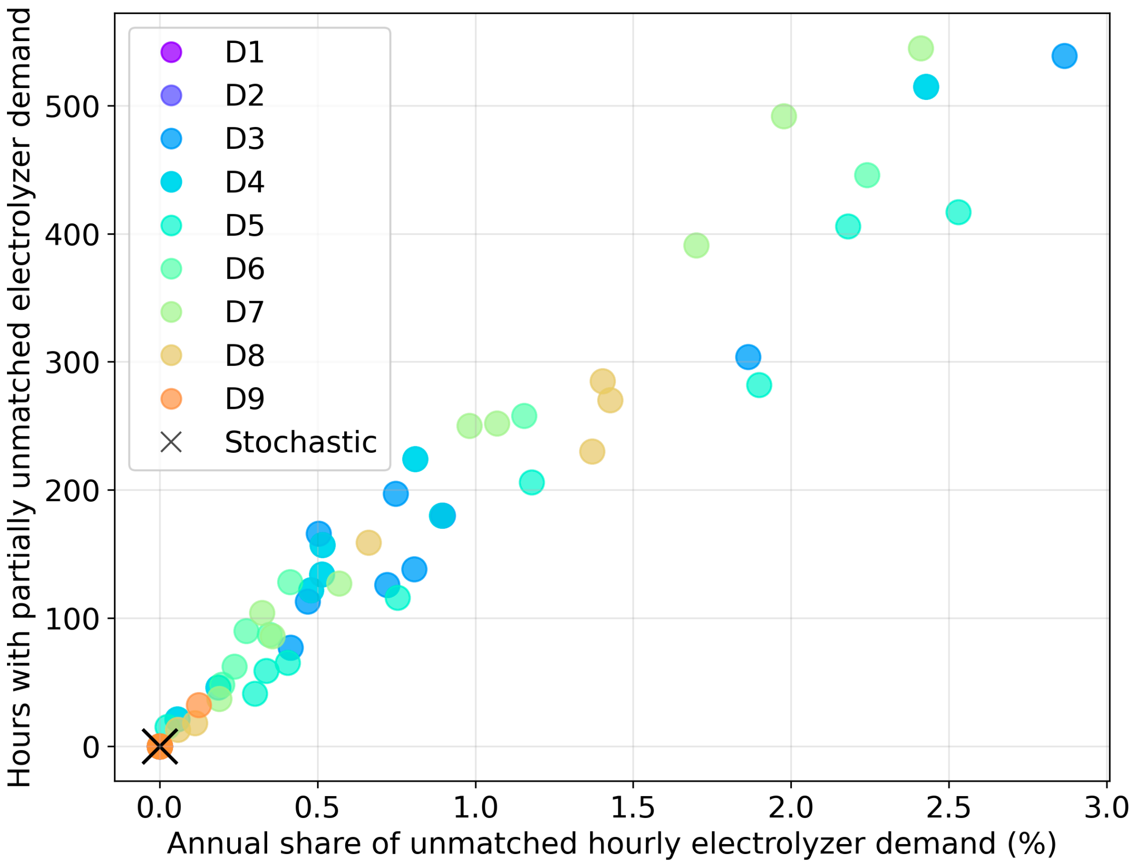


Figure 19. ***Failure to meet perfect hourly time-matching under out-of-sample cases.*** *Annual share of unmatched hourly electrolyzer demand vs. number of hours with partial hourly time-matching for out-of-sample cases. Each point represents an-out-of-sample case corresponding to one of the nine design scenarios (differentiated by color) under an hourly time-matching requirement. The method for computing these metrics is reported in 4.3.*

Figure 19 shows two indicators of how "robust" the H_2 project design in terms of meeting the hourly time-matching requirement: 1) the *share of unmatched electrolyzer demand* on the x-axis and 2) the number of hours in which full hourly time matching is not achieved on the y-axis. **The stochastic design solution is able to meet 100% of the hourly time-matching requirement across all out-of-sample scenarios. In contrast, the deterministic solutions often rely on the $\boldsymbol{TMR_{slack}}$ variable to relax the time matching constraint and source unmatched electricity from the grid.** This phenomenon is most pronounced for deterministic design cases with good VRE scenarios (i.e., the system was sized according to a year with higher VRE availability year, so less VRE and energy storage capacity was installed) when tested using out-of-sample scenarios with lower VRE availability. For example, *D3*, *D4*, *D5*, and *D7* comprise four of the five years with the highest average wind capacity factors (Figure 12), and their out-of-sample cases routinely experience more hours that fail to meet perfect hourly matching than in other cases (Figure 19).

Although the *share of unmatched electrolyzer demand* is higher across deterministic out-of-sample cases compared to stochastic out-of-sample cases, they never exceed 2.9% and are often nearly 0% (Figure 18). Intuitively, this is a low failure rate, and suggests that electrolyzer producer may be able to manage this by requiring that a H_2 off-taker accommodate this level of flexibility in their H_2 supply. However, we identify two dynamics related to the contracted battery that potentially lead to the model achieving higher levels of hourly matching than might be expected in practice. First, the PPA battery systems are oversized relative to the electrolyzer — average PPA battery power capacity across the nine deterministic cases is 2.18GW (see Figure 14A), which is greater than the average electrolyzer capacity of 1.51GW. In other words, the PPA battery is capable of supplying more power than the electrolyzer could possibly use, which suggests that it is being sized for some secondary function besides reliability/cost of the H_2 project. Second, across the deterministic model run for design, only 29.9% of the PPA battery's electricity throughput is used to meet the hourly time-matching requirement, which means the remaining 70.1% is used simply for bridge balancing[1]. These two dynamics — the oversizing of battery power capacity relative to electrolyzer capacity and the battery energy throughput primarily serving the grid— of the contracted battery in the deterministic design cases with hourly matching indicate that there is a "diversion effect" for battery resources. That is, under the current modeling framework **battery capacity that is built primarily to service the grid is possibly being designated as a PPA resource**. We discuss the implications of this, from a modeling and a policy perspective, in the following section.

The number of hours in which the hourly requirement is relaxed (Figure 19, x-axis) is a useful metric for considering how often electrolyzer operators would either need to turn to a real-time hourly EAC market for purchasing EACs to meet their time-matching obligations or require H_2 consumers to reduce consumption. Unless the current formulation of the PTC is adjusted, any hour where full time matching is not achieved will result in the H_2 produced during that hour not

[1] The share of PPA battery electricity that is counted towards the time-matching requirement is calculated by considering how much electricity the battery discharged at any given to fill the gap between electrolyzer demand and PPA VRE generation. This quantity is summed across all hours of the year then divided by the battery's total energy throughput.

receiving the full \$3/kgH_2 tax credit, even if the volume of unmatched electricity is relatively low. Figure 20 shows the impact that not receiving the PTC for this volume of H_2 would have on LCOH for the out-of-sample cases, with a maximum increase of \$0.15/kg H_2. To put this number in perspective, electrolytically produced H_2 needs to achieve and LCOH of \$1/kg H_2 to be competitive with fossil-fuel based H_2 production. Thus, even increases on the order of \$0.1/kgH_2 may be consequential.

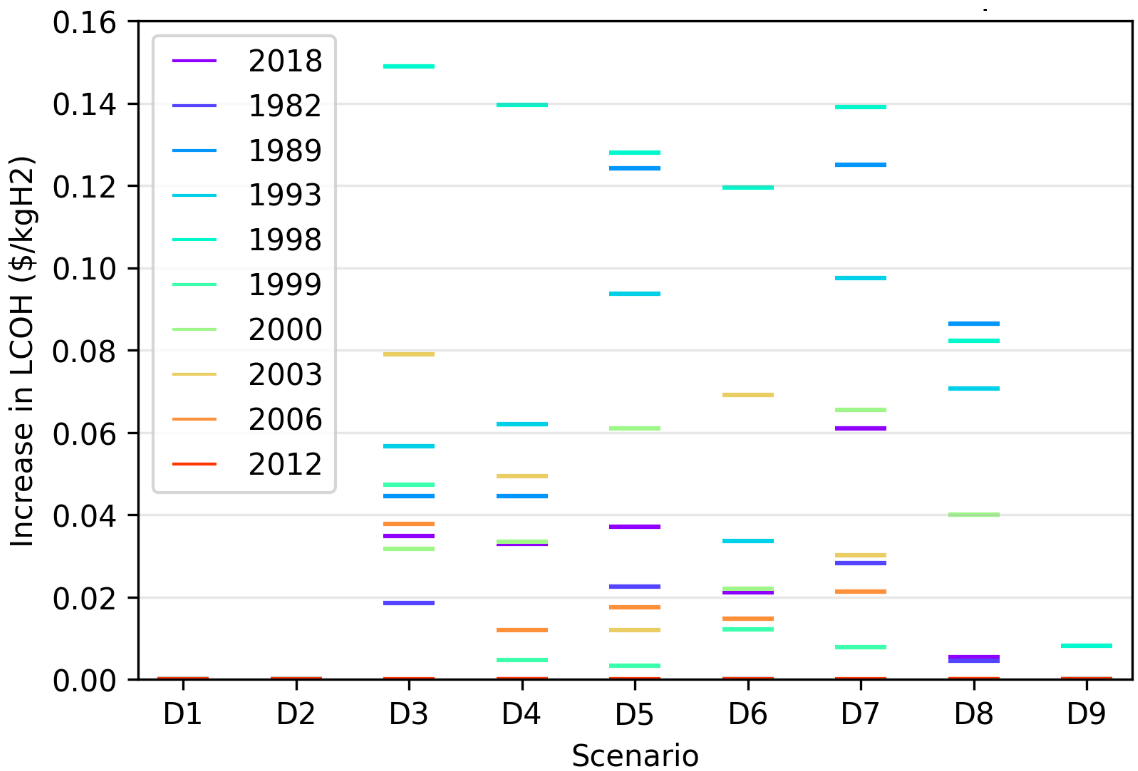


Figure 20. **Impact of lost PTC value on LCOH.** Data corresponds to the out-of-sample scenarios (distinguished by color) for each deterministic design case (labeled “DX”). Markers represent the increase in LCOH resulting from not receiving the PTC for all H_2 produced in hours without perfect time matching, relative if the full PTC was awarded for all H_2 produced.

4.5 Policy Interpretation

From the perspective of electrolyzer developers, we show the importance of designing a system with inter-annual VRE uncertainty in mind. We confirm that a more system design that accounts for VRE uncertainty across years comes at a modest cost premium — a reality ignored by the existing literature. Such a design may be necessary for electrolyzer operators to provide reliable H_2 supply to an off-taker with limited flexibility in their H_2 consumption pattern (e.g. an industrial facility for ammonia production). Furthermore, a robust system design may shield electrolyzer operators from large year-to-year fluctuations in cost of H_2 production that is driven by VRE availability and grid electricity prices.

In the context of hourly time matching, we show that a robust project design — i.e., a design based on a stochastic model — is characterized by 1) significantly more H_2 storage capacity and 2) a diversified mix of solar + wind VRE resources. Furthermore, we show that the deterministic modeling approaches lead to widely varying mixes of contracted energy storage resources, generally under-sizing H_2 storage and overemphasizing batteries.

We also illustrate the need for a market for hourly electricity attribution certificates (EACs) once an hourly time-matching requirement is implemented. Specifically, we identify what a robust project design might look like, but in practice, actually building and contracting for all the resources that constitute a robust system design may be infeasible. For example, in our case study of ERCOT, we find for an electrolyzer project that supplies 18.418 tonnes of H_2/hour (i.e., 1 GW electrolyzer) may require roughly 2,500 tonnes of H_2 storage (equivalent to 137 hours of H_2 demand). For context, the maximum estimated H_2 storage capacity of one of the 379 salt caverns in the U.S is 1,000 tonnes, and the largest liquefied above ground H_2 storage project in the U.S. stores 230 tonnes of H_2 [38]. Furthermore, electrolyzer developers, especially smaller enterprises, may not have the capacity to contract with the diverse mix of VRE resources needed for a robust system design. We find that electrolyzer projects that are not fully robust across multiple VRE scenarios may not be able to achieve full hourly matching with their contracted resources for hundreds of hours in a year. Unless there is a market for hourly EACs that electrolyzer operators can turn to in these instances, they will either have to forfeit the PTC for all H_2 produced in those hours or curtail their production.

This raises an important question for regulators: what reasonable flexibilities can be incorporated into the PTC qualifying standards that make deployment feasible but safeguard against emission increases? In Chapter 3, we identify state RPS policies as a mechanism that makes the less stringent annual time-matching requirement sufficient for reducing the emissions risk. This chapter's findings that inter-annual VRE uncertainty makes implementation more complicated and increases the costs of hourly time matching beyond what the literature estimated reinforces the case for relaxing the hourly requirement in regions with sufficient RPSs. This argument was echoed by the California Air Resources Board and California Clean Energy Commission in a letter to addressed the Treasury and the White House [39]. We argue that, at the very least, regulators should consider giving electrolyzer operators some leeway to relax the hourly requirement, especially if hourly EAC markets fail to materialize.

Finally, we observe that batteries contracted by the electrolyzer to meet the time-matching requirement are, on average, sized to be larger than the peak electrolyzer power consumption and a majority of their energy throughput serves the power sector, not the electrolyzer. Recall from 0 that a cap on the sale of excess electricity from contracted VRE resources is implemented to avoid a "diversion" effect, in which grid resources are nominally considered PPA resources but primarily serve grid demand. But this does not appear to preclude a similar "diversion" effect for batteries. In other words, batteries that would have been built for the grid may be getting designated as PPA resources. Mapping this to the real world, it may be the case that RPS policies, may not be sufficient to stop energy arbitrage resources (i.e., batteries) from being diverted towards H_2 projects. If such a phenomenon can similarly be expected for other loads, like data centers, that pursue time-matching to reduce scope 2 emissions, then the effect could be more VREs on the grid, but not additional energy arbitrage resources to accompany them. The answer may be RPS-like policies for battery capacity, but only 11 states currently have such targets, and only a subset are legally binding [40] [41]. This is a topic that requires further investigation.

Chapter 5: Conclusion

The hydrogen production tax credit (PTC), introduced in the Inflation Reduction Act, is a generous subsidy for low-carbon H_2 production technologies, including the nascent electrolyzer industry. Following the IRA's passage in August 2022, Treasury was tasked with determining key details related to its implementation, including what requirements grid-connected electrolyzers should have to follow to receive the full credit. This thesis aims to equip stakeholders — including the Treasury, regional governments, and industry — with insights into the emissions, cost, and feasibility of different PTC requirements (introduced in Chapter 2), so that the electrolyzer industry may scale in service of the U.S.'s climate commitments.

We begin by resolving a conflict in the literature over whether an annual or hourly time-matching requirement should be adopted (Chapter 3). We show that disparities in the emissions associated with a given time-matching requirement are driven by differences in the approach for modeling additionality. By interrogating how these different modeling approaches map to reality, and further modeling four relevant policy scenarios, we make the following policy-relevant conclusions:

1) The stricter hourly time-matching requirement is necessary to avoid high emissions associated with grid-connected electrolytic H_2 production, unless there are additional policies that force power sector decarbonization.
2) The less strict annual time-matching requirement is sufficient to achieve low emissions if there are policies that force power sector grid decarbonization — namely, state renewable portfolio standards (RPSs) or a high enough volume of private power-purchasing agreements (PPAs).
3) The Treasury should adopt a phased, regionally differentiated approach. In regions without policies that force power sector decarbonization, start with an annual requirement while the risk of high emissions associated with grid-connected H_2 production is lower, then transition to an hourly requirement as the emissions risk increases. Otherwise, simply adopt an annual requirement.

In December 2023, Treasury released its proposed guidelines, which reflect the phased approach we advocated for in an MIT Energy Initiative white paper [42] and article in Nature Energy [34].

By 2028, all grid-connected electrolyzers will have to meet an hourly requirement using additional low-carbon electricity. But the proposed guidelines do not differentiate based on regional policies or grid conditions.

The Treasury is currently reviewing public comments on its proposed guidelines. In this context, Chapter 4 explores a previously unanswered question: what is the impact of inter-annual VRE uncertainty on implementing an hourly requirement? This analysis quantifies how inter-annual VRE uncertainty presents additional cost and implementation challenges under hourly matching. These results equip the Treasury to better weigh the risks and benefits of including exemptions or flexibilities in how they implement an hourly requirement. We make the following policy-relevant conclusions:

1) Designing an electrolyzer project to be robust against inter-annual VRE uncertainty carries a cost premium under hourly time-matching requirements, and as a result the existing literature underestimates the costs associated with an hourly requirement.
2) Achieving hourly time matching will require the creation of a market for hourly energy attribute certificates (EACs) unless some degree of flexibility is included in the requirement itself or in the contracts that electrolyzer operators sign with off-takers.
3) The Treasury should consider a flexible approach to hourly time matching in regions with policies that mandate power sector decarbonization.

The findings are not only relevant for the PTC, but also for a host of similar policies being considered by other states/regional governments (e.g., Colorado [43], California [44], and Europe [12]) to incentivize H_2 production. More generally, these findings are also directly applicable to the broader topic of assessing Scope 2 emissions — i.e., the emissions associated with electricity consumption by companies. Although we anchor our analysis of time matching in the ongoing debate around PTC implementation, our modeling is fundamentally an examination of the emissions impact when any grid-connected load follows different clean energy procurement standards. Indeed, our analysis of electrolyzers without the flexibility of H_2 storage is equivalent to how we might model data centers. Recently, there has been a surge in voluntary efforts by corporate entities to manage Scope 2 emissions as part of achieving corporate sustainability goals [45] [46], as well as increasing interest among regulators and governments to mandate disclosures of Scope 2 emissions [47] [48]. Companies, such as Google and Meta, have begun to advocate for different electricity procurement standards, such as annual or hourly time matching [49]. Our findings regarding the cost and emissions of alternative temporal matching requirements could inform these corporate efforts to meet Scope 2 emissions targets/mandates. In particular, while some studies have argued for hourly time matching as the standard for Scope 2 emissions accounting [50] [51], our results suggest that context matters. In many instances, less stringent standards may be sufficient to ensure system wide emissions benefits.

The author of this thesis believes that, so far, the Treasury has done well. Transitioning from an annual to an hourly time-matching requirement presents challenges, but the alternative — a universal annual time-matching requirement — risks wasting hundreds of billions of public funds to scale a carbon-intensive electrolyzer industry. However, our results identify the opportunity for a regionally differentiated approach, in which regions with policies that drive power sector decarbonization can adopt looser requirements without increasing emissions. Further research is required to support the Treasury in implementing such an approach and to address limitations in our methodology. First, this work does not consider the spatial diversity of contracted VRE resources, which will likely be an important consideration for electrolyzer operators who may prefer to contract with a diverse portfolio of VREs to mitigate challenges associated with renewables variability and intermittency. In addition to enhanced modeling, this topic calls for an applied analysis into the extent to which challenges in contracting for such a portfolio, as well as sourcing sufficient H_2 storage capacity, may favor capital rich enterprises and preclude innovative market entrants. Second, our model does not consider "trajectory effects" — i.e., the evolving interplay between the power sector, electrolyzers, and policies (such as incremental RPS targets) over an extended time horizon. Third, our model only considers a hypothetical RPS scenario for ERCOT, but the regionally differentiated approach we recommend will require applied analysis of state RPSs, and their aggregate effect in the deliverability regions defined by DOE, to determine where it is appropriate to adopt less strict requirements.

Chapter 6: Supplemental Information

Supplementary Tables

Supplementary Table 1. Generation technology cost and performance parameters. A discount rate of 4% is used to annualize investment costs. Reported annualized cost account for the investment tax credit (ITC) for wind, solar and battery storage deployments, which as per the IRA is set to be 30%. Data corresponds to 2022 costs reported by the NREL Annual Technology Baseline 2022 edition [52]. To avoid instances of battery charging and discharging simultaneously, which is possible in a capacity expansion model formulated as linear program (LP), we penalize battery charging and discharging with a small but non-zero variable operating cost.

Technology	Lifetime (years)	Investment cost – power ($/MW)		Annualized CAPEX w/ ITC – Power ($/MW/year)	Investment cost – energy ($/MWh)		Annualized CAPEX w/ ITC– Energy ($/MWh/year)	Fixed operation and maintenance cost		Variable operating cost ($/MWh)
		W/o ITC	W ITC		W/o ITC	W/o ITC		Power ($/MW/year)	Energy ($/MWh/year)	
Solar PV	30	1176,000	823,200	52,105	-	-	52,105	22,721	-	0
Onshore wind	30	1428,000	999,600	56,185	-	-	56,185	17,781	-	0
Li-ion battery storage	15	255,150	178,605	16,064	296,100	207,270	18,642	6379	7403	1

Supplementary Table 2. H_2 production and storage technology cost and performance parameters. A discount rate of 4% is used to annualize investment costs. Data sourced from NREL H2A analysis and other literature [53] [38]. Cost and performance assumptions for natural gas reforming technologies sourced from NETL techno-economic analysis study [28]. The cost of feedwater for electrolyzer is relatively small compared to the cost of energy and thus is ignored in the analysis. SMR = Steam Methane Reforming. CCS = Carbon Capture and Storage. ATR = Autothermal reforming. Cost units of \$/MWH$_2$ are based on converting per tonne capital costs using H_2 lower heating value.

Technology	Lifetime	Investment cost		Annualized investment cost		Fixed operation and maintenance (FOM) cost -H_2 production rate ($/MWH$_2$/year)	Variable operating and maintenance cost (VOM) ($/t H_2)	Electrical power use (MWh/t H_2)	Natural gas (NG) use (MMBtu/t H_2)
		H2 production rate ($/MWH$_2$)	Energy ($/t H_2)	H_2 Production rate ($/MWH$_2$/y)	Energy ($/t H_2/y)				
Electrolyzer	20	1937,791	-	142,586	-	28,604	0	54.3	0
H_2 storage (tank)	30	-	587,000	-	33,929	-	0	-	0
H_2 storage compressor	15	2451,496	-	220,490	-	-	0	0.71	0
SMR-CCS	25	1324,505	-	84,784	-	36,872	241.99	-	185.9
ATR-CCS	25	1046,855	-	67,011	-	28,599	357.6	-	174.7

Supplementary Table 3. Fuel price assumptions for FRCC and ERCOT case studies. Data sourced from EIA Annual Energy Outlook 2022 [29] for 2021 prices. Natural gas and coal modeled with combustion CO_2 emissions factors of 0.05306 tCO_2/MMBtu and 0.09552 tCO_2/MMBtu, respectively. The natural gas cost for CCS technologies applies to both SMR-CCS and ATR-CCS technologies summarized in Supplementary Table 2.

Fuel	FRCC	ERCOT
Natural gas	4.15	2.03
Natural gas cost for CCS technologies	-	2.62
Coal	3.37	2.47
Uranium (for nuclear)	0.71	0.70

Supplementary Table 4. Existing power capacity in GW as of 2021 for ERCOT and FRCC. Generators clusters and technical characteristics (e.g., heat rate) were adapted from 2019 data sourced from PowerGenome [25] to match the 2021 capacity as reported by EIA [29]. Existing battery storage is assumed to have an energy capacity corresponding to a rated duration of 4 hours.

	FRCC	ERCOT
Coal	5.4	14.4
Natural gas combined cycle	31.1	35.1
Natural gas combustion turbine	10.2	7.0
Nuclear	3.7	5.0
NG steam turbine	4.1	10.8
Biomass	0.3	0.1
Hydro	0.04	0.5
Solar	4.8	9.1
Wind (onshore)	0.0	34.1
Diurnal battery storage	0.45	0.7

Supplementary Table 5. Characterization of electricity demand, variable renewable energy (VRE) resource availability and availability factors for other resources in the system. Availability factors refers to the fraction of nameplate capacity of the resource that can be utilized in each hour. For VRE resources, the availability factor, also known as capacity factor, varies from one hour to the next depending on weather conditions. In our modeling we assume constant availability factors for other resources, although these resources may also have unforced outages that could impact their hourly availability in practice. Power demand data was generated by multiplying each hour of a 2019 demand profile generated by PowerGenome [25] by a scalar, so that total annual power demand equaled the 2021 annual demand as reported in [29].

	FRCC	ERCOT
Peak power demand (GW)	48.3	75.7
Annual power demand (TWh)	245.9	388.9
Annual average capacity factor: onshore wind:	30.6%	46.3%
Annual average capacity factor: solar PV	26.6%	29.4%
Hourly maximum availability factor for various resources		
Coal, natural gas, and biomass	90%	
Nuclear	95%	

Battery	100%
Electrolyzers	95%

Supplementary Table 6. Component values for the levelized cost of H_2 in \$/kg H_2 for the "compete" additionality framework for the ERCOT case study under scenario with different H_2 demand (1, 5 GW equivalent power consumption), time-matching requirements (annual vs. hourly), and electrolyzer operation modes (Baseload vs. flexible). Levelized cost calculated per the description provided in Section 6.5. elec_sales = revenues earned from selling excess electricity to the grid using contracted power sector resources ; elec_purchases = cost of grid electricity purchased to operate the electrolyzer; electrolyzer_fixed_cost = annualized capital and fixed operating and maintenance (FOM) cost of the electrolyzer; elec_fixed_cost = annualized capital and FOM cost of contracted power sector resources, after accounting for investment tax credit (30%); h_2_storage= capital and FOM cost of gaseous H_2 storage system, which includes the capital cost of the compressor and tank. Excess electricity sales, as described in Section 3.1.3, is calculated as elec_sales - elec_purchases. Net electricity cost for H_2 production, as described in Section 3.1.3, is calculated as electicity_fixed_cost – excess_elec_sales. The values reported are plotted in the Figure 4A.

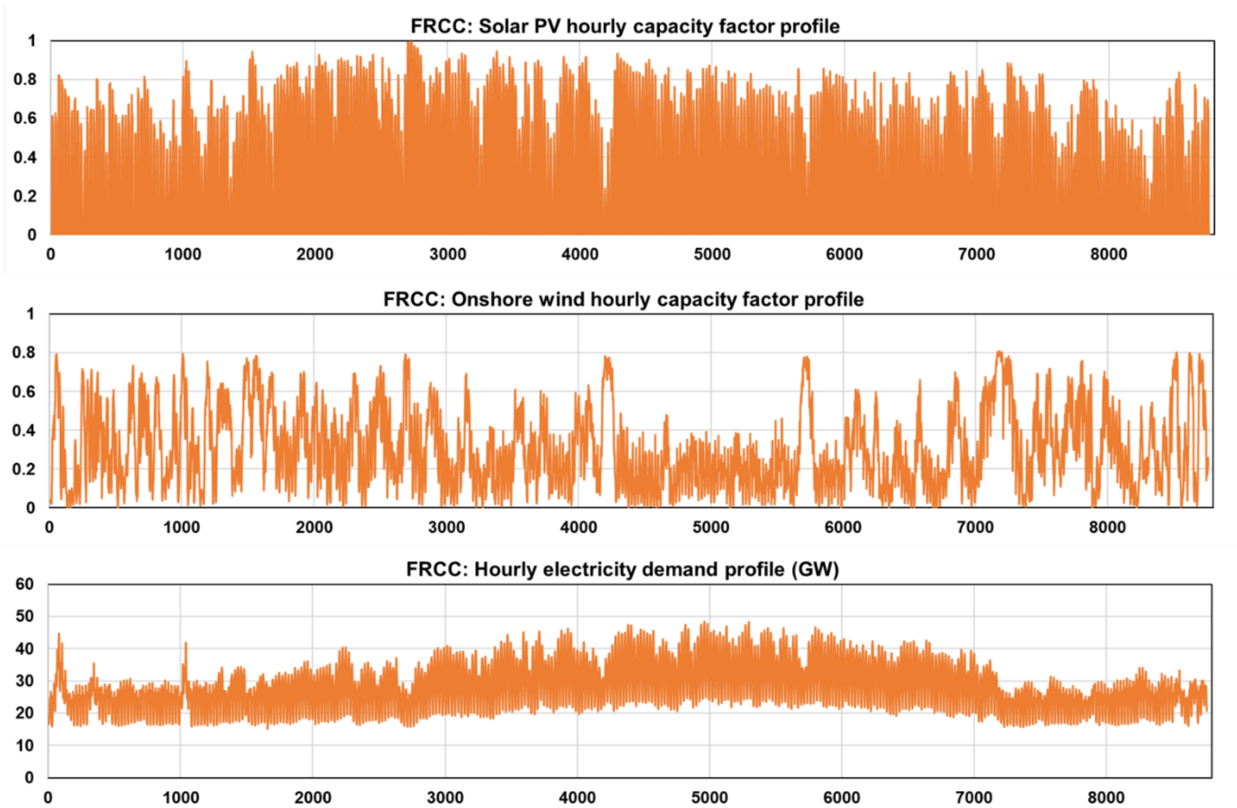
	elec_sales	**elec_purchases**	**elec_fixed_cost**	**electrolyzer_fixed_cost**	**h2_storage**	**Excess electricity sales**	**Net electricity cost for H_2 production**
S1: 1GW Base - Annual	-1.55	1.56	1.54	0.69	0	0	1.54
S2: 1GW Flex - Annual	-1.55	1.02	1.54	0.71	0.02	0.53	1.01
S3: 5GW Base - Annual	-1.08	1.58	1.43	0.69	0	-0.51	1.93
S4: 5GW Flex - Annual	-1.1	1.08	1.44	0.72	0.02	0.02	1.41
S5: 1GW Base - Hourly	-5.74	1.53	7.47	0.69	0	4.21	3.27
S6: 1GW Flex - Hourly	-4.2	0.97	4.52	0.8	0.11	3.23	1.29
S7: 5GW Base - Hourly	-3.76	1.32	6.39	0.69	0	2.44	3.95
S8: 5GW Flex - Hourly	-1.62	0.98	2.08	0.82	0.13	0.64	1.44

Supplementary Table 7. Component values for the levelized cost of H_2 in \$/kg H_2 for the "non-compete" additionality framework for the ERCOT case study under scenario with different H_2 demand (1, 5 GW equivalent power consumption), time-matching requirements (annual vs. hourly), and electrolyzer operation modes (Baseload vs. flexible). See description of Supplementary Table 7 for details. The values reported are plotted in the Figure 4B.

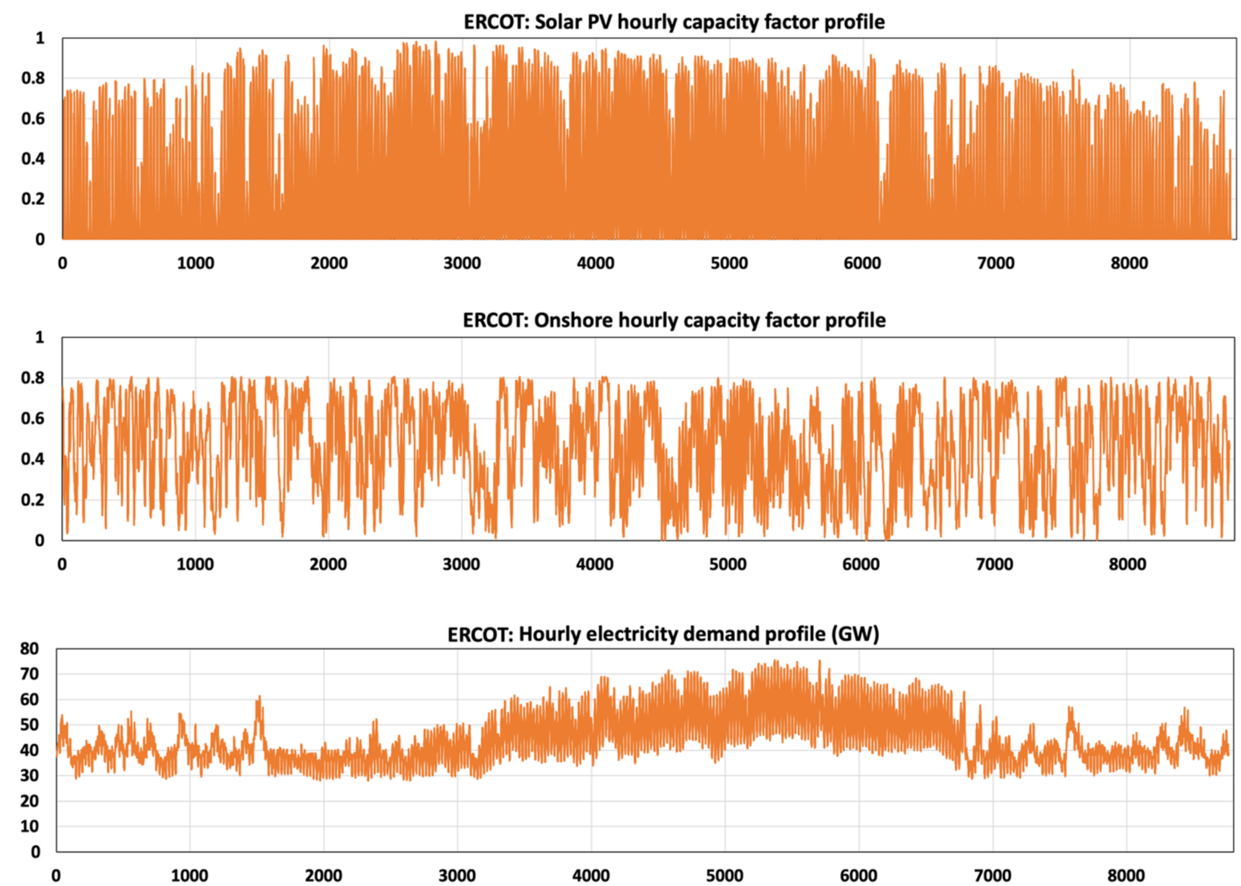
	elec_sales	**elec_purchases**	**elec_fixed_cost**	**electrolyzer_fixed_cost**	**h2_storage**	**Excess electricity sales**	**Net electricity cost for H_2 production**
S1: 1GW Base - Annual	-1.51	1.44	1.79	0.69	0	0.08	1.72

S2: 1GW Flex - Annual	-0.99	0.99	1.42	0.71	0.01	0	1.42
S3: 5GW Base - Annual	-1.7	1.77	1.95	0.69	0	-0.07	2.02
S4: 5GW Flex - Annual	-0.96	1.02	1.39	0.72	0.02	-0.06	1.45
S5: 1GW Base - Hourly	-3.86	1.13	6.44	0.69	0	2.73	3.71
S6: 1GW Flex - Hourly	-1.3	0.93	1.89	0.82	0.15	0.37	1.52
S7: 5GW Base - Hourly	-2.61	0.93	6.18	0.69	0	1.68	4.51
S8: 5GW Flex - Hourly	-1.24	0.92	1.87	0.82	0.15	0.32	1.55

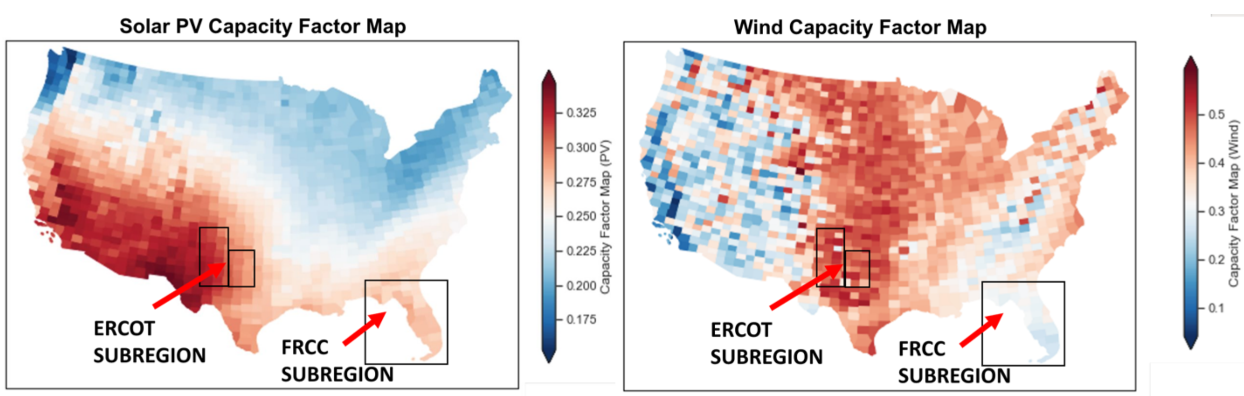
Supplementary Figures



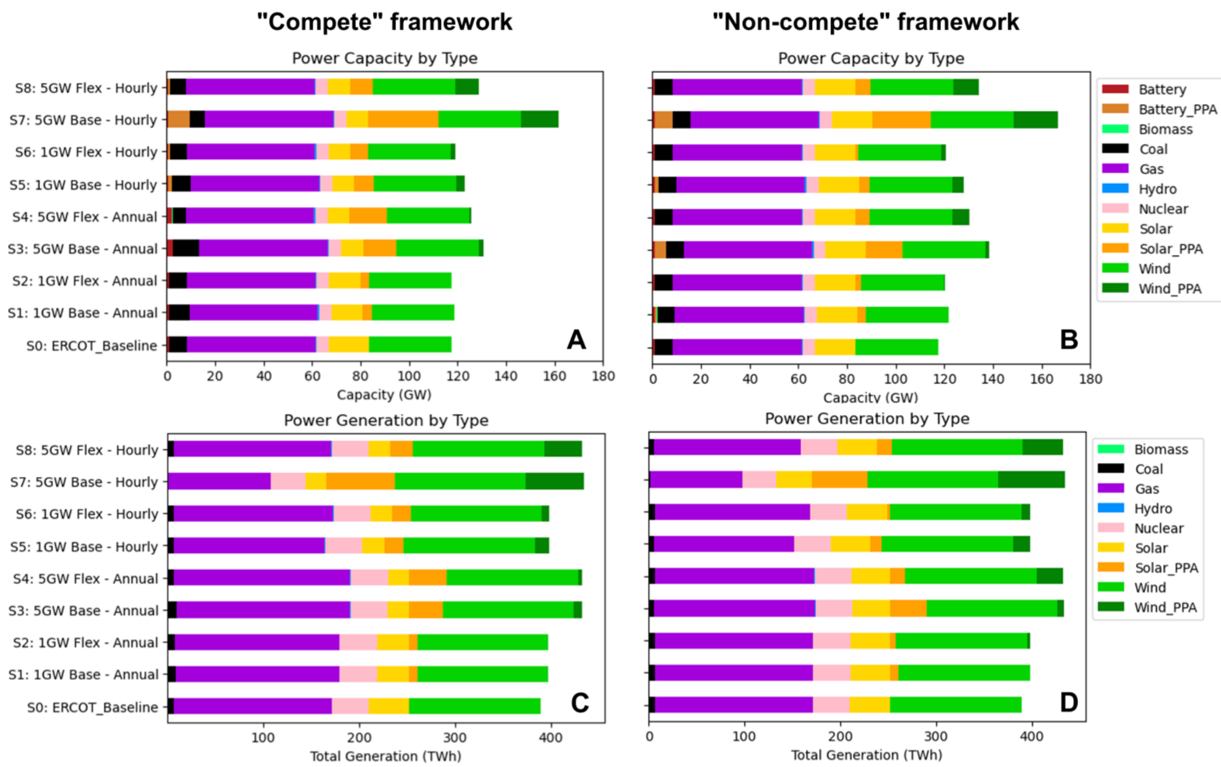
Supplementary Figure 1. Hourly resource availability profiles solar PV (top row) and onshore wind (middle row) as well as hourly electricity demand profile (bottom row) for FRCC case study. Details about the data inputs discussed in Methods – Power sector modeling assumptions.



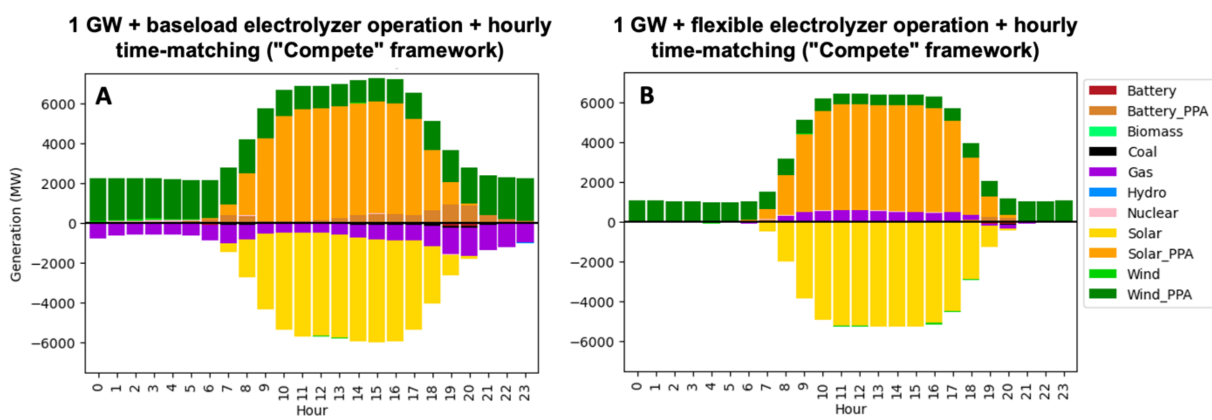
Supplementary Figure 2. Hourly resource availability profiles for solar PV (top row) and onshore wind (middle row), as well as hourly electricity demand profile (bottom row) for ERCOT case study. Details about the data inputs discussed in Methods – Power sector modeling assumptions.



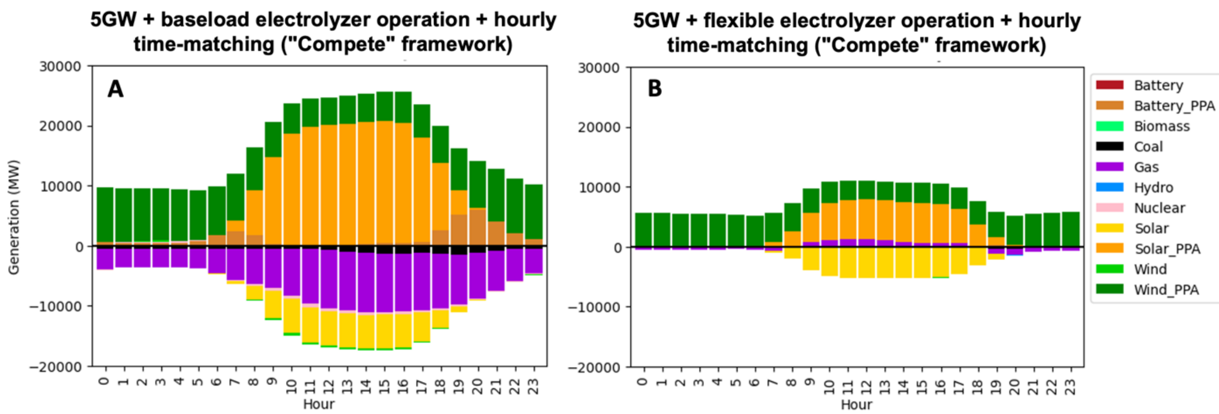
Supplementary Figure 3. Sub-regions for computing hourly capacity factors for solar and wind resources in ERCOT and FRCC. This figure is an adaptation of Supplementary Figure 2 from [26], which shows average annual capacity factors computed according to 2012 weather data. To compute hourly capacity factors for this paper, we average hourly capacity factors for the coordinate blocks in the highlighted regions.



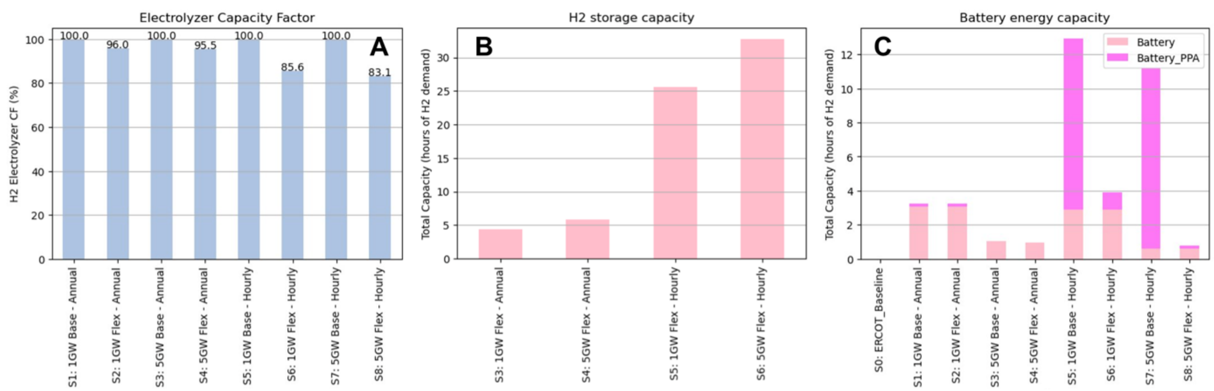
Supplementary Figure 4. Power generation and storage capacity (top row, A-B) and annual power generation (bottom row, C-D) resulting from electrolytic H_2 production under alternative H_2 demand scenarios, time-matching requirements, and additionality frameworks. Results correspond to ERCOT case study. Also shown are the results for the baseline grid scenario involving grid resource expansion without any H_2 demand, as defined in Figure 1.



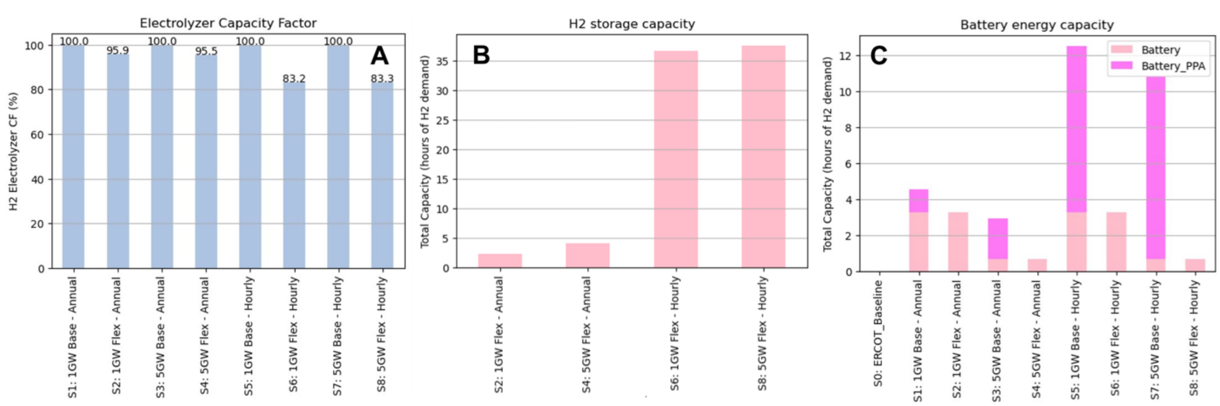
Supplementary Figure 5. Average hourly change in power system dispatch between cases with H_2 production vs. baseline grid in ERCOT for the scenarios with 1 GW H_2 demand, hourly time-matching requirements, "compete" additionality framework, and baseload electrolyzer operation (A) or flexible electrolyzer operation (B).



Supplementary Figure 6. Average hourly change in power system dispatch between cases with H_2 production vs. baseline in ERCOT for the scenarios with 5 GW H_2 demand, annual time-matching requirements, "compete" additionality framework, and baseload electrolyzer operation (A) or flexible electrolyzer operation (B).

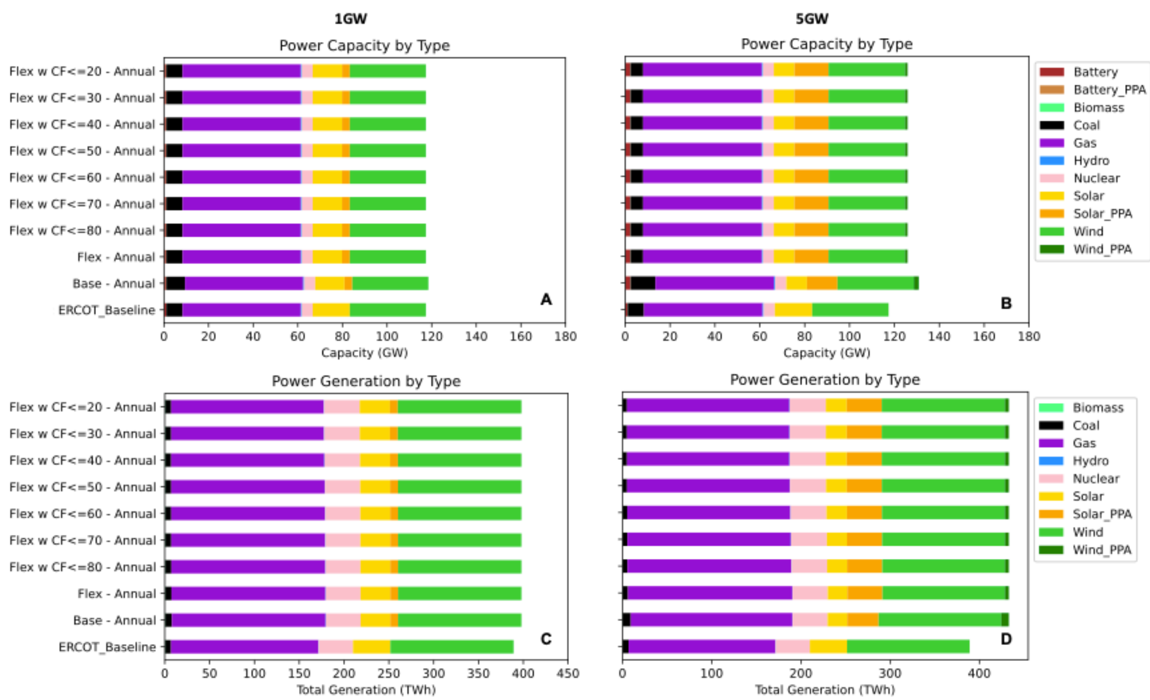


Supplementary Figure 7. Electrolyzer capacity factor (A), H_2 storage capacity (B) and battery energy capacity (C) for alternative H_2 demand scenarios, time-matching requirements under the "compete" additionality framework. Results correspond to ERCOT case study. H_2 and battery storage capacity reported in terms of hours of exogeneous H_2 demand that can be met with the available storage capacity when full. Electrolyzer capacity factor calculated based on available capacity in each hour, which is 95% of the installed capacity.

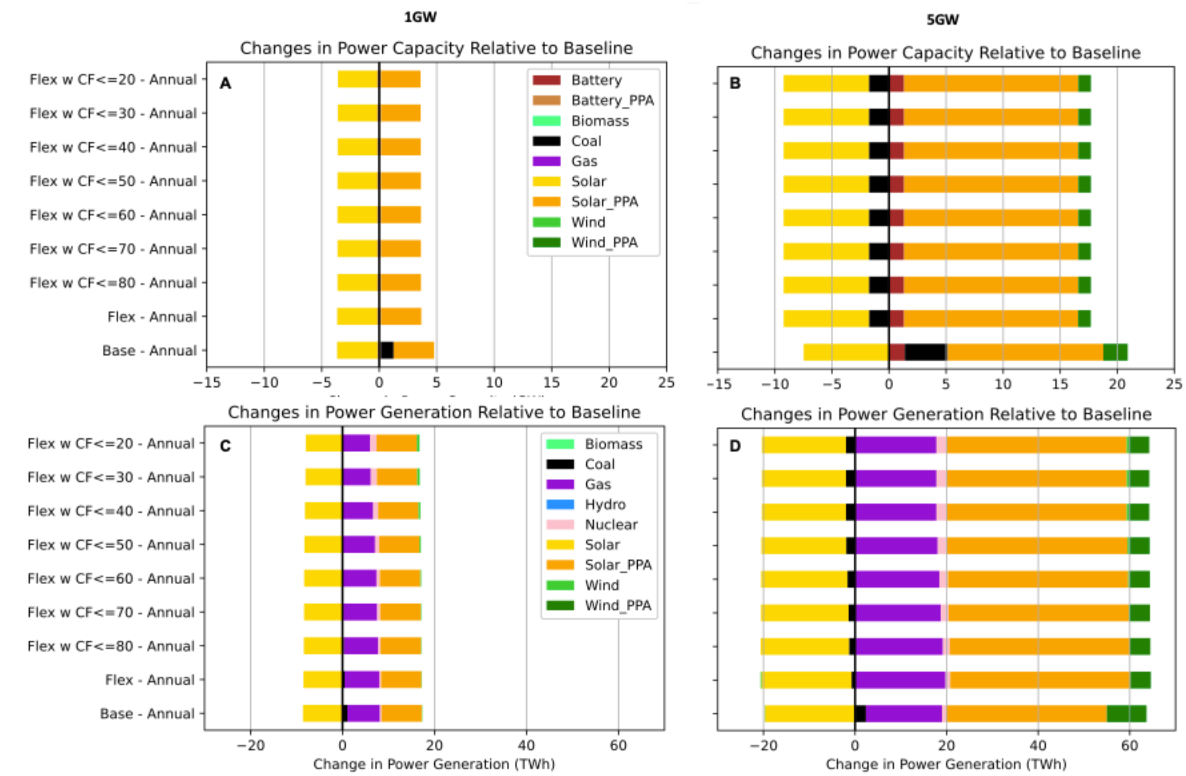


Supplementary Figure 8. Electrolyzer capacity factor (A), H_2 storage capacity (B), and battery energy capacity (C) for alternative H_2 demand scenarios, time-matching requirements under the "non-compete" additionality framework. Results correspond to

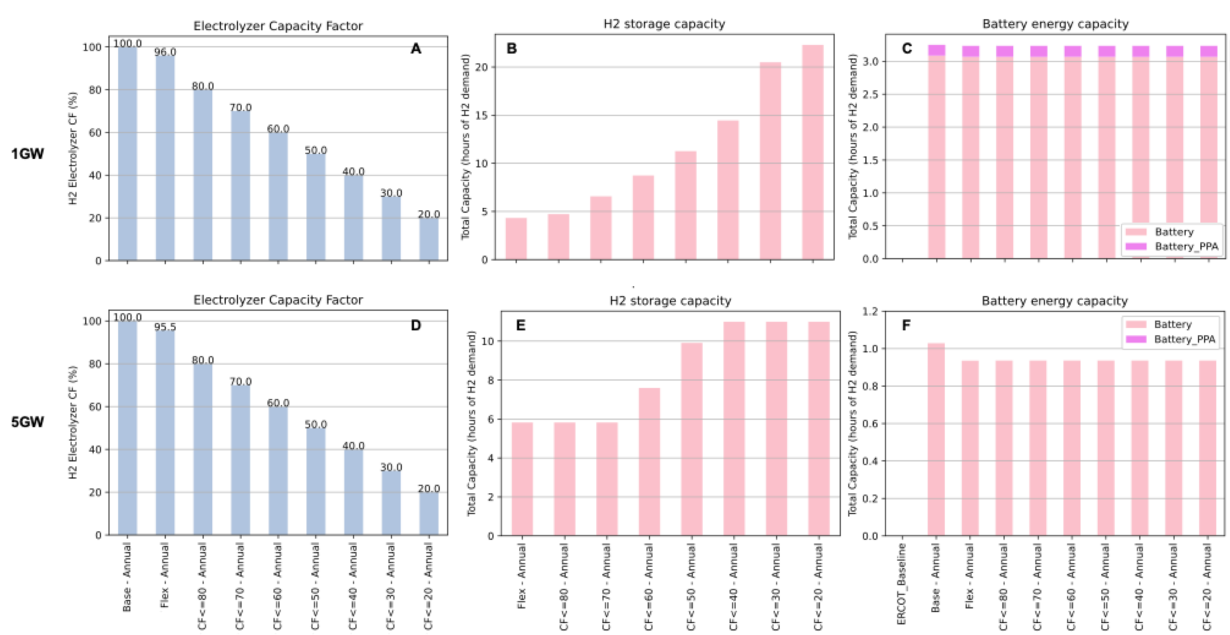
ERCOT case study. H_2 and battery storage capacity reported in terms of hours of exogeneous H_2 demand that can be met with the available storage capacity when full. Electrolyzer capacity factor calculated based on available capacity in each hour, which is 95% of the installed capacity.



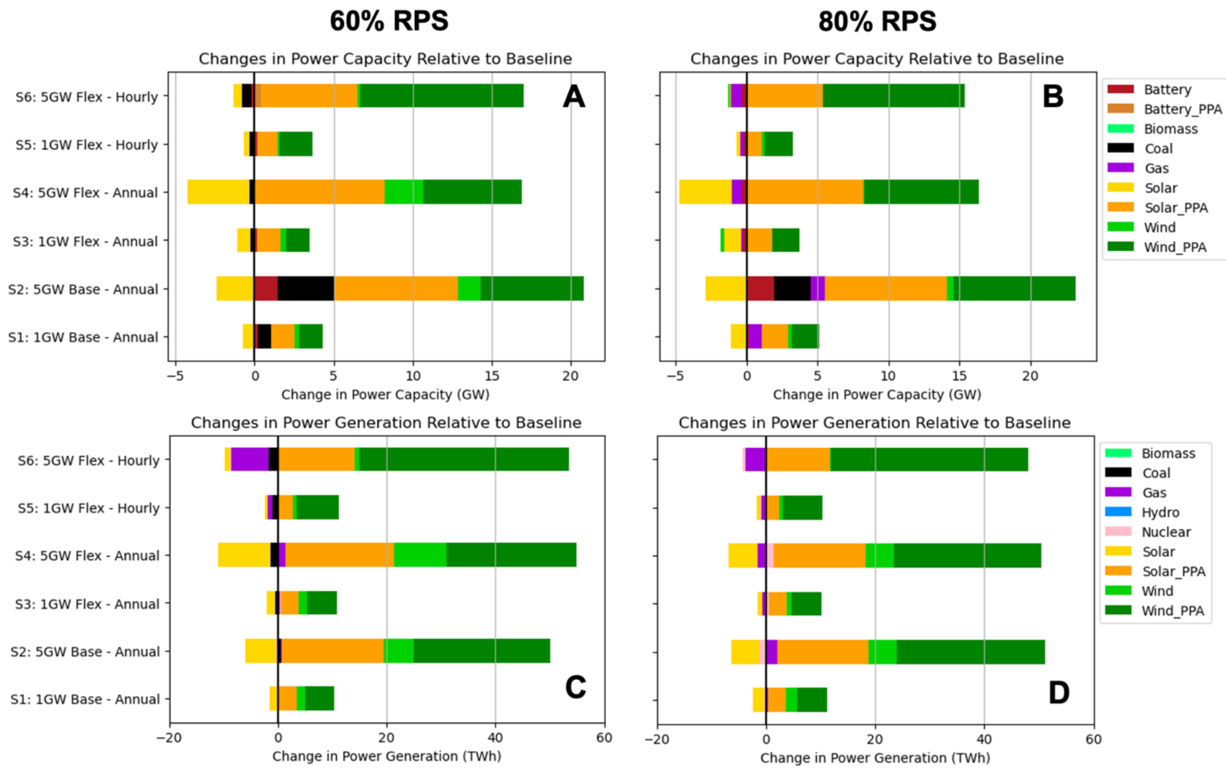
Supplementary Figure 9. Power generation and storage capacity (top row, A-B) and annual power generation (bottom row, C-D) resulting from electrolytic H_2 for scenarios with 1GW (1st column) and 5GW (2nd column) of electrolyzer demand under an annual time-matching requirement with baseload operation, flexible operation, and different upper limits on annual electrolyzer capacity factor (20%, 30%, 40%, 50%, 60%, 70%, and 80%). Results correspond to the ERCOT case study under the "compete" additionality framework. Also shown are the results for the baseline grid scenario involving grid resource expansion without any H_2 demand, as defined in Figure 1.



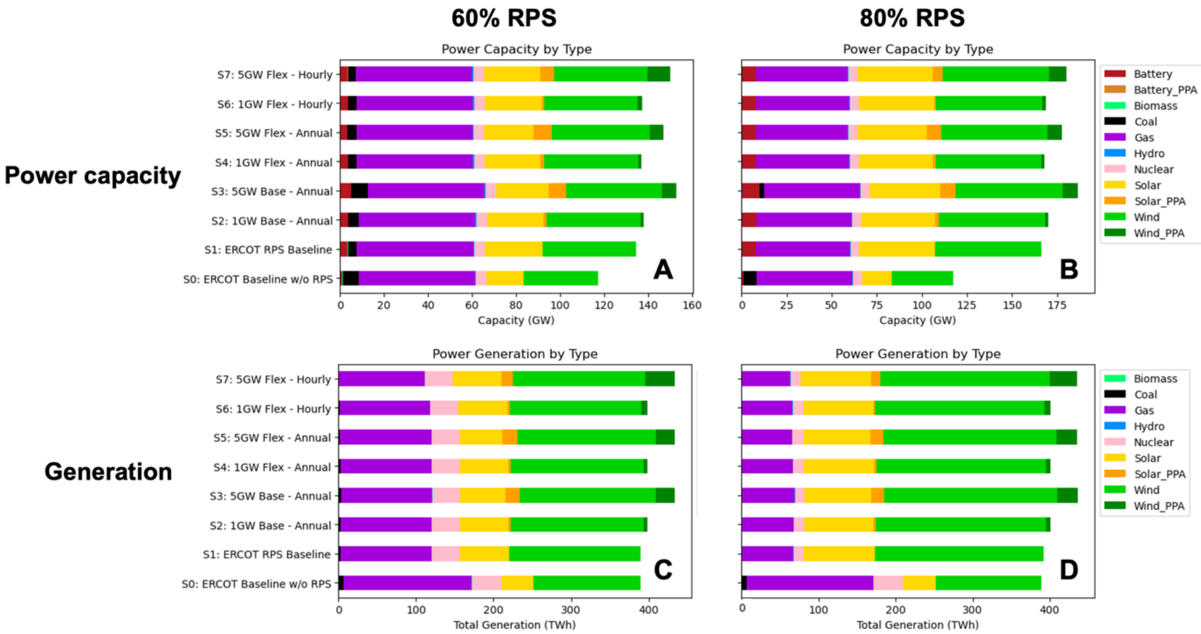
Supplementary Figure 10. Change in power generation and storage capacity (A, B) and annual power generation (C, D) resulting from electrolytic H_2 for scenarios with 1GW (1st column) and 5GW (2nd column) of electrolyzer demand under an annual time-matching requirement with baseload operation, flexible operation, and different upper limits on annual electrolyzer capacity factor (20%, 30%, 40%, 50%, 60%, 70%, and 80%). Results correspond to the ERCOT case study under the "compete" additionality framework and are reported relative to the baseline grid scenario involving grid resource expansion without any H_2 demand, as defined in Figure 1.



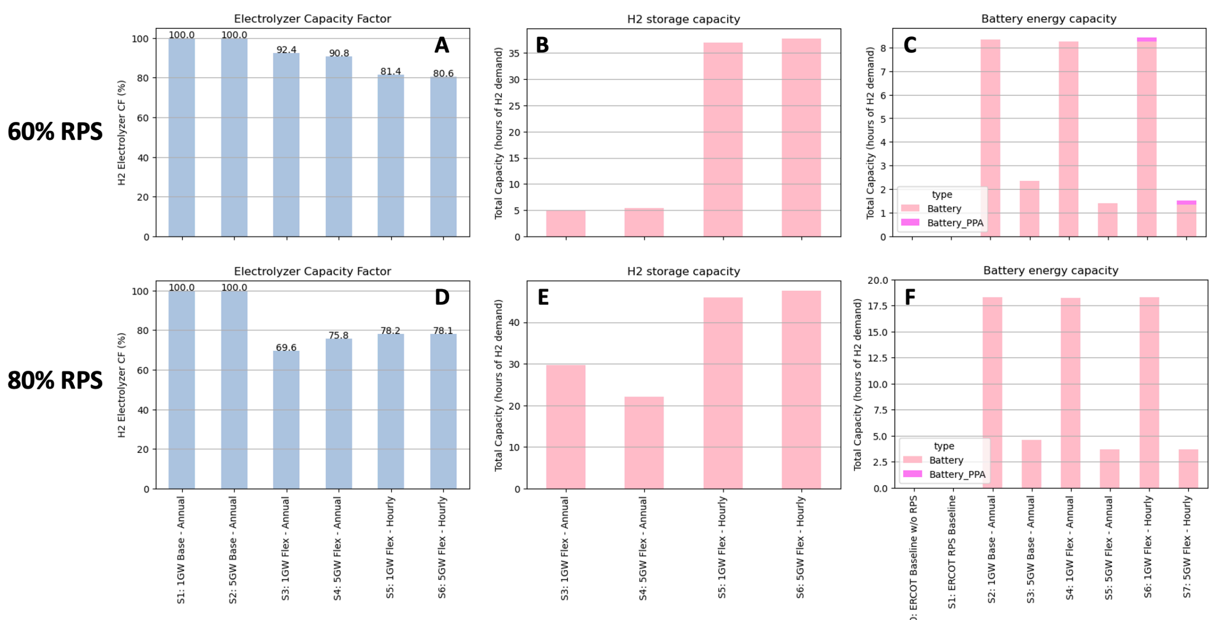
Supplementary Figure 11. Electrolyzer capacity factor (A, D), H_2 storage capacity (B, E) and Battery energy capacity (C, F) under baseload operation, flexible operation, and scenarios with different upper limits on annual electrolyzer capacity factor (20%, 30%, 40%, 50%, 60%, 70%, and 80%) with an annual time-matching requirement. Results correspond to the ERCOT case study under the "compete" additionality framework. H_2 and battery storage capacity reported in terms of hours of exogeneous H_2 demand that can be met with the available storage capacity when full. Electrolyzer capacity factor calculated based on available capacity in each hour, which is 95% of the installed capacity.



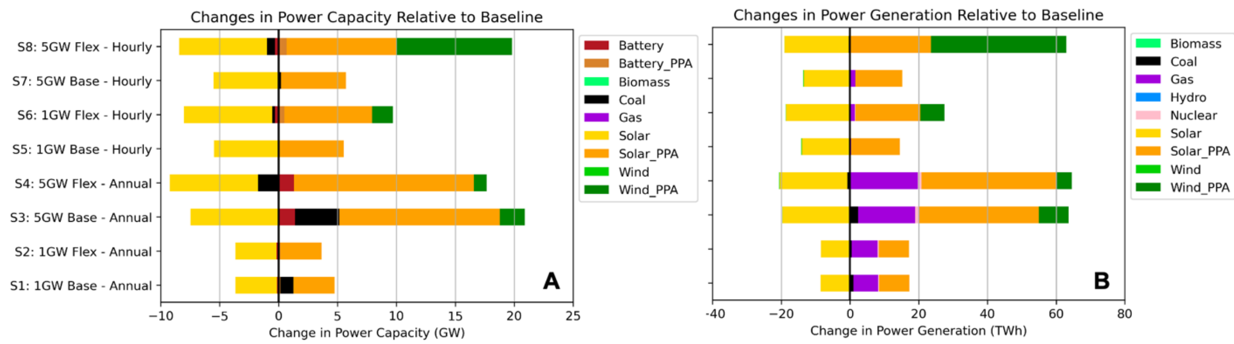
Supplementary Figure 12. Change in power generation and storage capacity (top row, A-B) and annual power generation (bottom row, C-D) resulting from electrolytic H_2 production under alternative H_2 demand scenarios, time-matching requirements, and electrolyzer operation modes under a 60% RPS (1st column) and an 80% RPS (2nd column). Results correspond to the ERCOT case study under "compete" additionality framework and are reported relative to the baseline grid scenario involving grid resource expansion with the relevant RPS and without any H_2 demand. Resources with suffix "_PPA" refer to resources added specifically to meet time-matching requirements for H_2 production.



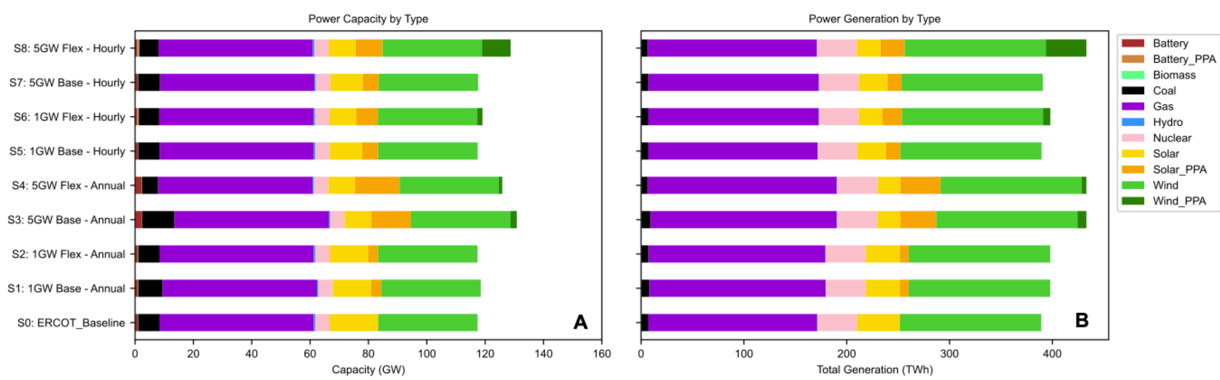
Supplementary Figure 13. Power generation and storage capacity (top row, A-B) and annual power generation (bottom row, C-D) resulting from electrolytic H_2 production under alternative H_2 demand scenarios, time-matching requirements, electrolyzer operation modes with a 60% RPS (1st column) and 80% RPS (2nd column). Results correspond to the ERCOT case study under the "compete" additionality framework. Also shown are the results for the baseline grid scenario involving grid resource expansion without any H_2 demand, as defined in Figure 1.



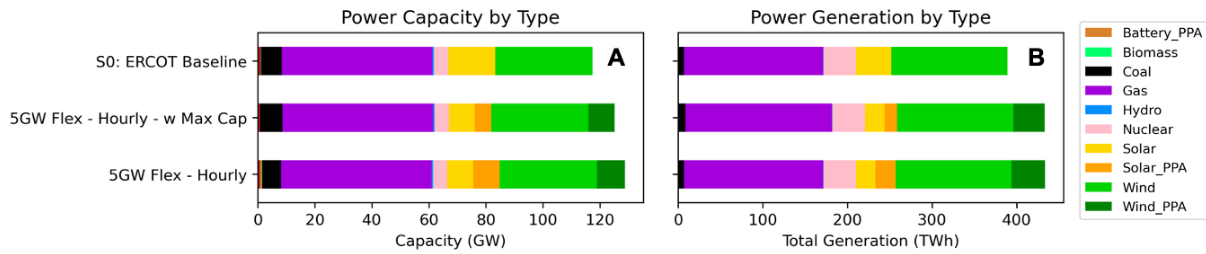
Supplementary Figure 14. Electrolyzer capacity factor (A, D), H_2 storage capacity (B, E) and battery energy capacity (C, F) for alternative H_2 demand scenarios, time-matching requirements under the "compete" additionality framework with a 60% RPS (top row) or 80% RPS (bottom row). Results correspond to the ERCOT case study under the "compete" additionality framework. H_2 and battery storage capacity are reported in terms of hours of exogeneous H_2 demand that can be met with the available storage *capacity when full. Electrolyzer capacity factor is calculated based on available capacity in each hour, which is 95% of the installed capacity.*



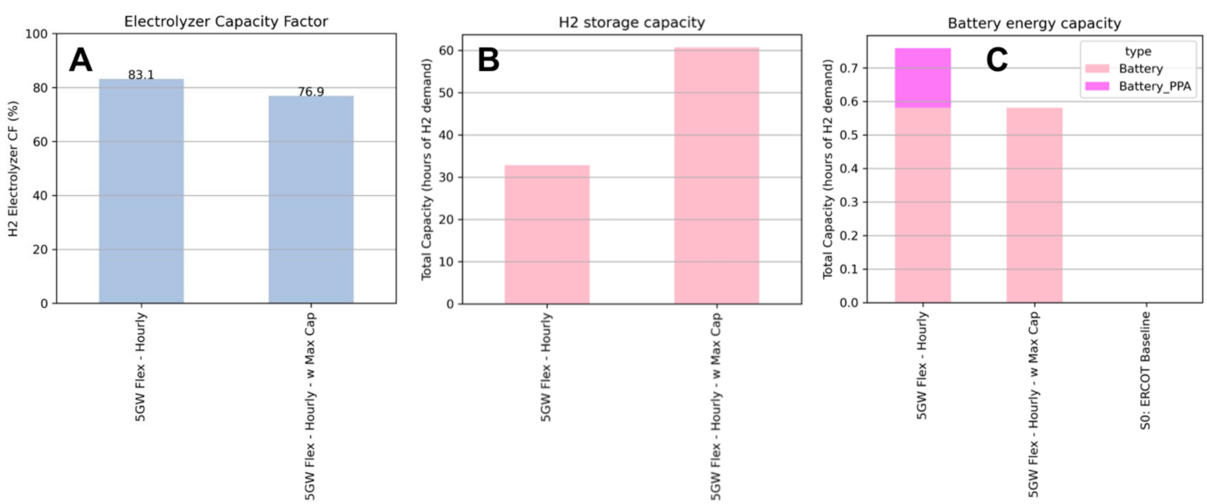
Supplementary Figure 15. Change in power generation and storage capacity (A) and annual power generation (B) resulting from electrolytic H_2 production under alternative H_2 demand scenarios, time-matching requirements, and electrolyzer operation modes under scenarios where NG-based H_2 production can compete with electrolysis for serving the H_2 demand. Results correspond to the ERCOT case study under the "compete" additionality framework and are reported relative to the baseline grid scenario involving grid resource expansion without any H_2 demand, as defined in Figure 1.



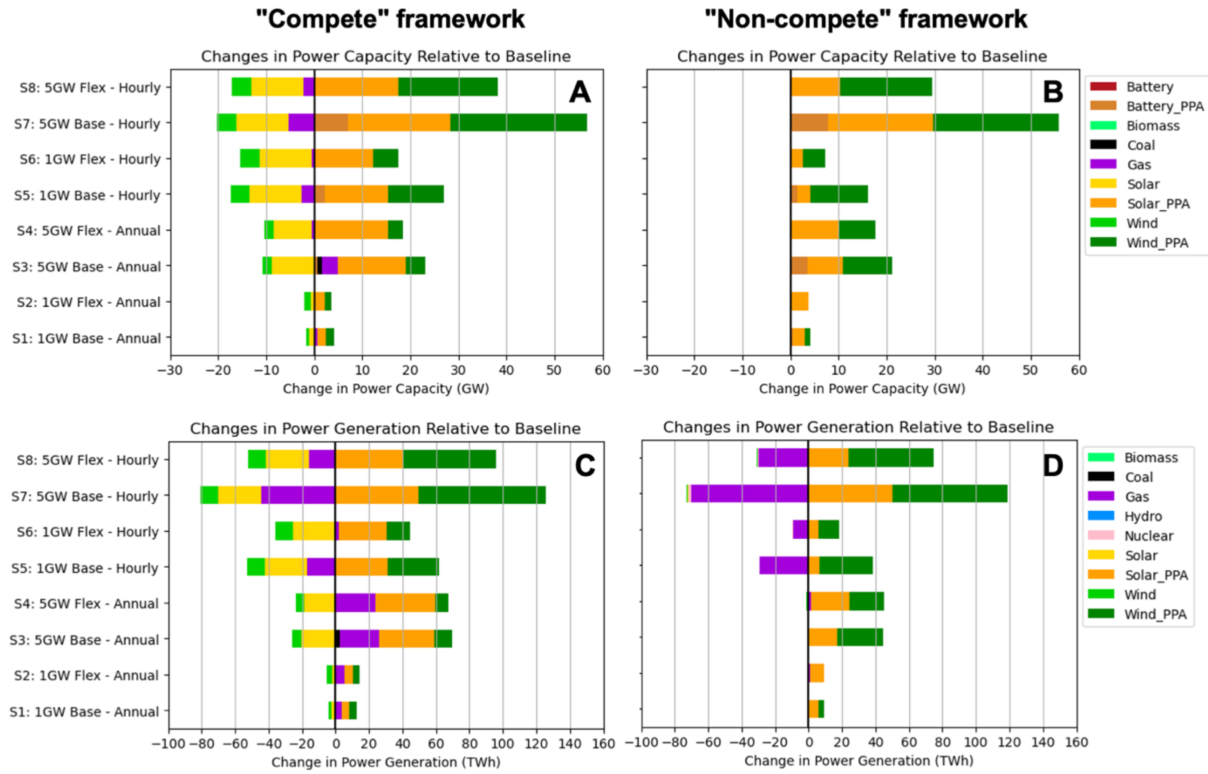
Supplementary Figure 16. Power generation and storage capacity (A) and annual power generation (B) resulting from electrolytic H_2 production under alternative H_2 demand scenarios, time-matching requirements, and electrolyzer operation modes under scenarios where NG-based H_2 production can compete with electrolysis. Results correspond to the ERCOT case study under the "compete" additionality framework. Also shown are the results for the baseline grid scenario involving grid resource expansion without any H_2 demand, as defined in Figure 1.



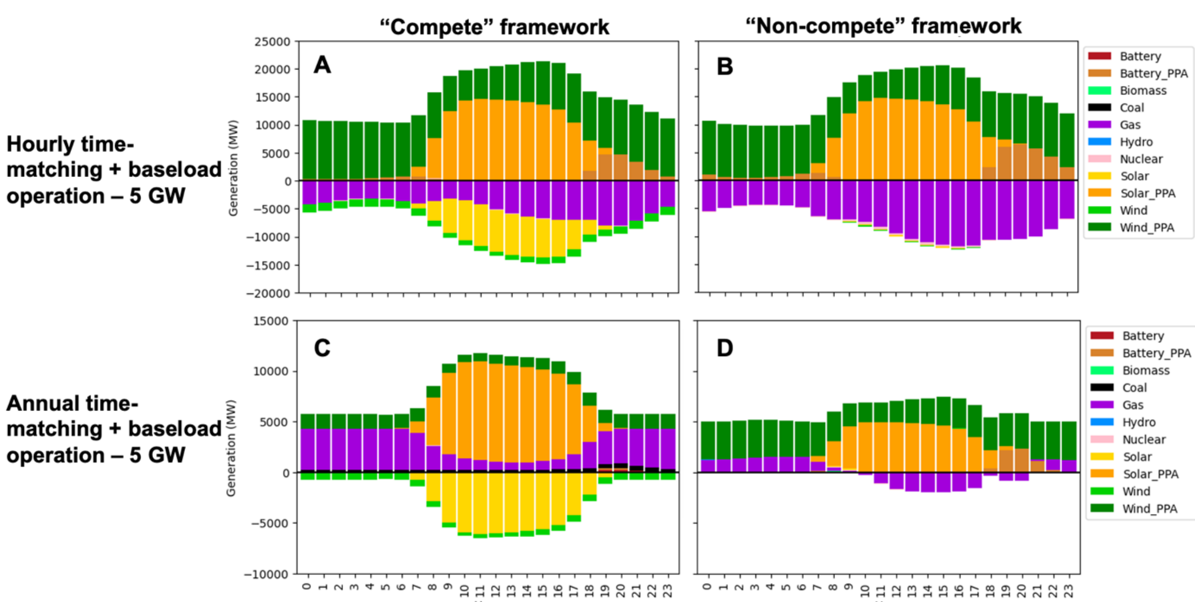
Supplementary Figure 17. Power generation and storage capacity (A) and annual power generation (B) resulting from electrolytic H_2 production in scenarios with and without a cap of 15GW on VRE deployment capacity with 5GW of electrolyzer demand, hourly time matching, and flexible electrolyzer operation under the "compete" additionality framework. Results correspond to the ERCOT case study. Also shown are the results for the baseline grid scenario involving grid resource expansion without any H_2 demand, as defined in Figure 1.



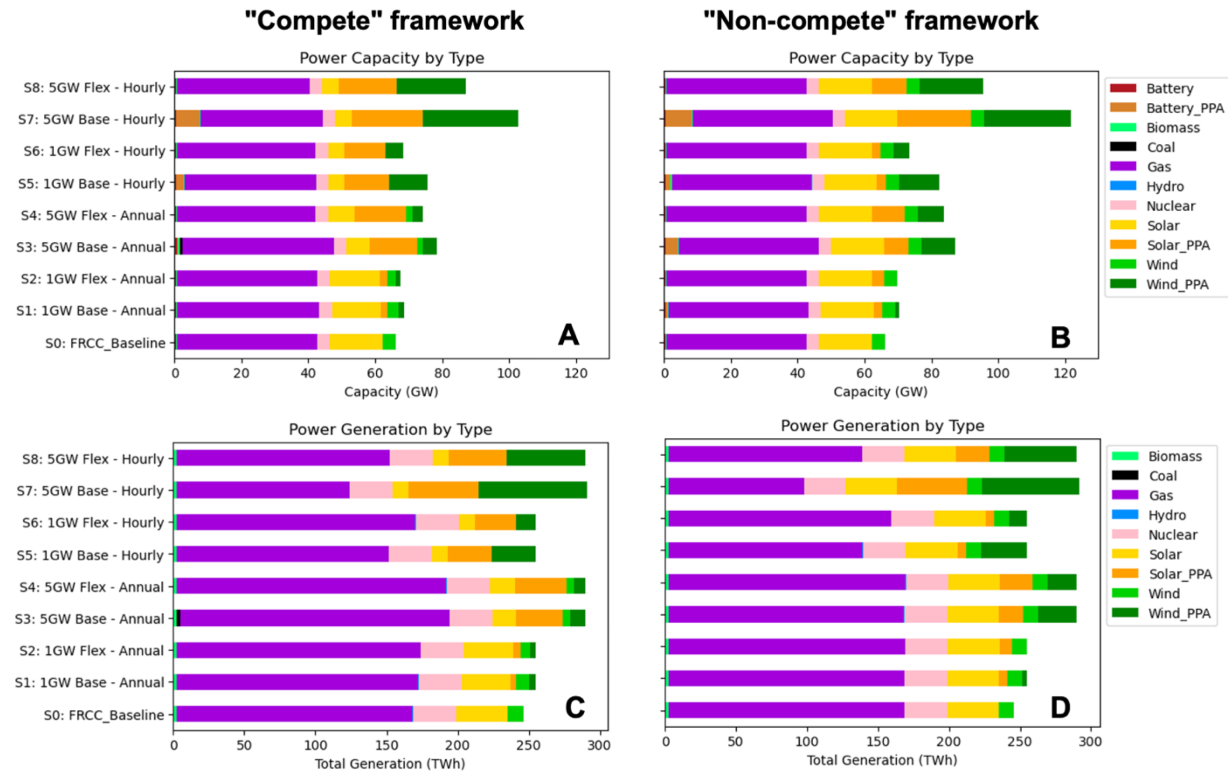
Supplementary Figure 18. Electrolyzer capacity factor (A), H_2 storage capacity (B), and battery energy capacity (C) for scenarios with and without a cap of 15GW on VRE deployment capacity with 5GW of electrolyzer demand, hourly time-matching, and flexible electrolyzer operation under the "compete" additionality framework. Results correspond to the ERCOT case study. H_2 and battery storage capacity reported in terms of hours of exogeneous H_2 demand that can be met with the available storage capacity when full. Electrolyzer capacity factor calculated based on available capacity in each hour, which is 95% of the installed capacity.



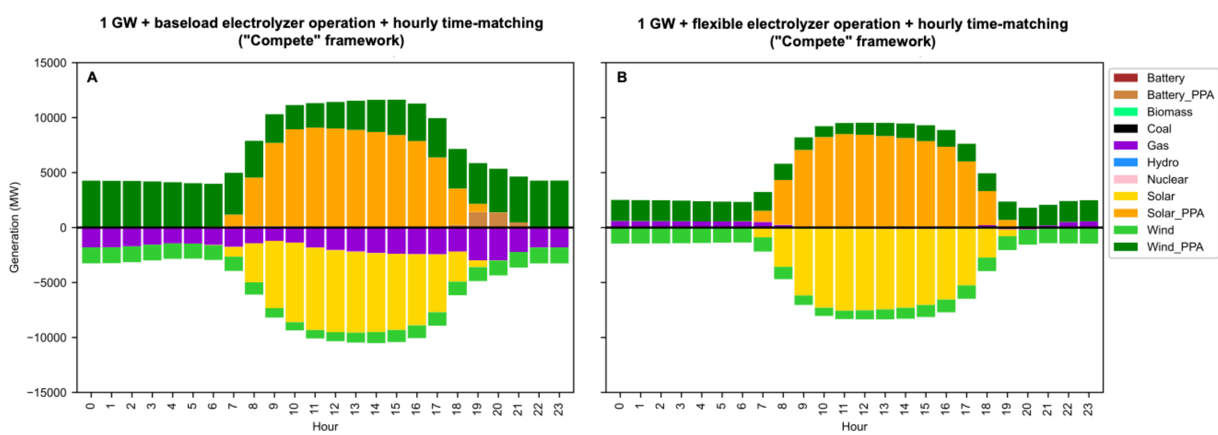
Supplementary Figure 19. Change in power generation and storage capacity (top row, A-B) and annual power generation (bottom row, C-D) resulting from electrolytic H_2 production under alternative H_2 demand scenarios, time-matching requirements, and additionality definitions. Results correspond to FRCC case study and are reported relative to the baseline grid scenario involving grid resource expansion without any H_2 demand, as defined in Figure 1.



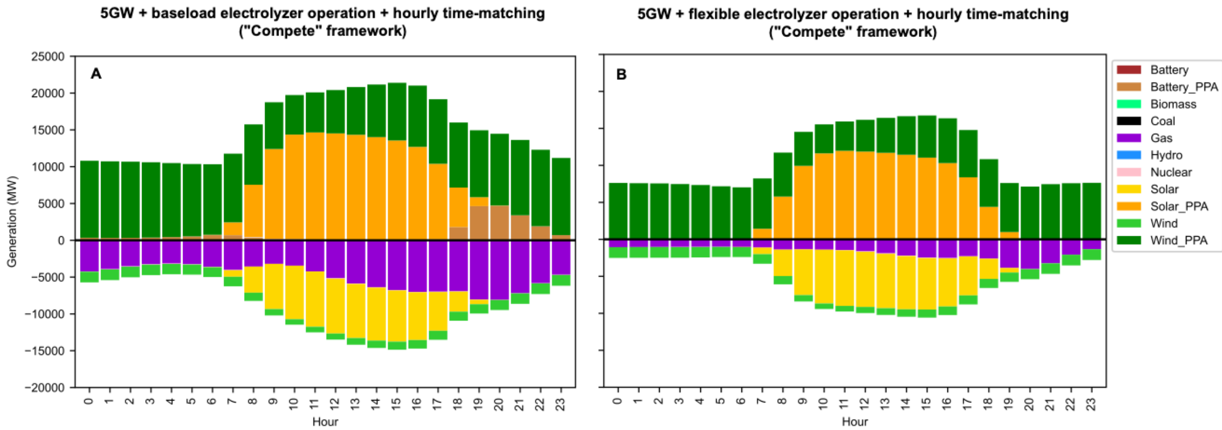
Supplementary Figure 20. Average hourly change in dispatch in FRCC between cases with H_2 production vs. baseline grid for the following scenarios under the "compete" (1st column) and "non-compete" definitions (2nd column) of additionality and hourly (top row) and annual time-matching requirements (bottom row): A and B: 5 GW of H_2 production with baseload electrolyzer operation *and hourly time-matching requirements. C and D: 5 GW of H_2 production with baseload electrolyzer operation and annual time-matching requirements.*



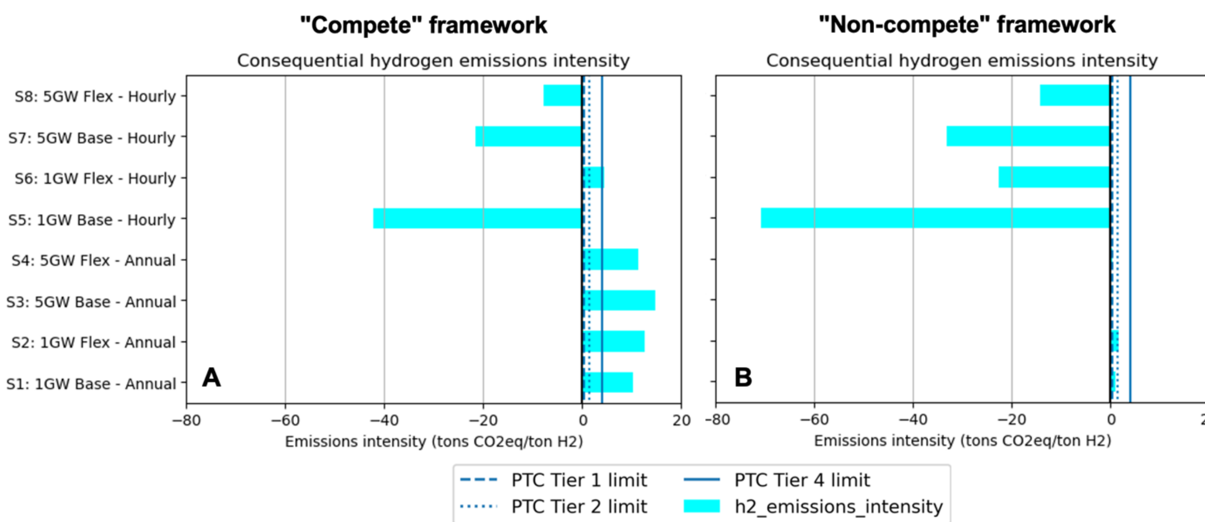
Supplementary Figure 21. Power generation and storage capacity (top row, A-B) and annual power generation (bottom row, C-D) resulting from electrolytic H_2 production under alternative H_2 demand scenarios, time-matching requirements, and additionality definitions. Results correspond to FRCC case study. Also shown are the results for the baseline scenario involving grid resource expansion without any H_2 demand, as defined in Figure 1.



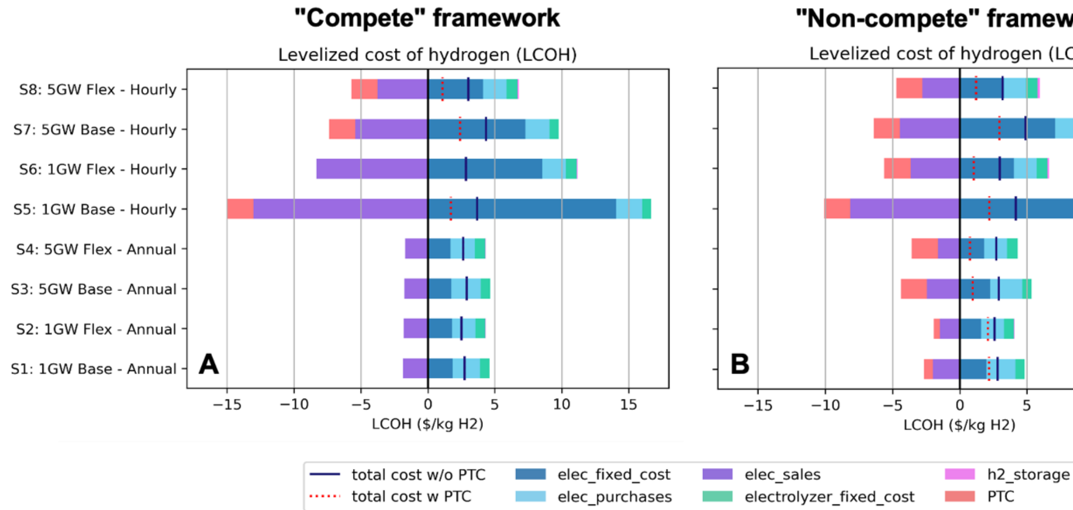
Supplementary Figure 22. Average hourly change in power system dispatch between cases with H_2 production vs. baseline in FRCC for the scenarios with 1 GW H_2 demand and hourly time-matching requirements, "compete" additionality framework and baseload electrolyzer operation (A) or flexible electrolyzer operation (B).



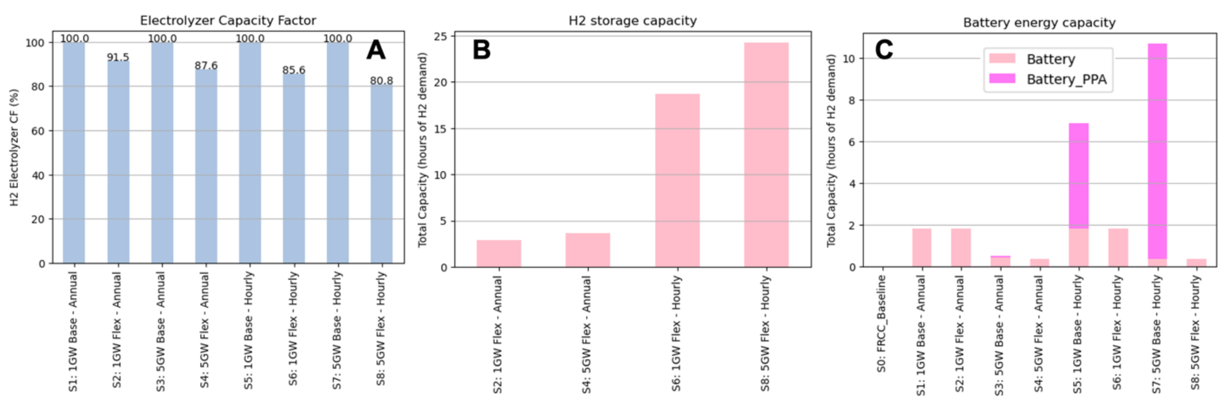
Supplementary Figure 23. Average hourly change in power system dispatch between cases with H_2 production vs. baseline in FRCC for the scenarios with 5 GW H_2 demand, annual time-matching requirements, "compete" additionality framework and baseload electrolyzer operation (A) or flexible electrolyzer operation (B).



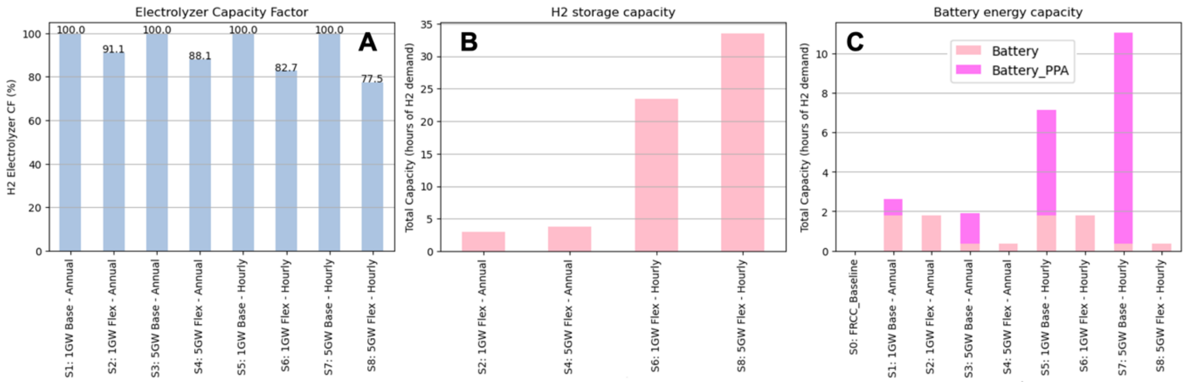
Supplementary Figure 24. Consequential emissions intensity of H_2 production for alternative exogeneous H_2 demand levels, electrolyzer operation modes, and time-matching requirement under the "compete" and "non-compete" frameworks of additionality described earlier and highlighted in Figure 1. Results correspond to the FRCC case study and are reported relative to the baseline grid scenario involving grid resource expansion without any H_2 demand, as defined in Figure 1. Also shown are threshold emissions intensity values for H_2 PTC in the IRA, with the production meeting the Tier 1 limit eligible for up to \$3/kg PTC while those meeting Tier 2 and Tier 4 limits are eligible for PTC in the amount of \$1.0/kg and \$0.6/kg, respectively.



Supplementary Figure 25. Levelized cost of H_2 for the FRCC case study under scenario with different H_2 demand (1, 5 GW equivalent power consumption), time-matching requirements (annual vs. hourly), additionality frameworks ("compete" vs "non-compete") and electrolyzer operation modes (Baseload vs. flexible). Levelized cost calculated per description provided in Section 6.5. elec_sales = revenues earned from selling excess electricity to the grid using contracted power sector resources ; elec_purchases = cost of grid electricity purchased to operate the electrolyzer; electrolyzer_fixed_cost = annualized capital and fixed operating and maintenance (FOM) cost of the electrolyzer; elec_fixed_cost = annualized capital and FOM cost of contracted power sector resources, after accounting for investment tax credit (30%); h_2_storage= capital and FOM cost of gaseous H_2 storage system, which includes the capital cost of the compressor and tank. The total cost with PTC (total cost w PTC) shows the LCOH after accounting for PTC based on consequential emissions for each case.



Supplementary Figure 26. Electrolyzer capacity factor (A), H_2 storage capacity (B) and battery energy capacity (C) for alternative H_2 demand scenarios, time-matching requirements under the "compete" additionality framework. Results correspond to FRCC case study. H_2 and battery storage capacity reported in terms of hours of exogeneous H_2 demand that can be met with the available storage capacity when full. Electrolyzer capacity factor calculated based on available capacity in each hour, which is 95% of the installed capacity.



Supplementary Figure 27. Electrolyzer capacity factor (A), H_2 storage capacity (B) and battery energy capacity (C) for alternative H_2 demand scenarios, time-matching requirements under the "non-compete" additionality framework. Results correspond to FRCC case study. H_2 and battery storage capacity reported in terms of hours of exogeneous H_2 demand that can be met with the available storage capacity when full. Electrolyzer capacity factor calculated based on available capacity in each hour, which is 95% of the installed capacity.

Chapter 7: Work Cited

[1] J. M. Deutch and E. J. Moniz, "How America Can Make Industrial Policy Work," *Foreign Affairs*, Sep. 07, 2022. Accessed: May 04, 2024. [Online]. Available: https://www.foreignaffairs.com/united-states/how-america-can-make-industrial-policy-work?check_logged_in=1&utm_medium=promo_email&utm_source=lo_flows&utm_campaign=registered_user_welcome&utm_term=email_1&utm_content=20230925

[2] "Impacts of IRA's 45V Clean Hydrogen Production Tax Credit." Electric Power Research Institute. Accessed: Apr. 30, 2024. [Online]. Available: https://www.epri.com/research/products/000000003002028407

[3] U.S. Congress, "Text - H.R.5376 - 117th Congress (2021-2022): Inflation Reduction Act of 2022," legislation, Aug. 2022. Accessed: Dec. 16, 2022. [Online]. Available: http://www.congress.gov/

[4] "Hydrogen," IEA. Accessed: Apr. 30, 2024. [Online]. Available: https://www.iea.org/energy-system/low-emission-fuels/hydrogen

[5] D. S. Mallapragada, E. Gençer, P. Insinger, D. W. Keith, and F. M. O'Sullivan, "Can Industrial-Scale Solar Hydrogen Supplied from Commodity Technologies Be Cost Competitive by 2030?," *Cell Rep. Phys. Sci.*, vol. 1, no. 9, p. 100174, Sep. 2020, doi: 10.1016/j.xcrp.2020.100174.

[6] International Energy Agency, "The Future of Hydrogen – Analysis." Accessed: Feb. 14, 2023. [Online]. Available: https://www.iea.org/reports/the-future-of-hydrogen

[7] "Unpacking the Proposed Guidance on the 45V Tax Credit for Clean Hydrogen," Resources for the Future. Accessed: May 09, 2024. [Online]. Available: https://www.resources.org/common-resources/unpacking-the-proposed-guidance-on-the-45v-tax-credit-for-clean-hydrogen/

[8] "Assessing Lifecycle Greenhouse Gas Emissions Associated with Electricity Use for the Section 45V Clean Hydrogen Production Tax Credit." U.S. Department of Energy. [Online]. Available: https://www.energy.gov/sites/default/files/2023-12/Assessing_Lifecycle_Greenhouse_Gas_Emissions_Associated_with_Electricity_Use_for_the_Section_45V_Clean_Hydrogen_Production_Tax_Credit.pdf

[9] W. Ricks, Q. Xu, and J. D. Jenkins, "Minimizing emissions from grid-based hydrogen production in the United States," *Environ. Res. Lett.*, vol. 18, no. 1, p. 014025, Jan. 2023, doi: 10.1088/1748-9326/acacb5.

[10] B. Haley, "45V Tax Credit: Three-Pillars Impact Analysis," evolved-energy. Accessed: May 09, 2024. [Online]. Available: https://www.evolved.energy/post/45v-three-pillars-impact-analysis

[11] "A Case Study of Transmission Limits on Renewables Growth in Texas," 2023.

[12] *Commission Delegated Regulation (EU) 2023/1184 of 10 February 2023 supplementing Directive (EU) 2018/2001 of the European Parliament and of the Council by establishing a*

Union methodology setting out detailed rules for the production of renewable liquid and gaseous transport fuels of non-biological origin, vol. 157. 2023. Accessed: Apr. 30, 2024. [Online]. Available: http://data.europa.eu/eli/reg_del/2023/1184/oj/eng

[13] NRDC, et al., "Joint Letter on 45V Implementation." Feb. 23, 2023. [Online]. Available: https://www.nrdc.org/sites/default/files/2023-03/joint-letter-45v-implementation-20230223.pdf

[14] "CHFC Statement on Treasury's Proposed Guidance for the 45V Clean Hydrogen Production Tax Credit." Clean Hydrogen Future Coalition, Dec. 21, 2023. [Online]. Available: https://cleanh2.org/wp-content/uploads/CHFC-Statement-on-Treasury-proposed-45V-guidance-12.21.2023-pre-release-of-guidance-1.pdf

[15] "Re: Section 45V Credit for Production of Clean Hydrogen and Additionality." Fuel Cell and Hydrogen Energy Association, May 04, 2023. [Online]. Available: https://static1.squarespace.com/static/53ab1feee4b0bef0179a1563/t/6452ad18d54ae3543c305f15/1683139864709/FCHEA+Additionality+Sign+On+Letter+Final+2023-5-4.pdf

[16] E. Zeyen, I. Riepin, and T. Brown, "Hourly versus annually matched renewable supply for electrolytic hydrogen," Zenodo, Dec. 2022. doi: 10.5281/zenodo.7457441.

[17] "DOLPHYN model." MIT Energy Initiative, Jan. 18, 2023. Accessed: Feb. 13, 2023. [Online]. Available: https://github.com/macroenergy/DOLPHYN

[18] J. Joshi, "Do renewable portfolio standards increase renewable energy capacity? Evidence from the United States," *J. Environ. Manage.*, vol. 287, p. 112261, Jun. 2021, doi: 10.1016/j.jenvman.2021.112261.

[19] G. Barbose, "U.S. State Renewables Portfolio & Clean Electricity Standards: 2023 Status Update," LBNL, 2023.

[20] "Corporate Clean Energy Buying Tops 30GW Mark in Record Year," BloombergNEF. Accessed: Sep. 07, 2023. [Online]. Available: https://about.bnef.com/blog/corporate-clean-energy-buying-tops-30gw-mark-in-record-year/

[21] J. Rand *et al.*, "Queued Up: Characteristics of Power Plants Seeking Transmission Interconnection As of the End of 2022," Aug. 2023, Accessed: Sep. 07, 2023. [Online]. Available: https://escholarship.org/uc/item/7w87m1pr

[22] "A Power Grid Long Enough to Reach the Sun Is Key to the Climate Fight," BloombergNEF. Accessed: Sep. 07, 2023. [Online]. Available: https://about.bnef.com/blog/a-power-grid-long-enough-to-reach-the-sun-is-key-to-the-climate-fight/

[23] U.S. Energy Information Administration (EIA), "Utility Scale Facility Net Generation." Accessed: Feb. 22, 2023. [Online]. Available: https://www.eia.gov/electricity/annual/html/epa_03_07.html

[24] "The Future of Energy Storage," Main. Accessed: Jul. 27, 2022. [Online]. Available: https://energy.mit.edu/publication/the-future-of-energy-storage/

[25] "PowerGenome." MIT, Feb. 16, 2023. Accessed: Feb. 22, 2023. [Online]. Available: https://github.com/PowerGenome/PowerGenome

[26] A. Bose, N. Lazouski, M. L. Gala, K. Manthiram, and D. S. Mallapragada, "Spatial Variation in Cost of Electricity-Driven Continuous Ammonia Production in the United States," *ACS Sustain. Chem. Eng.*, vol. 10, no. 24, pp. 7862–7872, Jun. 2022, doi: 10.1021/acssuschemeng.1c08032.
[27] "Henry Hub Natural Gas Spot Price (Dollars per Million Btu)." Accessed: Nov. 22, 2023. [Online]. Available: https://www.eia.gov/dnav/ng/hist/rngwhhdm.htm
[28] E. Lewis *et al.*, "Comparison of Commercial, State-of-the-Art, Fossil-Based, Hydrogen Production Technologies," United States Department of Energy, National Energy Technology Laboratory (NETL), Apr. 2022. [Online]. Available: https://www.osti.gov/biblio/1862910
[29] U.S. Energy Information Administration (EIA), "Annual Energy Outlook 2022 - Electric Power Projections by Electricity Market Module Region." Accessed: Feb. 14, 2023. [Online]. Available: https://www.eia.gov/opendata/v1/qb.php?category=4577612
[30] Hydrogen Europe et al., "Joint statement of the EU industry: Pragmatic regulatory framework necessary for hydrogen market." Jul. 2022. [Online]. Available: https://hydrogeneurope.eu/wp-content/uploads/2022/07/2022.07_Joint-Letter-by-18-Industry-Associations-on-REDII-DA.pdf
[31] "PEM Electrolyzer Capacity Installations in the United States," U.S. Department of Energy, May 2022.
[32] "Section 45V Credit for Production of Clean Hydrogen; Section 48(a)(15) Election To Treat Clean Hydrogen Production Facilities as Energy Property," Federal Register. Accessed: May 01, 2024. [Online]. Available: https://www.federalregister.gov/documents/2023/12/26/2023-28359/section-45v-credit-for-production-of-clean-hydrogen-section-48a15-election-to-treat-clean-hydrogen
[33] C. Robles, "DOE sides with industry on hydrogen tax rules," E&E News by POLITICO. Accessed: May 09, 2024. [Online]. Available: https://www.eenews.net/articles/doe-sides-with-industry-on-hydrogen-tax-rules/
[34] M. A. Giovanniello, A. N. Cybulsky, T. Schittekatte, and D. S. Mallapragada, "The influence of additionality and time-matching requirements on the emissions from grid-connected hydrogen production," *Nat. Energy*, vol. 9, no. 2, pp. 197–207, Feb. 2024, doi: 10.1038/s41560-023-01435-0.
[35] J. R. Birge and F. Louveaux, Eds., "The Value of Information and the Stochastic Solution," in *Introduction to Stochastic Programming*, New York, NY: Springer, 1997, pp. 137–152. doi: 10.1007/0-387-22618-4_4.
[36] "Resource Adequacy 2022." Accessed: May 07, 2024. [Online]. Available: https://www.ercot.com/gridinfo/resource/2022
[37] "Review of Value of Lost Load in the ERCOT Market." ERCOT, Feb. 01, 2024.
[38] D. D. Papadias and R. K. Ahluwalia, "Bulk storage of hydrogen," *Int. J. Hydrog. Energy*, vol. 46, no. 70, pp. 34527–34541, Oct. 2021, doi: 10.1016/j.ijhydene.2021.08.028.

[39] "RE: Comment on Proposed Rule – Credit for Production of Clean Hydrogen, Election to Treat Clean Hydrogen Production Facilities as Energy Property." California Air Resources Board, et al., Feb. 26, 2024. [Online]. Available: https://archesh2.org/wp-content/uploads/2024/02/CA-45V-Letter-2-26-24-Finalpost.pdf

[40] "State by State: A Roadmap Through the Current US Energy Storage Policy Landscape." Accessed: May 10, 2024. [Online]. Available: https://www.morganlewis.com/pubs/2024/03/state-by-state-a-roadmap-through-the-current-us-energy-storage-policy-landscape

[41] "PNNL: Energy Storage: Energy Storage Policy Database." Accessed: May 10, 2024. [Online]. Available: https://energystorage.pnnl.gov/regulatoryactivities.asp

[42] T. Cybulsky, Anna, M. Giovanniello, T. Schittekatte, and D. Mallapragada, "Producing hydrogen from electricity: how modeling additionality drives the emissions impact of time matching requirements," In Review, working paper, May 2023. doi: 10.21203/rs.3.rs-2834020/v1.

[43] K. Priola, L. Cutter, S. Vigil, and B. Titone, *Advance The Use Of Clean Hydrogen*.

[44] C. E. Commission, "GFO-23-307 - Large-Scale Centralized Clean Hydrogen Production (H2CENTRAL)." Accessed: May 10, 2024. [Online]. Available: https://www.energy.ca.gov/solicitations/2024-03/gfo-23-307-large-scale-centralized-clean-hydrogen-production-h2central

[45] M. Solomon, "Corporate Climate Action: Analyzing the Recent Surge of Climate Commitments," RMI. Accessed: May 10, 2024. [Online]. Available: https://rmi.org/corporate-climate-action-analyzing-the-recent-surge-of-climate-commitments/

[46] "Corporate Clean Power Buying Grew 12% to New Record in 2023, According to BloombergNEF," BloombergNEF. Accessed: May 10, 2024. [Online]. Available: https://about.bnef.com/blog/corporate-clean-power-buying-grew-12-to-new-record-in-2023-according-to-bloombergnef/

[47] "SEC.gov | SEC Adopts Rules to Enhance and Standardize Climate-Related Disclosures for Investors." Accessed: May 10, 2024. [Online]. Available: https://www.sec.gov/news/press-release/2024-31

[48] "Directive - 2022/2464 - EN - CSRD Directive - EUR-Lex." Accessed: May 10, 2024. [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=uriserv%3AOJ.L_.2022.322.01.0015.01.ENG&toc=OJ%3AL%3A2022%3A322%3ATOC

[49] "An optimal clean energy procurement strategy? Google and others are working on it.," Utility Dive. Accessed: May 10, 2024. [Online]. Available: https://www.utilitydive.com/news/an-optimal-clean-energy-procurement-strategy-google-and-others-are-working/695367/

[50] I. Riepin and T. Brown, “On the means, costs, and system-level impacts of 24/7 carbon-free energy procurement.” arXiv, Dec. 06, 2023. Accessed: May 09, 2024. [Online]. Available: http://arxiv.org/abs/2403.07876
[51] Q. Xu, W. Ricks, A. Manocha, N. Patankar, and J. D. Jenkins, “System-level impacts of voluntary carbon-free electricity procurement strategies,” *Joule*, vol. 8, no. 2, pp. 374–400, Feb. 2024, doi: 10.1016/j.joule.2023.12.007.
[52] National Renewable Energy Laboratory, “Annual Technology Baseline - 2022.” Accessed: Feb. 22, 2023. [Online]. Available: https://atb.nrel.gov/
[53] B. James, W. Colella, J. Moton, G. Saur, and T. Ramsden, “PEM Electrolysis H2A Production Case Study Documentation,” NREL/TP--5400-61387, 1214980, Dec. 2013. doi: 10.2172/1214980.