When Batteries meet Hydrogen: Dual-storage investments for load-shifting purposes

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Abstract

Problem definition: Power systems account for nearly 40% of global emissions. As the world tries to reduce emissions by increasing renewable penetration, storage technologies are playing an increasingly important role in matching variable renewable supply with demand. In addition to the already-popular Lithium-Ion batteries, alternative technologies are being experimented with, like hydrogen or compressed-air storage. This paper investigates capacity co-investment and usage of two distinct storage technologies and its impact on costs and renewable penetration.

Methodology/results: In our model, a utility can invest in up to two distinct storage technologies - an energy-limited, high-efficiency technology like batteries, and a power-limited, low-efficiency technology like hydrogen - to serve demand while minimizing costs. We introduce the concept of conflict states - times when there is not enough excess solar energy to fully utilize both technologies, and one must take priority - and study the impact of operational priority on renewable penetration. When storage capacities are given, prioritizing batteries maximizes renewable penetration, due to hydrogen's lower efficiency. However, when the priority is set before storage capacities are chosen, e.g., by a regulator, we identify conditions under which the result is reversed, and renewable penetration is maximized when hydrogen is prioritized.

Managerial implications: Based on real-world calibrations, we: (i) find that utilities can profitably use hydrogen not just for seasonal storage, as so often evoked, but also for diurnal storage; (ii) find that prioritizing hydrogen during its early adoption may increase demand met through storage by up to 19%; and (iii) identify cases when a dual-tech storage strategy leads to no benefit compared to a single-tech strategy, when it can lead to lower costs, by up to 25-30%, and when it can even lead to renewable penetration levels that are simply unattainable with a single technology.

1 Introduction

In the last decade, the energy sector has experienced a paradigm shift, with a remarkable rise in investments in renewable energy, notably wind and, even more so, solar power. This surge is not merely a trend, but a manifestation of a global commitment to tackle the urgent challenges posed by climate change. In fact, many countries around the world have pledged ambitious renewable electricity targets well beyond current levels. To mention a few examples: The US is aiming to generate 100% carbon-free energy by 2035 (Donohoo-Vallett et al. 2023); the EU's goal is to increase its renewable share from 22.5% in 2022 to 42. 5% in 2030 and 100% in 2050 (Parliament of European Union 2023); and China plans to triple its renewable capacity between 2023 and 2030 (Howe 2023).

Among renewable energies, solar energy has seen massive cost reductions: installation prices went from \$5,124 to \$876 per kilowatt between 2010 and 2022 (IRENA 2023) making it the cheapest way to generate energy in many markets. This cost advantage, combined with supportive government policies, has propelled solar power to become by far the single largest new source of non-fossil energy —85% of newly built energy capacity in 2022 was renewable, with solar alone accounting for more than half at 56% (Haegel and Kurtz 2023).

Yet this rapid transition towards renewables also creates its own set of challenges. The intermittent nature of solar power makes it increasingly difficult to match electricity supply with demand. Looking at markets characterized by a high solar penetration reveals some of the issues: California's struggle with high daytime solar generation followed by peak load (demand) after dark has become so pronounced that it has received its own name - the *duck curve*, named after the shape that the net load graph resembles on sunny days (Denholm et al. 2015). Further south, Chile's solar curtailment increased by 86% between 2022 and 2023, following continued growth in the country's renewable capacity (Molina 2023), while Ireland curtailed 7-10% of all renewables each year since 2020 (IEA 2023).

To help integrate the growing amount of renewables while mitigating operational challenges, investments in energy storage technologies have soared in recent years[1], with lithium-ion batteries leading the way due to their high energy density, falling costs, and versatility in applications. According to Soltani and Skaug (2023), global battery capacity additions for grid storage have quadrupled from 6GW to 25GW between 2020 and 2022. The synergy between storage and solar is straightforward - charge in the sunniest hours and discharge when needed, typically after sunset.

Although batteries have become the storage technology of choice, energy storage firms, policymakers, and researchers have been exploring several alternatives. A popular technology that is gaining traction is hydrogen storage, with both the US and EU formalizing long-term hydrogen strategies (Satyapal et al. 2023, Commission of European Union 2020) with billions earmarked for infrastructure investment. Hydrogen storage uses electrolyzers to convert electrical energy into

[1]Additional options to help renewable integration are transmission expansion and demand response programs (Denholm et al. 2021)

chemical energy, storing surplus renewable energy in the form of hydrogen gas, which can later be converted back into electricity. An approach for large-scale hydrogen storage that has gained a lot of momentum is the use of underground salt caverns, which provide a safe storage environment at a low cost (Caglayan et al. 2020).

Comparing hydrogen storage with battery storage reveals a fundamental difference in energy management. For batteries, the typical constraint is in how much energy they can hold (expressed in kilowatt hours, kWh), which can be increased by buying more battery cells, while their power —how much energy can be transferred per unit of time (expressed in kilowatts, kW) is quite high, enough for most applications. For hydrogen, it is the reverse: The typical constraint is in power (kW) which can be increased by buying more electrolyzers, while the amount of energy that can be held (kWh) is quite large if hydrogen is stored as a gas in salt caverns. This limitation in power is shared by several other technologies, like compressed-air, or various forms of chemical storage (ammonia or synthetic gas), henceforth referred to as *hydrogen-like* technologies.

To investigate how this fundamental difference in storage operations impacts technology investments, we build a model where a firm, e.g., a utility, must decide how much energy storage capacity to build in order to store excess solar generation during the day and serve demand at night. The firm can simultaneously invest in two storage technologies, which differ in their cost of adding one unit of energy storage capacity (kWh) and power capacity (kW) —a stylized way of capturing the aforementioned difference between batteries and hydrogen-like technologies. In addition, we also account for the fact that hydrogen-like technologies are typically less efficient than batteries,[2] and that solar output is stochastic during the day - see Section 3.2.1 for the details.

Our model yields several results. We begin by studying *diurnal* load-shifting operations - when excess solar energy is used to serve demand the following night - a setting that, at the time of writing, frequently occurs in many states in the world. We are able to derive closed-form solutions for the firm's storage investment decisions. Based on these, we develop two adjusted cost parameters, one for each storage technology, with the property that a technology is never invested in when its adjusted cost is above one - a quick way of gauging profitability and succinctly relating the key model parameters. Interestingly, we are able to show that even over this diurnal time-frame hydrogen can be a profitable investment due to its different way of operating than batteries. This is in contrast to much of the literature, press, and policy proposals that portray hydrogen as a primarily long-term, seasonal storage solution —see for example Reuß et al. (2017), International Energy Agency (2019), Uniper (2024).

We then discuss the role played by *operational priority* - that is, the need to decide which storage technology takes precedence over the other. This choice matters during what we call *conflict* states - i.e., moments when there is not enough excess energy to fully utilize both storage technologies - and studying the role played by operational priority is one of the objectives of this study. As we

[2]For example, hydrogen's efficiency is about 45%-50%, and compressed-air storage's is around 70%, while lithium-ion batteries' efficiency is about 90%.

are going to demonstrate, operational priority plays another important role in driving profitability, capacity investments, and how much demand is met via storage.

For example, we show that when operational priority is set, e.g., by a regulator, before capacities are chosen, prioritizing hydrogen over batteries can maximize renewable penetration under certain conditions. This occurs despite the fact that hydrogen loses more energy than batteries in the charge-discharge process due to its lower efficiency. The increase in renewable penetration in these cases is not because the utility reduces hydrogen capacity to minimize energy loss; in fact, quite the contrary. We show that the utility builds more hydrogen capacity when it is given operational priority, not less, and despite increasing the share of the more inefficient technology, renewable penetration increases. These results highlight the importance of operational priority, which can be a valuable lever for policy makers not only to promote investments in a given technology in addition to (or in place of) costlier subsidies, but also as a way to help increase renewable penetration.

We then expand our diurnal model to study *seasonal* load-shifting - when excess energy is stored to serve demand weeks or even months later. This lets us answer the question of how batteries and hydrogen investments will develop over time. In particular, we identify two important technology tipping points for hydrogen investment and show that its adoption could vary starkly across markets even when technology costs in said markets are the same.

In the last section of the paper, we calibrate our model with data from three European markets and their 2030 renewable targets. In line with our analytical results, our numerical analyses show that before hydrogen is used for seasonal load-shifting, the use of hydrogen is typically called for; its use will become profitable for diurnal load-shifting —as early as 2027/2028. We also find that, depending on the cost trajectory, giving hydrogen priority may increase the demand met with renewables by up to 19%. Lastly, we compare single-technology and dual-technology scenarios. We identify settings in which having access to both technologies gives no advantage compared to investing only in one. Conversely, we also show that investing in both techs can reduce costs by up to 25-30% and, perhaps surprisingly, even allow the utility to reach higher levels of renewable penetration.

Our paper uses a stylized model to shed light on the combined usage of different storage technologies. To the best of our knowledge, it is the first paper in the operations literature to study this topic. Our model allows us to (i) solve for the optimal investment decisions in closed form for both diurnal and seasonal load-shifting regimes; (ii) identify which parameters are key, like our adjusted-cost terms, in driving investment choices; (iii) show how operational priority affects renewable penetration and capacity investments; (iv) identify and characterize two tipping points for hydrogen adoption; (v) quantify the magnitude of our effects via calibration with real data; and (vi) obtain high-level insights about the penetration of both technologies in various markets and the potential (or lack thereof) for reducing costs and increasing renewable penetration when employing both technologies as opposed to a single one.

Overall, our results inform players in the energy space - utilities, technology companies, and policy makers - on the potential advantages of combining different storage technologies, the conditions under which these advantages materialize, their operational drivers, and how much the benefits amount to.

2 Literature Review

Our work relates to several streams of literature: It draws on a long history in operations management in making inventory and capacity decisions under uncertainty, connects with the rapidly expanding body of sustainable operations, and relates to work in other fields like energy policy, economics, and electrical engineering.

At a high level, the dynamics of renewable energy storage resemble inventory decisions under uncertainty, with the caveat that in our setting, uncertainty comes mainly from supply in the form of intermittent renewable generation, while in the canonical inventory model, uncertainty comes from consumer demand. Within this vast literature, we want to mention the seminal work of Arrow et al. (1951) on how to choose the optimal stock-up level under fluctuating demand. For a broad review of studies on optimal capacity decisions under uncertainty, see instead Song et al. (2020).

In our model, the firm considers to invest simultaneously in two different types of storage technologies, which is reminiscent of several decisions in the operations literature where a firm has to optimize inventory or capacity of different kinds, or that differ along one or more attributes. In this vein, Goyal and Netessine (2007) study the choice of a firm to build capacity of two types - flexible and dedicated. They show that flexible capacity is not always the optimal choice, and that both types can coexist. Allon and Van Mieghem (2010), in a dual-sourcing context, show that the optimal capacity investment is a combination of base-production and surge-production capacities. Li and Debo (2009) compare the value and capacity impacts of second sourcing versus sole sourcing. Wu et al. (2023) study when storage inventories should be centralized or decentralized across multiple locations - where location can be thought of as the differentiating attribute. Our paper extends the literature by introducing a model where a firm optimizes over two types of (storage) capacity that differ along three dimensions - cost of storage space (energy), cost of transfer speed (power), and efficiency.

Among the larger operations literature, there is a growing body of work in sustainable and energy operations specifically studying questions on renewable power and storage investment that our paper draws upon. Atasu et al. (2020) provide a great review of the sustainable operations literature at large, so we focus our attention here on the specific energy operations sub-field. With renewable power reducing in cost over many years, a lot of attention in the field has been dedicated to understanding under which circumstances to invest in renewable power, and how the intermittency of renewables impacts said decision. Drake et al. (2016) and Aflaki and Netessine (2017) study the investment and operation decision for technologies with heterogeneous emission intensity, comparing solar or wind power vs. gas generation under carbon pricing. Wu and Kapuscinski (2013) focus on how increasing renewable power in a grid can lead to increased curtailment, why it might decrease emissions, and under which circumstances it can help reduce overall system cost. Going from grid-level analysis to residential decision making, Sunar and Swaminathan (2021) shows that households' investment in their own solar panels can both increase renewable adoption and even increase the profitability of the utility serving said customers; Babich et al. (2020) investigates how different subsidy policies accelerate solar investment by households; and Okafor et al. (2023) uses an analytical model to make the case for a servicizing business model as a way to efficiently deliver renewable energy to households in developing countries. Beyond the capacity investment angle, many papers have studied the question of how a shift towards renewable energy affects market participants. Agrawal and Yücel (2022) and Fattahi et al. (2022) study how to increase the responsiveness of demand to more volatile generation, while Singh and Scheller-Wolf (2021), Alizamir et al. (2016), and Guajardo (2018) investigate how utilities have to adapt their tariffs and business model in response to rooftop/solar energy investments.

Within the energy operations field, the stream of work our paper is most closely related to is that of stylized modeling of storage operations. Wu et al. (2012) derive a policy to operate a (natural gas) seasonal energy storage under variable prices by incorporating the future uncertain value of energy in the focal period's operational decision; they show how this logic can be applied to multi-day or multi-season setups. More recently, energy storage is mostly studied in the presence of renewable generation, as in Zhou et al. (2019), who study the optimal inventory decisions for a battery under transmission constraints; they show that the profit from operating the storage is concave with respect to the level of energy stored in the battery. Kaps et al. (2023) studies the joint investment of renewables and energy storage, identifies lower and upper bounds for the optimal solution, and shows that solar and batteries can become strategic substitutes at high levels of investment in either - a result which Peng et al. (2024) confirms and expands upon by characterizing the different modes of charging/discharging pairs that a battery can operate in, which can be used to approximate its value. These method insights are expanded on by some empirical papers, such as Karaduman (2021), which show that storage may be unprofitable in certain market settings from a large-scale investor perspective even if it increases consumer welfare. Kaps and Netessine (2023) focus on the aforementioned decentralized case, where households invest in solar and batteries and show that in Germany, households with such investment reduce their grid demand by nearly half.

Despite the many different facets that the storage operations literature has covered, to the best of our knowledge, our paper is novel in that we study the investment in two storage technologies. Additionally, we explicitly model their different power (speed of charge/discharge) vs. energy (amount of storage) capabilities - a distinction that much of the previous literature has simplified away. Kaps et al. (2023) only analyzes one storage technology for which they only consider the energy dimension as they focus on the solar-plus-storage investment dynamic. Hu et al. (2015) show that considering duration matters in the renewable context, and Peng et al. (2024) highlights the variability of battery charging and discharging throughout the day, but ours is the first paper to explicitly study the power and energy trade-off with multiple storage technologies. The study of multiple storage technologies has been undertaken in other fields, for example the long-duration energy storage (LDES) field, but these studies rely on simulations or optimization frameworks, which are good tools when it comes to incorporating lots of details in the analysis, but lack the transparency of analytical models, and the understanding that comes with them. Examples of such papers are the techno-economic optimization models used by Penev et al. (2019), Mayyas et al. (2022), comparing the cost (savings) of operating batteries and fuel cells in different grids, and Pellow et al. (2015), analyzing how much energy a reference system of batteries and electrolyzers could store in a year - both papers consider capacity as exogenously set. In electrical engineering, some papers have numerically optimized specific configurations of hybrid storage systems for micro-grid or mobility applications, although typically focusing on e.g., voltage or grid-stability impacts of an installation, taking again capacities as given. See Hajiaghasi et al. (2019) for a review of the field. Another area of research studying multiple storage technologies is within the energy policy field, where large integrated models are used to predict, e.g., decarbonization pathways - but are based on numerical equilibrium analysis without tractable results, see Bussar et al. (2016) for an analysis of a hypothetical 2050 European power system with large-scale renewable penetration relying on batteries, pumped hydro, and hydrogen as storage technologies, or Jafari et al. (2022) for a review of studies in the energy policy field.

The closest paper to our setup is Günther et al. (2018), who model how two storage technologies with different power and energy costs can be combined to achieve a given amount of combined capacity, a process they call hybridization. However, they take this combined capacity goal as given and focus more on power flow optimization, rather than the longer-term renewable penetration and cost objectives we study.

In sum, to the best of our knowledge, our paper is the first to develop and solve an analytical model where a firm optimizes over two types of storage technologies that differ along three dimensions - cost of storage space, cost of transfer speed, and efficiency. We use this model to showcase several new findings on the optimal storage capacity levels, on the impact of operational priority of storage on renewable penetration and capacity investments, on the adoption path of hydrogen, and on the advantages of combining two distinct storage technologies instead of relying only on one.

3 Model

3.1 Preliminaries

We study a setting with the following characteristics: (i) during the day, there is an excess of solar energy generation (energy generated is higher than demand), the extent of which is stochastic due to, e.g., variable weather conditions; (ii) at night, due to the absence of solar energy generation, fossil-fuel backup plants must be run to help meet demand; (iii) there are two distinct, non mutually-exclusive storage technologies available in the market, with different performance profiles, that can be charged in the day and discharged at night to replace fossil-fuel backup generation.

An example of such a setting would be a grid comprised of base-load generation (e.g., nuclear, geothermal, biomass, hydro), a substantial amount of intermittent renewables, solar in particular, and gas-peaking plants. For storage, two plausible technology options could be lithium-ion batteries and hydrogen. As discussed in the introduction, this setting is close to what many countries target for their electricity systems in the mid-term future.

3.2 Setup

In our model, a utility must decide how much energy storage to build, for the purpose of shifting energy from times with excess generation to times with excess demand. The utility must serve all demand over T consecutive, 24-hour periods, minimizing overall costs. Before we can formalize the utility's problem, we need to introduce a few key components of the model. We begin by describing how energy generation and demand evolve over time in the next section; then, describe the two available storage technologies in Section 3.2.2; and finally, introduce storage allocation policies and the model timeline in Sections 3.2.4 and 3.2.5.

3.2.1 Energy Generation and Demand

Define the *Net Energy Profile* as a function that, at any point in time, measures the difference between all non-fossil energy generated and demand - positive net energy means that energy supply exceeds demand, negative net energy means that demand exceeds supply.[3] Figure 1 shows how input data (panel a) translate into a net energy profile (panel b), for an average day in Germany using 2030 projections.

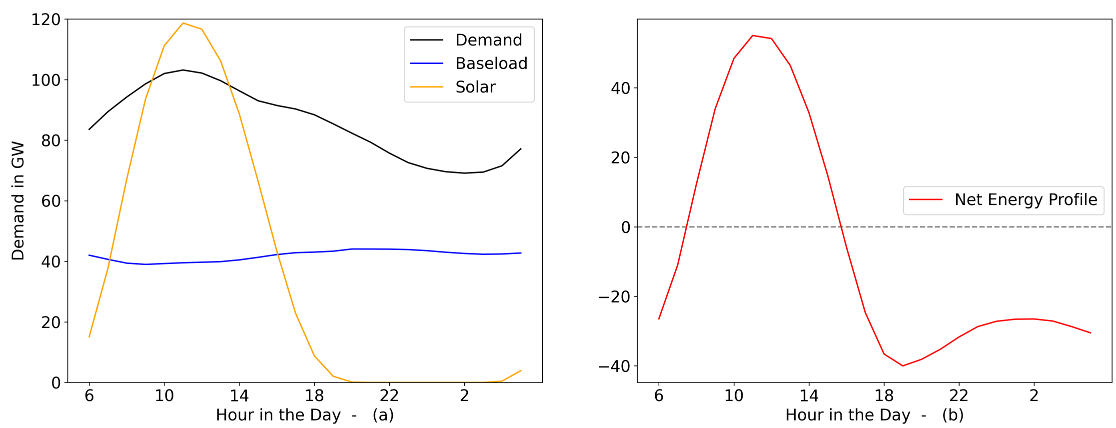


Figure 1: Visualization of Excess Solar Generation in Future Grid with High Solar Penetration. Net Energy Profile in Panel (b) equals Demand minus Baseload minus Solar from Panel (a).

To keep the analysis tractable while preserving the essence of this pattern, we impose structure

[3] For readers familiar with the concept of net load (e.g., in the context of California's duck curve), the net energy profile can be thought of as being equal to base-load generation minus the net load.

on the shape of the net energy profile. In any period, we assume that there is a 12-hour interval (day) during which the net energy profile is weakly positive, followed by a 12-hour interval (night) during which the net energy profile is negative. More specifically, during the day, excess energy generation is variable, and it assumes the shape of an isosceles triangle, which captures in a stylized way the solar generation pattern - low and rising in the morning, peaking in the middle of the day, waning in the afternoon.[4] On the sunniest possible day, the height of the triangle is equal to Q, and its base spans L hours, with $L \leq 12$ - see Figure 2. On any given day t, the height of the triangle is $q_t \sim U\left[0, Q\right]$, with the base of the triangle shrinking proportionally to its height (it is equal to $q_t \frac{L}{Q}$); the varying size of the triangle can be thought as capturing variations in weather or seasons.

During the night, we assume that the net energy profile follows an upside-down triangular pattern, with a negative peak of magnitude D shortly after the sun sets. In a stylized manner, this pattern captures the high energy needs that most electricity grids face in the early evening hours, due to high demand but no solar generation, and the lower energy demand later in the night.[5] Total energy demand at night is $D * 12/2 = 6D$. The chosen net energy profile is stochastic during the day and deterministic overnight because inter-day variation in solar output is typically much larger than inter-day variation in demand. For simplicity and WLOG, we will henceforth set the value of D to 10; one can think of the available excess renewable power Q as being scaled by the peak excess demand D —we show in Appendix B.1 how to perform this calibration based on real-life data.

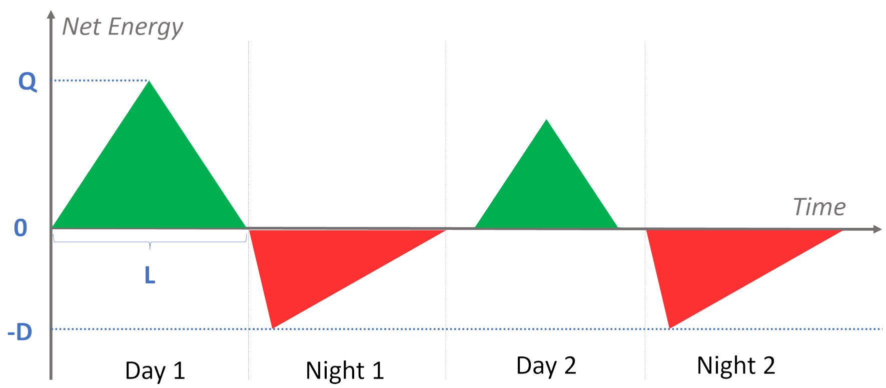


Figure 2: Example of Net energy profile in the model

3.2.2 Energy Storage Technologies

A defining feature of our model is to consider two distinct storage technologies. Such technologies differ along three dimensions: (i) round-trip efficiency (henceforth simply efficiency), which represents the fraction of energy that is *not* lost during a charge-discharge cycle;[6] (ii) module cost, which

[4]Empirically, daily solar generation resembles a smoothed triangle, see as an example Figure 12 in Appendix B.2.

[5]The peak in the early evening is chosen for realism, but our results hold regardless of the time of the nightly peak.

[6]An efficiency of 90% means that whenever 1kWh of energy is charged, only 0.9kWh can be discharged.

is the cost of increasing the maximum amount of energy that can be stored in a given technology by one unit, measured in dollars per kilowatt-hour ($/kWh); and (iii) power cost, which is the cost of increasing the maximum amount of energy that can be exchanged (charged or discharged) per unit of time by one unit, and is measured in dollars per kilowatt ($/kW). As a reminder, the relation between energy and power is that energy is the integration of power over time.[7]

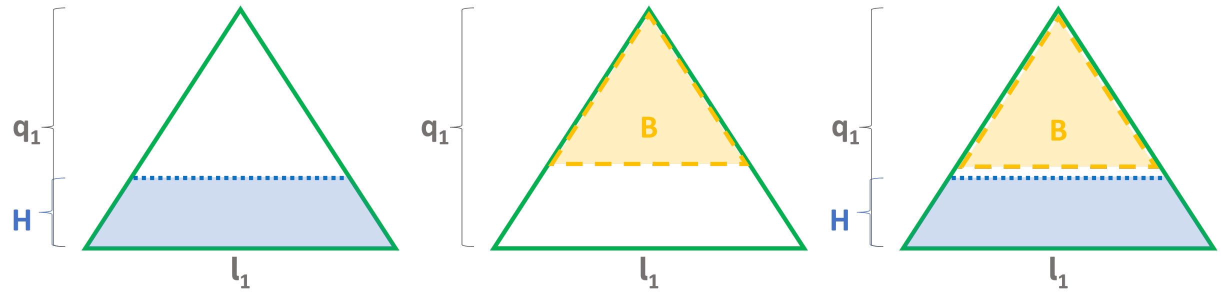
More specifically, technology B is a high-power, high-efficiency technology: We assume that this technology has unlimited (or high-enough), free power, perfect efficiency, but costly modules - each unit of *storage* capacity (kWh) costs $c_B > 0$. Technology B approximates the characteristics of lithium-ion batteries: Their power is so high to never be a constraint for load-shifting operations; their efficiency is extremely high, in the 85-95% range; and higher storage (i.e., energy capacity) comes at a higher cost - one has to buy more battery cells. By contrast, H is a high-storage, lower-efficiency technology: We assume that this technology has unlimited (or large-enough) free storage capacity, less-than-perfect efficiency, $e < 1$, but costly power - each unit of *power* capacity (kW) costs $c_H > 0$. Technology H approximates the characteristics of several existing technologies, such as compressed air storage, but most notably hydrogen storage: As mentioned in the introduction, hydrogen can be stored in salt caverns at a very low cost (Papadias and Ahluwalia 2021, Talukdar et al. 2024); its efficiency is in the 45-50% range; and the expensive aspect of hydrogen are the electrolyzers that allow the conversion from energy to hydrogen and vice versa. In our model, this means that for hydrogen-like technologies, higher power capacity comes at a higher cost.

The characteristics of the two technologies in our model have been chosen to approximate existing storage technologies that are either already popular or considered very promising, and yet feature fundamentally different characteristics, making the question of their optimal combined usage both theoretically interesting and practically relevant. Henceforth, we will refer to technologies B and H simply as batteries and hydrogen, with the understanding that the model can also hold for other technology pairs. We will continue to use B and H to refer to the installed capacity of the two technologies (storage and power capacity, respectively).

Having introduced the two storage technologies, we want to note that they interact with the net energy profile in different ways because of their different characteristics. Technology H, having limited power, is employed by charging/discharging all excess energy up to its power capacity. This means that H operates at the base of the triangle - see Figure 3, panel (a) for a charging example.

Technology B, on the contrary, has unlimited power but limited capacity, so in principle the utility can use it to charge (discharge) any amount of energy at any point in time, so long as its storage capacity is not full (empty); in our model, technology B is operated to charge energy (serve demand) at the peak of the triangle; see Figure 3, panel (b), for a charging example. By doing so, the utility maximizes the energy jointly charged/discharged by both technologies by minimizing the possibility of overlap - see Figure 3, panel (c). This is what the utility would want to do if

[7] For example, if an empty storage technology with efficiency 80% and power equal to 1kW continuously charges for a full hour, it loads up 1kWh of energy, and can discharge 0.8kWh.



(a) Hydrogen Charging **(b)** Battery Charging **(c)** Combined Charging

Figure 3: Operational Difference In Charging Behavior For Both Storage Solutions

it knew the realization of q_t at the beginning of period t, which is realistic given that in practice day-ahead forecasts are very reliable.

3.2.3 Back-Up Generation

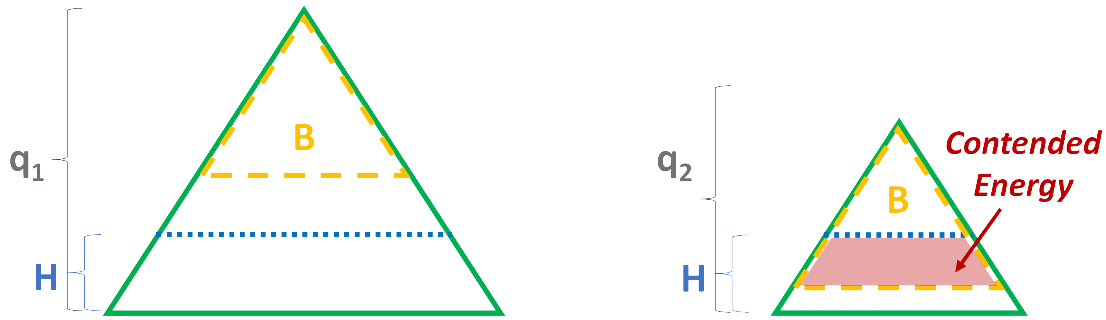
Following the literature, we assume that any demand not met through solar or storage is met through conventional back-up plants (e.g., gas peakers) at a marginal cost g per unit of energy (Kaps et al. 2023, Peng et al. 2024). We do not model price variability to keep the model tractable. While this is a simplification, it looks increasingly plausible that in the near future, which our model aims to capture, price variability will be less prominent. This is because backup plants will increasingly rely on the same energy source - natural gas - which has the lowest environmental impact among all other fossil fuels,[8] is present in large quantities on the planet, and unlike other energy sources (e.g., nuclear), can be fired up with relatively short notice. In such a scenario with a single dominant conventional technology, the shape of the merit order curve will be considerably flatter compared to the current situation characterized by a diversity of energy sources (nuclear, coal, lignite, gas, oil), leading to smaller variability in prices.

3.2.4 Operational Priority

For any installed storage capacity pair (B, H) there can be *conflict* between the two technologies, that is, there can be some energy that either technologies can charge. This is best explained with the help of Figure 4, which focuses on charging examples (discharging examples are analogous). In panel (a), a lot of solar energy is generated during the day, so that capacity of both storage technologies is fully utilized and there is even some energy that cannot be charged —there is no conflict. Panel (b), by contrast, shows an example of conflict, that is, when solar energy in the day is not enough to fully utilize both technologies, and some energy can be captured by either technology —we call this contended energy. In such cases, it must be decided how the contended

[8]E.g., natural gas is the only fossil fuel that is considered green by the 2022 European Commission Taxonomy(Council of European Union 2022).

energy is allocated between the two technologies. In some cases, this decision could be made by the utility, while in other cases, a regulator could pass a regulation to rule that one technology must take precedence over the other, as an attempt to affect the utility's investment decision - a scenario that our paper aims to investigate. To allow for the study of both cases and their implications, we assume that said priority is set before the utility makes capacity decisions, abstracting away from who sets the priority,[9] as discussed next.



(a) No Conflict

(b) Conflict

Figure 4: Distinguishing cases without conflict (when excess renewables $\geq$ storage capacities) and with conflict in storage operations

3.2.5 Model Timeline

The model is organized around three stages.

Stage 1: Operational priority is set. We distinguish between two storage priorities: battery-first and hydrogen-first, where the technology being given priority is always charged and discharged first.[10]

Stage 2: The utility decides how much capacity to build of each technology, with the objective to serve all demand at the lowest expected cost. Storage capacity B will be measured in kWh and power capacity H will be measured in kW. Demand and renewable capacity are exogenous.

Stage 3: Charging/discharging operations are executed for T, 24-hour consecutive periods, following the priority determined in Step 1. Any demand at night that cannot be met through either of the two storage technologies is met through conventional back-up generation.

3.3 Diurnal Load-shifting

Having introduced the main elements of the model, we now proceed to solve it, that is, find the optimal investment decisions (Stage 2) that minimize the cost of serving demand over the T 24-hour

[9]The case in which the utility decides on priority before it makes capacity decisions is equivalent to the utility deciding both priority and capacity at the same time.

[10]These allocations are appealing in practice due to their simplicity, transparency, ease of implementation, and verifiability.

periods (Stage 3) plus the cost of investment, taking operational priority (Stage 1) as given; then, we will investigate the impact of operational priority.

It is known that multi-period storage problems are very challenging to solve (see e.g., the recent works of Kaps et al. (2023), Peng et al. (2024), Lauinger et al. (2024)), and studying investment in two different technologies makes the problem even more challenging. In this paper, we will deal with this inherent source of complexity by separately studying two settings. Following terminology by Twitchell et al. (2023), we begin by studying *diurnal load-shifting*, that is, the case in which all energy stored during the day can be discharged at night (and is thus never carried to the following day). Formally, for this case we set $Q \leq Q' = D12/L = 120/L$. This setting is studied in the present section. The second setting, *seasonal load-shifting*, deals with the possibility that energy may need to be carried beyond the first night, and will be studied in Section 3.4.

Under diurnal load shifting, the system is somewhat easier to study for two reasons. First, because all T periods become stochastically equivalent (no energy is left in storage at the beginning of each day), which implies that the optimal investment decision is the one that minimizes the average cost per period. Second, because the amount of energy that can be charged is always lower than the amount of energy that can be discharged, which allows us to simplify certain expressions. Formally, the problem of the utility is:

$$\max_{H,B} \left\{ g\mathbb{E}_{q_t}\left[c_\tau(B|q_t) + c_{3-\tau}(H|q_t)\right] - c_B B - c_H H \right\}, \quad B \geq 0, H \geq 0, \tau \in \{1,2\}, \tag{1}$$

where $\mathbb{E}$ is the expectation operator, $c_\tau(B|q_t)$ and $c_{3-\tau}(H|q_t)$ measure the energy charged (and discharged) in period t, when sunlight realization is q_t, by technology B and H respectively, the priority of each storage technology being identified in the subscript, with $\tau = 1$ corresponding to battery-first priority. Expected demand met via storage is multiplied by g to measure its cost-saving impact, since every unit of demand met this way saves g in the cost of burning fossil fuels in backup plants. The terms above take the following form (see Appendix A.1 for details):

$$\begin{aligned}
c_1(B|q_t) &= \min\left[B, \frac{q_t^2 L}{2Q}\right], \\
c_2(H|q_t) &= e \min\left[H, q_t - \sqrt{\frac{2BQ}{L}}\right] \frac{L(q_t + (q_t - \min\left[H, q_t - \sqrt{\frac{2BQ}{L}}\right]))}{2Q}, \\
c_1(H|q_t) &= e \min[H, q_t] \frac{L(q_t + (q_t - \min[H, q_t]))}{2Q}, \\
c_2(B|q_t) &= \min\left[B, \frac{(q_t - H)^2 L}{2Q}\right].
\end{aligned} \tag{2}$$

3.3.1 Optimal Capacity Investments

Having introduced the problem, we turn to studying the optimal capacity investments. We denote with X^*_ω the optimal capacity investment in technology X if it has operational priority ω - e.g., B^*_1 represents the optimal battery capacity under battery-first priority.

Proposition 1. Optimal Capacity Investments - Diurnal

Under diurnal load-shifting, the optimal capacity investments are:

$$\begin{aligned}
&\textit{Battery } 1^{st} \begin{cases} B_1^* = \frac{QL}{2}\left(\left(1-\frac{c_B}{g}\right)^+\right)^2, \\ H_2^* = Q\Big(1-\sqrt{\frac{c_H}{geL/2}+\left(1-\frac{c_B}{g}\right)^2}\Big)^+, \end{cases} \\
&\textit{Hydrogen } 1^{st} \begin{cases} B_2^* = \frac{QL}{2}\left(\left(\sqrt{\frac{c_H}{geL/2}}-\frac{c_B}{g}\right)^+\right)^2, \\ H_1^* = Q\left(1-\sqrt{\frac{c_H}{geL/2}}\right)^+, \textit{with } (a)^+ = max(0,a). \end{cases}
\end{aligned} \tag{3}$$

The importance of Proposition 1 is twofold. First, it provides closed-form solutions for optimal capacities - tractable investment results which are an important building block for many subsequent analyses. Second, the expressions themselves are revealing of several interesting properties of the optimal capacity choices.

To begin, remember that Q defines the maximum possible amount of excess solar at any point in time and L the longest possible duration of excess solar in a day. As it turns out, these two parameters have very different impact on optimal capacities. Specifically, optimal capacities grow linearly in Q - this holds for both technologies and both operational priorities. By contrast, optimal capacities are not linear, and marginally decreasing, in L (with the exception of B_1^*). Thus, having a higher peak of excess energy and having excess energy for longer play two very different roles in storage sizing.

We also learn that optimal capacities depend on technology costs via two adjusted-cost terms, hereby defined as $c_B^{adj} = \frac{c_B}{g}$ and $c_H^{adj} = \frac{c_H}{geL/2}$. Both adjusted-cost terms contain the capacity unit cost of the respective technology divided by the backup cost g. As one would expect, this means that all capacities, irrespective of technology and priority, are increasing in back-up cost, however the relation between capacities and back-up cost is highly non-linear, an effect that we will study in more detail in Proposition 7. Hydrogen's adjusted cost, c_H^{adj}, is obtained by further dividing c_H by (i) hydrogen's efficiency e, thereby inflating hydrogen's unit cost (since $e < 1$) to account for the round-trip energy lost; and (ii) the average duration for which excess solar is available $L/2$, thereby lowering hydrogen's unit cost to account for the fact that hydrogen can work at full power for up to L consecutive hours.

Lastly, we learn that Q, L, c_B^{adj}, and c_H^{adj} are the *only* parameters one needs to consider to derive optimal capacity choices.

Proposition 2. Investment Conditions

- *When batteries have priority, the two technologies are invested in under the following iff conditions:*

$$\begin{aligned}
&B_1^* > 0 \textit{ iff } c_B^{adj} < 1, \\
&H_2^* > 0 \textit{ iff } \begin{cases} c_B^{adj} > 1 \Rightarrow\ B_1^* = 0 \ \wedge\ c_H^{adj} < 1, \\ c_B^{adj} < 1 \Rightarrow\ B_1^* > 0 \ \wedge\ c_H^{adj} < 2c_B^{adj} - (c_B^{adj})^2. \end{cases}
\end{aligned} \tag{4}$$

- *When hydrogen has priority, the two technologies are invested in under the following iff conditions:*

$$H_1^* > 0 \text{ iff } c_H^{adj} < 1,$$
$$B_2^* > 0 \text{ iff } \begin{cases} c_H^{adj} > 1 \Rightarrow H_1^* = 0 \wedge c_B^{adj} < 1, \\ c_H^{adj} < 1 \Rightarrow H_1^* > 0 \wedge c_B^{adj} < \sqrt{c_H^{adj}}, \text{ where } c_H^{adj} = \frac{c_H}{geL/2}, c_B^{adj} = c_B/g. \end{cases} \quad (5)$$

We continue with our result in Proposition 2, which lays out conditions for technologies to be invested in. Specifically, investment in storage is undertaken when a technology's *adjusted* cost is low enough. That is, when the unit cost is low enough and the backup cost is high enough —remember that both c_H^{adj} and c_B^{adj} relate to those two costs. This also means that hydrogen is more likely to be invested in when excess solar duration, L, is large. Interestingly, a large excess solar duration L may rule out investment in batteries when hydrogen has priority (see B_*^2), highlighting the interdependence between the two storage technologies.

At least as interesting is what investment conditions do *not* depend on: In Proposition 2 there is *no sign of* Q. Thus, while the duration of the excess renewables, L, plays a role in promoting (hydrogen) or even deterring (battery) storage investments, Q does not play any role. Managerially, this means that hydrogen storage will likely be first invested in those markets where excess renewables are available for longer hours, not necessarily in those with the most renewables as common wisdom would suggest.

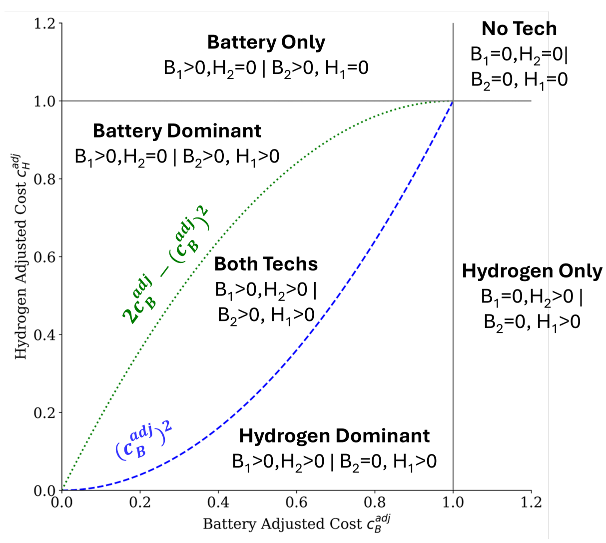


Figure 5: Conditions under which none, one, or both storage technologies are invested in under the different priorities. Backup-cost g normalized to 1.

We condense these insights from Proposition 2 into the graphical representation of Figure 5, which provides a quick way to assess where a given technology pair is located within the capacity investment-space. In Figure 5, we normalize the backup cost to 1, so that the technology costs are expressed relative to the backup cost. The x-axis plots the adjusted battery cost, c_B^{adj}, and the y-axis plots the adjusted hydrogen cost c_H^{adj}. The graph shows six areas. The first thing to note is that adjusted costs determine simple and effective adoption thresholds above which storage technologies are not adopted: Specifically, when a technology's adjusted cost is higher than 1, no investment is made in that technology, regardless of its operational priority.

When adjusted costs are less than 1, we can identify three areas of interest: *Battery Dominant*, *Both Techs*, and *Hydrogen Dominant*. In the Battery (Hydrogen) Dominant area, hydrogen (batteries) are only invested in if they have priority. Only in the *Both Techs* area are both technologies invested in under both prioritization schemes, which happens when the adjusted battery cost and the adjusted hydrogen cost satisfy these conditions: $(c_B^{adj})^2 < c_H^{adj} < 2c_B^{adj} - (c_B^{adj})^2$.

3.3.2 The Impact of the Operational Priority

Having characterized the optimal capacity choices, we now turn to studying the role of operational priority. As discussed in the introduction, many countries have set goals to vastly improve the share of demand met with renewable energy in the near future. Thus, we want to study the impact of operational priority on renewable storage penetration, henceforth simply renewable penetration, defined as the percentage of nightly demand being met with renewable generation. We begin by studying this question for the case in which storage capacities are given (i.e., exogenous). Let $c_{B=1}(B,H) = E[c_1(B|q_t)] + E[c_2(H|q_t)]$ be the expected energy charged in a day under battery-first priority for a given storage capacity pair (H,B). Let $c_{H=1}$ be the analogous amount under hydrogen-first priority. We have the following result:

Proposition 3. Effect of Priority on Renewable Penetration (exogenous capacities) *For a fixed capacity pair (B,H), prioritizing battery technology always results in higher renewable penetration compared to prioritizing hydrogen technology. Formally, $c_{B=1}(B,H) \geq c_{H=1}(B,H)$.*

Proposition 3 establishes that prioritizing batteries over hydrogen always leads to higher renewable penetration. The reason is that batteries are more efficient, and therefore, the more energy is charged into batteries, the less energy is lost in the charging-discharging process and the more demand is met with renewable energy.

This can be seen mathematically by looking at Equations (6), where we express the amount of demand served under battery-first and hydrogen-first priority, respectively, for a given set of investments, as the sum of three terms,[11] which capture demand met via batteries using non-contended energy (left term), via hydrogen using non-contended energy (right term), and via the prioritized technology using contented energy (term in the middle).

[11]see Appendix A.3 for a formal definition of all terms and the derivation of the expressions.

$$
\begin{aligned}
c_{B=1}(B,H) &= \frac{1}{Q}\Big[\underbrace{\int_0^{q_0}\frac{q_t^2 L}{2Q}dq_t + \int_{q'}^{Q} B dq_t}_{\text{Battery}} + \underbrace{\int_{q_0}^{q'} B dq_t}_{\text{Contended}} + \underbrace{e\Big(\int_{q_0}^{q'}\psi(q_t - \sqrt{\frac{2BQ}{L}}, q_t)dq_t + \int_{q'}^{Q}\psi(H,q_t)dq_t\Big)}_{\text{Hydrogen}}\Big] \\
c_{H=1}(B,H) &= \frac{1}{Q}\Big[\underbrace{\int_0^{q_0}\frac{q_t^2 L}{2Q}dq_t + \int_{q'}^{Q} B dq_t}_{\text{Battery}} + e\underbrace{\int_{q_0}^{q'} B dq_t}_{\text{Contended}} + \underbrace{e\Big(\int_{q_0}^{q'}\psi(q_t - \sqrt{\frac{2BQ}{L}}, q_t)dq_t + \int_{q'}^{Q}\psi(H,q_t)dq_t\Big)}_{\text{Hydrogen}}\Big]
\end{aligned} \tag{6}
$$

We see that while the amount of non-contended energy charged is the same regardless of operational priority (left and right terms), the amount of contended energy charged (middle term) is strictly lower when hydrogen has priority (bottom expression) due to its lower efficiency reducing the energy used to meet demand through storage.

Managerially, the implication of Equations 6 and Proposition 3 is that if capacities are fixed, batteries (i.e., the more efficient technology) should always be prioritized if one aims to maximize renewable penetration.

The next proposition investigates the case of endogenous capacities, that is, when operational priority is set first, for example, by a regulator, and then storage capacities are chosen by the utility to meet all demand at the lowest cost.

Proposition 4. Effect of Priority on Renewable Penetration (endogenous capacities)
When capacities are chosen after the operational priority has been set, prioritizing the less efficient hydrogen technology results in higher renewable penetration if $e \geq \bar{e}$ *and* $c_B \in (\underline{c}_B, \bar{c}_B)$*. Formally,* $c_{B=1}(B_1^*, H_2^*) < c_{H=1}(B_2^*, H_1^*)$ *, if* $e \geq \bar{e} \ \wedge \ c_B \in (\underline{c}_B, \bar{c}_B)$*, where* $\bar{e} = \frac{-5+6\sqrt{1-c_H^{adj}}+\sqrt{c_H^{adj}+4c_H^{adj}}}{1+\sqrt{c_H^{adj}}+c_H^{adj}}$*,* $\underline{c}_B = \sqrt{\frac{1}{3}\sqrt{e^2 c_H^{adj} - 2ec_H^{adj} + c_H^{adj}} + \frac{1}{3}(c_H^{adj} + 1 - e - c_H^{adj} e)}$*,* $\bar{c}_B \in (1 - \sqrt{(1 - c_H^{adj})}), \sqrt{c_H^{adj}})$*, and* g *is normalized to 1.*

Proposition 4 shows that considering the impact of operational priority on investment can flip the result of Proposition 3, and prioritizing batteries can actually decrease renewable penetration (it does so when $e \geq \bar{e} \ \wedge \ c_B \in (\underline{c}_B, \bar{c}_B)$. To better understand this result, we need to understand how operational priority affects investment decisions. On the one hand, prioritizing hydrogen could prompt *more* investment in hydrogen since everything else being equal, hydrogen ends up being used more often. On the other hand, prioritizing hydrogen could prompt *less* investment in hydrogen precisely because hydrogen is used more often, as this means wasting more energy due to its lower efficiency (recall Equations 6).

The next proposition determines which of these two effects prevails by establishing a clear relation between operational priority and capacity levels.

Proposition 5. Operational Priority: Impact On Capacity
Capacity investment in a given technology τ is always greater when it has operational priority, irrespective of its efficiency. Formally, $\tau_1^* \geq \tau_2^*$, where $\tau \in \{H, B\}$.

Proposition 5 shows that one of the two effects discussed above is always stronger, and prioritizing a technology always increases its investment amount. In particular, this means that, given the right technology parameters, a regulator who wanted to increase investment in hydrogen - to increase renewable penetration, or for strategic reasons like diversification of the energy portfolio - could mandate operational priority of hydrogen over batteries instead of spending taxpayers' money on subsidies. This also means that the result shown in Proposition 4 - that hydrogen priority can increase renewable penetration - is not caused by a decrease in hydrogen investment, but rather, by an increase. This effect occurs especially when hydrogen capacity is very low if not prioritized ($H_2^* \approx 0$, see Appendix A.4 for more details). Conceptually, the initial unit of hydrogen, on average, can be used $L/2$ hours per day, leading to $eL/2$ units of nightly demand being met through renewables, while a marginal unit of battery is used at most 1 time per day. If the hydrogen capacity that is added when shifting from battery to hydrogen priority ($H_2^* - H_1^*$) is used often enough, the net effect is an increase in renewable penetration, despite hydrogen's lower efficiency (and batteries being invested in and used less).

This result is important for policymakers, as it highlights the possibility that prioritizing a less efficient, non-battery technology like hydrogen over incumbent lithium-ion solutions can actually increase renewable penetration, in addition to boosting investments in hydrogen. This is particularly likely to occur when utilization is a key factor in whether or not hydrogen is invested in. We numerically investigate how close multiple hydrogen-like technology currently are to reaching this condition in Section 5.2.

3.4 Seasonal Load-shifting

We now move to consider the alternative scenario case where renewable capacity is large enough, $Q > Q' = 120/L$, so that excess generation during the day can exceed demand at night, meaning that if enough capacity is built, stored energy can be used to serve demand weeks or even months into the future. We call the days where excess generation in the day exceeds demand at night sunny days, and the other days dark days.

Solving such a seasonal model poses challenges that make it analytically intractable, for the reasons already discussed in Section 3.3. However, it is possible to use the model presented for diurnal load-shifting and, with some changes, adapt it to create a scenario with seasons, where shifting energy from a day to several weeks or months later is valuable, and expressions are still somewhat tractable. To do so, we assume that within the span of a year, all sunny days occur sequentially, and are followed by all dark days, thus forming a sunny season and a dark season - yet, we retain stochasticity of excess generation during each day in each season. We achieve this by drawing excess energy realization for each day (after investment decisions are made) and then re-arranging the days so that all periods with $q_t > Q'$ happen first (sunny season), followed by all other periods where $q_t \leq Q'$ (dark season). This is meant to capture real-life seasonality for countries not close to the equator, where summer days have predictably longer days of sunshine and higher solar outputs than the rest of the year, but the exact realization for a given day, and to a lower extent the duration of a given season, are still uncertain - see Appendix B.3 where we show real-world solar seasonality patterns to support this assumption.

We make two additional, mild assumptions. We assume that seasons are long enough that it is not financially viable (or technically infeasible) for batteries to charge energy in the sunny season only to discharge it in the dark season. [12] We also assume that hydrogen will be able to discharge its energy across the year.[13]

3.4.1 Optimal Capacity Investments

In the next proposition, we present closed-form investment solutions for seasonal load-shifting —we use superscript S to denote the optimal capacities under seasonality (see Appendix A.6 for details).

Proposition 6. Optimal Capacity Investments - Seasonal
Under seasonal load-shifting, i.e. $Q > Q'$, the optimal capacity investments are:

$$
\begin{aligned}
&\textit{Battery } 1^{st} \begin{cases} B_1^S = \min\left[\frac{QL}{2}\left(\left(1-\frac{c_B}{g}\right)^+\right)^2, 60\right], \\ H_2^S(B_1^S) = \begin{cases} H_2^*(B_1^*) = Q\Big(1-\sqrt{\frac{c_H}{geL/2}+\Big(1-\frac{c_B}{g}\Big)^2}\Big)^+, \ \textit{if } c_B > g\Big(1-\sqrt{\frac{120}{LQ}}\Big), \\ Q\Big(1-\sqrt{\frac{c_H}{geL/2}+\frac{60}{QL/2}}\Big)^+, \ \textit{if } c_B \leq g\Big(1-\sqrt{\frac{120}{LQ}}\Big), \end{cases} \end{cases} \\
&\textit{Hydrogen } 1^{st} \begin{cases} B_2^S(H_1^S) = \min\left[\frac{QL}{2}\left(\left(\sqrt{\frac{c_H}{geL/2}}-\frac{c_B}{g}\right)^+\right), 60\right], \\ H_1^S = H_1^* = Q\left(1-\sqrt{\frac{c_H}{geL/2}}\right)^+. \end{cases}
\end{aligned}
\tag{7}
$$

The optimal capacity investments shown in Proposition 6 are analogous in structure to the ones originally introduced in Proposition 1. However, the added complexity of seasonality brings with it two important considerations. First, battery capacity is limited by nightly demand. This is because under seasonal load shifting consecutive days of excess generation mean that no charge beyond nightly demand can be discharged.

Second, if battery has priority, the investment in hydrogen now is piece-wise continuous: If $c_B > g(1-\sqrt{\frac{120}{LQ}})$, batteries operate as before and the optimal capacity is identical to the diurnal load-shifting case; but, if $c_B \leq g(1-\sqrt{\frac{120}{LQ}})$, batteries are sufficiently cheap - and solar sufficiently

[12] This simply rules out some unrealistic parameter combinations. Indeed, building extra battery capacity so it can be charged once in the sunny season to hold that energy until it can be discharged once in the dark season would be unprofitable even decades from now, as using batteries frequently is key to making them profitable.

[13] That is, yearly efficiency-adjusted charge is no greater than yearly unmet demand, which is realistic, as building more hydrogen capacity would be hardly profitable.

available - that seasonality starts limiting the battery's ability to discharge, which in turn increases the relative investment in hydrogen[14]. Importantly, this means that once renewable availability is large enough to occasionally exceed unmet demand at night, the balance of storage technologies is (weakly) tipped toward hydrogen due to its ability to accumulate charge across consecutive periods at no extra cost. As such, Proposition 6 provides a possible analytical justification for why hydrogen is frequently touted as a seasonal storage solution.

3.4.2 Comparative Statics of Investment

The seasonal load-shifting case brings about interesting effects that are worth discussing. For this reason, we now turn to studying how investments change when the back-up cost increases. Remember that the backup cost g shows up in the denominator of both c_B^{adj} and c_H^{adj}, which are the sole parameters related to technology costs that affect capacity levels. Hence, an increase in the backup cost can proxy for cost reduction in both technologies, in addition to proxy for a price increase in electricity, of course, which are both interesting scenarios to discuss. In this section, we focus on the case of battery priority, which is probably the more interesting case to study given the large amount of battery capacity currently installed; we present comparative statics for the case of hydrogen priority in Appendix A.7 for completeness.

Proposition 7. Comparative Statics
If batteries are operated first, optimal capacity investments changes with respect to back-up cost g as follows:

$$
\begin{aligned}
&\frac{\partial B_1^S}{\partial g}\begin{cases} = 0 \ , \ \text{if } g < c_B, \\ = LQ\frac{c_B(g-c_B)}{g^3} \ , \ \text{if } c_B \le g < c_B/\left(1-\sqrt{\frac{120}{LQ}}\right), \\ = 0 \ , \ \text{if } g > c_B/(1-\sqrt{\frac{120}{LQ}}), \end{cases} \\
&\frac{\partial H_2^S}{\partial g}\begin{cases} = 0 \ , \ \text{if } g < \frac{c_B^2 eL}{2c_B eL - 2c_H}, \\ = \frac{Q(c_B eL(c_B-g)+c_H g)}{g^2\sqrt{eL\left(eL(c_B-g)^2+2c_H g\right)}} \ , \ \text{if } \frac{c_B^2 eL}{2c_B eL-2c_H} < g < c_B/\left(1-\sqrt{\frac{120}{LQ}}\right), \\ = \frac{c_H Q^{3/2}}{\sqrt{2}g\sqrt{egL(c_H Q+60eg)}} \ , \ \text{if } g > c_B/\left(1-\sqrt{\frac{120}{LQ}}\right). \end{cases}
\end{aligned} \tag{8}
$$

Two things are noteworthy from Proposition 7. First, the investment in batteries is marginally decreasing as back-up costs grow and stops growing altogether (i.e., first derivative is zero) if back-up cost become sufficiently large because the demand that batteries can serve becomes discharge-limited when $c_B = g\left(1-\sqrt{\frac{120}{LQ}}\right)$. At that point, further technology improvements will not spur further investments, which is an interesting threshold to identify for long-term capacity planning. Second, the impact of back-up cost on hydrogen investment is highly dynamic. Initially, if $g <$

[14] If battery is not prioritized (i.e., for B_2^S) for this to happen we need the following condition to hold $\frac{c_H}{e} = c_B\sqrt{\frac{120L}{Q}} + \frac{60g}{Q} + \frac{c_B^2 L}{2g}$; see derivation in Appendix A.6.

$\frac{c_B^2 eL}{2c_B eL - 2c_H}$, an increase in back-up cost exclusively benefits batteries. Afterwards, increases in back-up cost lead to a (marginally decreasing) increase in hydrogen investment, and once batteries hit their discharge-limit, there is a jump-discontinuity in the derivative and hydrogen investment grows faster in back-up costs - which occurs at the threshold $g(1 - \sqrt{\frac{120}{LQ}})$.

Together, these results can be conceived as two technology tipping points for hydrogen: The first tipping point occurs when one marginal unit becomes profitable next to batteries - which is not impacted by the degree of seasonality (the condition does not depend on Q). As long as markets have similar costs, this predicts approximately similar initial adoption of hydrogen across regions. The second technology tipping point occurs when seasonality limits battery discharge - which varies across markets, in part depending on their level of renewable investment and determining the scale of hydrogen adoption.

In Figure 6, we present the different investment regions under seasonal load-shifting, as an extension to Figure 5 for the diurnal load-shifting case. The two figures are identical for a substantial portion of the parameter space, but seasonality impacts capacity decision at the limits[15].

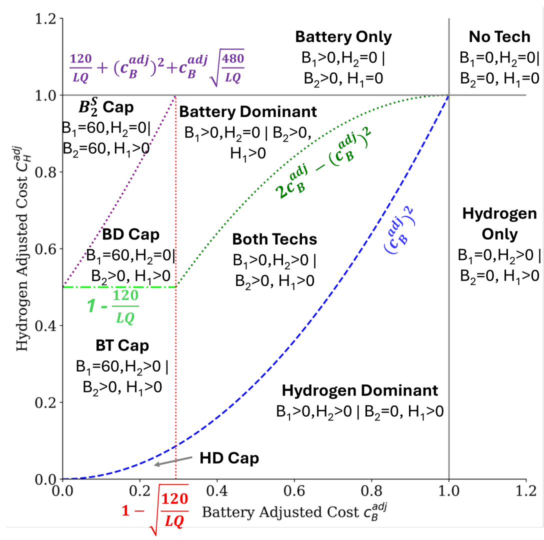


Figure 6: Conditions under which none, one, or both storage technologies are invested in under the different priorities.

Figure 6 contains a lot of details. The main insights from the non-seasonality result carry over, but in this figure, beyond checking whether capacity is positive or not, as done in Figure 10, we also cover the case when the batteries hit the discharge limit, something unique to seasonal load-shifting. The main change from Figure 5 is that, under seasonality, there are more cost combinations where hydrogen is invested in - see regions *Both Techs* and *BT Cap* compared to the *Both Techs* region from Figure 5. Because of the cap, if battery costs c_B are lower than the threshold $1 - \sqrt{120/L/Q}$, battery capacity B_1^S hits the discharge cap, which in turn accelerates

[15]For the conditions that depend on Q, we assumed $Q = 20$ - the plot has the same structure for other values of $Q \geq Q'$, but the relative magnitude of areas shifts, see Appendix A.7.1 for an introduction of the cases

hydrogen's adoption. Additionally, in the top left corner, there is a range of parameters where batteries are so cheap that even de-prioritized batteries reach that cap $B_2^S = 60$.

Having studied the seasonal case, it is useful to reflect on what drivers move markets towards seasonality, as this will impact storage operations. First, having a higher renewable availability (higher Q), naturally increases the degree of seasonality, as this increases the odds that excess energy exceeds the nightly demand. However, a second element to consider is the backup cost, as countries with higher back-up costs will be affected sooner by seasonality (remember that we normalize everything by the back-up cost g, so graphically, a higher back-up cost is equal to moving the vertical line $(1 - \sqrt{120/L/Q})$ further right). Importantly, this means that countries with the highest resource availability won't necessarily be the first who need to rely on hydrogen, as not using excess solar in the summer may be optimal if electricity prices (g in the model) are low. However, in countries where conventional generation is costly, and excess solar in the summer is valuable, the effects of seasonality will be felt first - batteries reach their discharge cap and hydrogen starts being invested in.

4 Data

Regions Data. We want to calibrate our analytical results based on current technology and renewable data from different markets to understand how our analytical results translate into real-life storage adoption. To do so, we use three sets of data for different regions: i) historical demand, generation, and power price time-series, ii) future renewable capacity and demand targets, and iii) storage cost estimates from current day and forecasts until the year 2030. First, we obtain the demand and generation time-series from two different sources. For Germany and France, we download 2023 demand, generation, and price data from the European Network of Transmission System Operators (*ENTSO-E*)[16]. For the Spanish island of La Palma, we obtain 2019 data from Kaps et al. (2023). France and Germany both have ambitious renewable generation targets, but while the former heavily relies on nuclear power to achieve those, Germany entirely phased out this firm, non-emitting technology, and plans to scale up solar and wind. In contrast, La Palma's demand is largely served by diesel generation with only a little solar but the island is part of a European Union (EU) initiative to accelerate the transition towards clean energies on islands[17]. We detail in Appendix B.1 how we translate the time-series data into our model estimates. We use the average price in the year as the back-up cost estimates.

For future renewable and demand targets, we use the legislation targets that France (de Transition Écologique et Solidaire (MTES) 2023) is reviewing and Germany (Bundestag 2022) has passed, as well as a 100 MW solar capacity target for La Palma. We assume that newly built capacity of any technology has the same capacity factor/utilization as existing capacity. We summarize the region-

[16]`https://transparency.entsoe.eu/`

[17]https://clean-energy-islands.ec.europa.eu/countries/spain/la-palma

specific estimates that we use in the model in Table 1. All variables are scaled to the respective

Table 1: Model Parameters and Price Data for Regions at 2030

	Unit	France	Germany	La Palma
Peak Excess (Q)	MW	12.43	9.24	8.83
Max Excess Duration (L)	h	12	12	11
Backup Cost (g)	\$/MWh	105	105	229
Days with Excess (f)	%	70	56	100

regional average nightly demand. France has the highest peak renewable excess at 12.43 (meaning that on the sunniest day, excess generation is 1.243 times as large as the average nightly demand), in large part due to over 50 nuclear reactors providing base-load generation: Since demand in our model is overall demand minus base-load generation, this means that the demand to be covered by renewables/gas is lower. For comparison, Germany plans to have 215GW of solar by 2030 (France plans for 60GW) but has lower peak renewable excess as the country has no equivalent non-fossil base-load generation. Both countries had virtually identical average power prices in 2023 of \$105[18]. By contrast, La Palma has significantly higher electricity cost, due to the high cost of getting fuel to the island, and the smaller, less efficient oil power plant providing the energy.

While increased investment in renewables will lead to excess renewable generation most days during the year, there will still be days in winter when there is no excess generation at all. *Days with Excess* represents the fraction of days in a year in which there is excess generation, and it varies by country. Our projections show that both France and Germany will have no excess generation for several weeks in winter even in 2030, due to demand being higher than renewable generation. To account for this, we employ an inflated cost of storage, obtained by dividing the real (un-inflated) cost by *Days with Excess*, as storage won't be discharged during those days in the year. La Palma is closer to the Equator and, therefore, will have excess generation throughout the year. Please see Appendix B.1 for a more detailed discussion of the parameter estimation.

Technology Data. For the technology cost estimates, we use the 2023 National Renewable Energy Lab's utility-scale lithium-ion battery forecasts (Cole et al. 2023) for battery cost prediction from 2023 to 2030 and the reversible power-to-gas estimates from Glenk and Reichelstein (2022) for solid oxide electrolyzer for the same time-frame and assume 50% efficiency in the conversion process. While both technologies are expected to decline in cost over time, battery's cost decrease is expected to be less pronounced compared to hydrogen, due to the former being a relatively more mature technology. We will mostly focus on hydrogen as a conversion-limited technology but also provide cost estimates for compressed-air (from Hunt et al. (2023) with cost reductions based on Dufek et al. (2023)), a more mature technology relative to hydrogen, with lower cost-reduction

[18] $\approx$ 97€ converted at the 2023 average EUR:USD exchange rate

potential but higher efficiency (70%). A summary of these estimates is provided in Table 2.

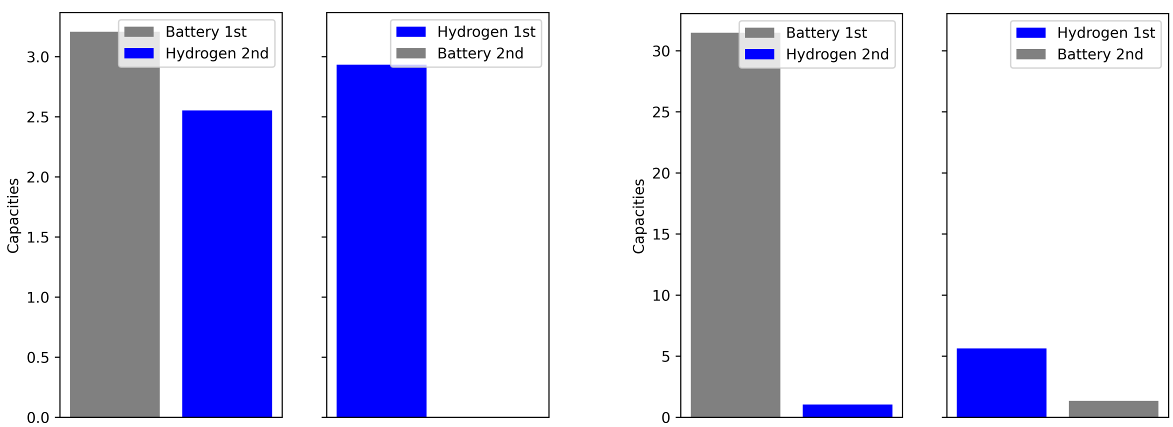
Technology	Unit	2023	2024	2025	2026	2027	2028	2029	2030
Battery	\$/kWh	463	443	388	376	363	351	338	326
Hydrogen	\$/kW	2,300	1,898	1,566	1,293	1,067	880	726	600
Compressed-Air	\$/kW	1,898	1,840	1,784	1,730	1,677	1,625	1,576	1,527

Table 2: Unadjusted Storage Technology Cost Projections from 2023 to 2030

5 Numerical Results

5.1 Capacity Investments Based On Priority

We begin the numerical section by investigating how the optimal investment results from Proposition 1 look like, using estimates for storage costs in 2030 from Table 2, under different storage priorities. In Figure 7, we show the optimal storage investment in Germany and La Palma, distinguishing between battery-first (left panel) and hydrogen-first (right panel) priorities.[19]



(a) Germany **(b)** La Palma

Figure 7: Optimal Capacity Investments In Battery and Hydrogen as of 2030

In Germany, under battery-first priority, both batteries and hydrogen are profitable for load-shifting and are invested in, but at moderate capacity levels (see y-axis), partially because winters are relatively long. This is in line with the observed growth of investments in batteries and commercial projects for hydrogen as of this writing.

Under hydrogen-first priority, results are quite different. With hydrogen operating first, its optimal investment increases by 16%, while batteries in this setting are not invested in at all as hydrogen uses most of the excess renewables. This finding underscores that operational priority can have a decisive impact on whether there is co-existence of technologies (in this case with

[19](See Appendix B.4 for the French results, which are similar to Germany's)

battery priority) or a winner-takes-all scenario (in this case with hydrogen priority), something policy-makers should be well aware of.

In La Palma, depicted in Figure 7, panel (b), seasonality is virtually nonexistent and $Q < Q'$ by 2030 (see Table 1) so we are in an empirical setting with near-perfect diurnal load-shifting conditions. For battery-first, this translated into a ten-fold higher investment in Batteries compared to Germany (relative to demand), also aided by the higher electricity prices. Hydrogen investment are much lower under this priority, but still positive. When priorities are changed to hydrogen-first, hydrogen investment quadruples and battery investment shrinks but remains positive.

Contrast these results to how press articles, as well as many academic studies, associate hydrogen with seasonal load-shifting. Our analytical result from Proposition 1 and the numerical calibration performed here both highlight that hydrogen can be profitably invested in even for diurnal load-shifting and even when it is not prioritized. The reason for this is that batteries' marginal value does not change with the duration of excess renewable generation, giving hydrogen an edge during days with long hours of excess solar. This can lead to hydrogen investments even before seasonal load-shifting becomes feasible or profitable.

5.2 Operational Priority Effects on Charges

We now turn our attention to renewable penetration: In particular, we want to empirically investigate the impact that prioritizing conversion-limited technologies, such as hydrogen or compressed-air, can have on renewable penetration, as a follow-up to Proposition 4.

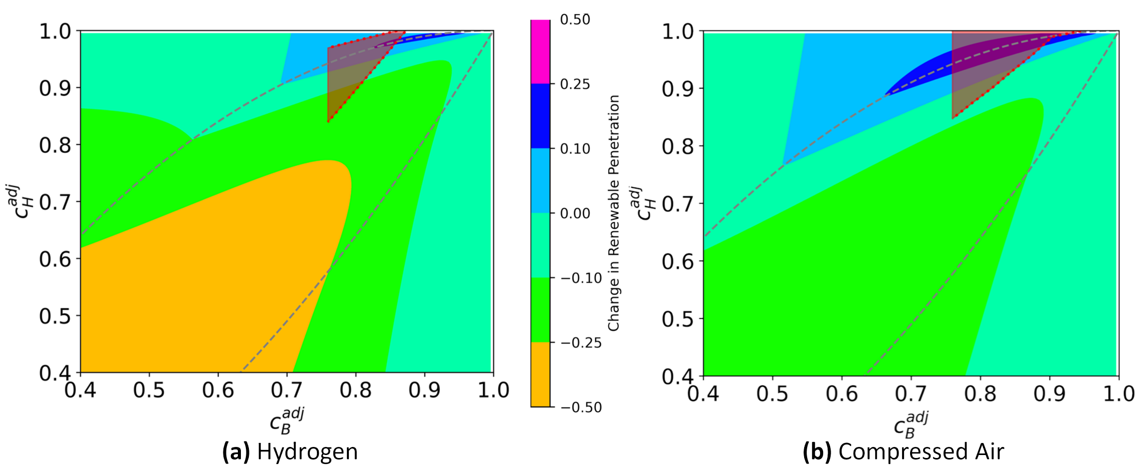


Figure 8: Change In Renewable Penetration When Operational Priority Is Given to Hydrogen (a) or Compressed Air (b)

In Figure 8, we plot the change in demand met through renewables when a conversion-limited technology - hydrogen in the left panel and compressed air in the right panel - is prioritized over batteries, as a function of storage costs. As with Figure 5, adjusted Battery costs are shown on the x-axis and adjusted hydrogen/compressed-air costs on the y-axis, so that a cost of 1 for both technologies is equivalent to marginal profitability of the first unit with priority. We overlay cost forecasts on both figures, in red, to highlight which part of the graph is relevant for our purpose. For battery cost, we use the linear forecasts from Table 2, while for the largely immature hydrogen technology, we use a range of rates to capture the higher degree of uncertainty around cost - specifically, from 2026 onward cost declines at a range between 25% and 150% of batteries' cost decline. For compressed air, the chosen range is narrower given that the technology is more mature relative to hydrogen - cost reduction is between 0 and 17%, where 17% is NREL's highest estimate for cost reduction by 2030.

Three things are worth commenting on from the analysis. First, we see that the effect size of prioritizing hydrogen or compressed air can be substantial. In the upper right corner of the figure, i.e., the area where both technologies are barely profitable, prioritizing hydrogen allows up to 19% more demand to be met via storage. For compressed air, due to its higher efficiency, this area is even larger, and so is the increase in demand being met - up to 24%.

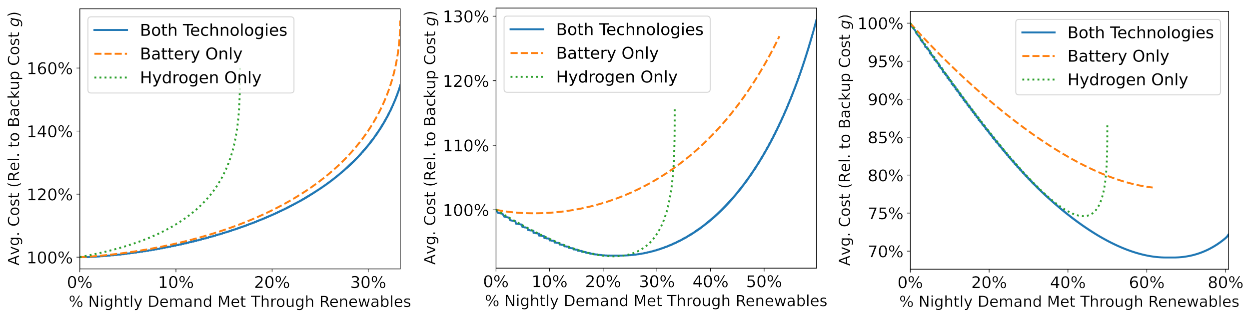
Second, the range in which prioritizing hydrogen increases renewable penetration is relatively small compared to the whole parameter space; however, it is exactly this range that matters in practice today - the case where both technologies are barely profitable, and hydrogen is quite a bit more costly than batteries. This can also be seen by the position of the red cones, which, as explained, show how technology costs are expected to develop until 2030.

Having said that - and this is our third point - it remains difficult to make predictions: Whether giving priority to a conversion-limited technology results in an increase in renewable penetration (i.e., overlap between the red cone and the blue area) is highly dependent on which technology will ultimately prevail (hydrogen, compressed air, or some alternative) and on the rate at which the conversion-limited technologies become cheaper compared to batteries' cost decline. Based on the current cost-estimates, this likely holds true for compressed-air for many years to come, while for hydrogen it is hard to say, given that there is more uncertainty in its cost forecasts.

5.3 Single vs Dual Technology: Implications on Cost and Renewable Penetration

We conclude our numerical results section by investigating how much of a difference it makes to be able to jointly invest in two storage technologies, compared to investing only in one. More specifically, we want to look at how the cost incurred by the utility to meet demand - storage investment costs plus the cost of meeting demand with backup plants - changes as a function of the level of renewable penetration targeted, comparing the two single-technology scenarios (battery-only and hydrogen-only) with a scenario in which the utility can build both batteries and hydrogen. To do this, we set the cost of running back-up generators (g) to \$100/MWh - approximately the average wholesale price for Germany and France (as per Table 1) for Figure 9 panels (a) and (b), and to \$200/MWh for Figure 9 panel (c).[20]

[20] For the interested reader, Appendix B.5 considers a similar analysis, but only looking at storage investment costs.



(a) Costs of 2024, $Q = D$, $g = \$100/MWh$

(b) Costs of 2030, $Q = 2D$, $g = \$100/MWh$

(c) Costs of 2030, $Q = 3D$, $g = \$200/MWh$

Figure 9: Average Storage + Backup Cost per MWh, as a Function of Renewable Penetration

Panel (a) in Figure 9 shows that, at 2024 technology costs and maximum excess solar equal to peak demand ($Q = D$), load-shifting with *any* storage technology is not profitable (cost increases in renewable penetration for all options) even at European wholesale-prices —and in fact, at the moment, storage technologies are not yet employed for load-shifting purposes. This is in sharp contrast to panel (b), where at 2030 technology cost and double the excess renewable power, using energy storage to load-shift *can* lower costs (plots are below 100). However, the joint usage of hydrogen and batteries does not lower costs much compared to the best single technology, hydrogen in this case, *if the objective is merely cost minimization*. The advantage of dual technology becomes instead important if the objective is to achieve a relatively high renewable penetration target, in which case substantial cost reduction in the order of 20-25% can be achieved, although costs may increase compared to no load-shifting.

Consider now the plots in panel (c), where renewable availability is highest at $Q = 3D$, and back-up costs are also high - \$200/MWh. Here, we note something new compared to the other panels: A dual-technology strategy allows the firm not only to achieve lower costs than any single-tech strategy, but also to reach renewable penetration levels that are simply unattainable with a single technology (hydrogen stops at 50% and battery at 60%). The reason why no single technology can obtain high penetration levels differs for each technology. Battery-only is constrained by its inability to shift energy across seasons - something valuable when excess energy in a day can be higher than unmet demand at night - as a battery large enough to do that would have a prohibitively high cost. Hydrogen-only, instead, can shift energy across days, but is constrained by its low efficiency: When operated in isolation, even for the high renewable generation setup, hydrogen cannot go beyond 50% renewable penetration because it cannot meet a high enough fraction of demand, as too much energy is lost in the conversion process. By contrast, installing less capacity of both technologies really works: Their combined strengths outweigh their respective weaknesses, achieving otherwise unattainable levels of renewable penetration and lowering costs at the same time - an effect that becomes more noticeable as the seasonality of solar availability increases.

6 Discussion

Our paper provides a tractable approach to studying co-investment in a storage-constrained technology (like batteries) and a power-constrained technology (like hydrogen) in order to shift excess renewable energy across time to replace fossil fuel generation.

To the best of our knowledge, this is the first paper in the operations literature to study joint investment in two energy storage technologies. Our model allows us to solve for the optimal investment decisions in closed form under both diurnal and seasonal load-shifting regimes. These expressions allow us to define adjusted costs for both technologies, which can be used to guide technology investment and adoption, and allow us to gain insights into the (at times unintuitive) roles played by different parameters.

Our model also allows us to show the importance of operational priority, which can be set preemptively by regulators to effectively promote investment in specific storage technologies and lead to higher renewable penetration, sometimes even when the technology being prioritized is the least efficient of the two.

Furthermore, we can identify and characterize two tipping points for hydrogen adoption and quantify the magnitude of our effects via calibration with real data from three markets. Depending on the cost trajectories, we find that giving hydrogen priority can increase renewable penetration by up to 19%. We also identify cases when a dual-tech storage strategy leads to no benefit compared to a single-tech strategy, when it can lead to lower costs, by up to 25-30%, and when it can lead to renewable penetration levels that are unattainable with a single technology.

Our findings revisit commonly held beliefs around hydrogen storage, for example, we show that it will turn a profit in diurnal load-shifting regimes years before its use for seasonal load-shifting will break-even; and that hydrogen storage will likely be first invested in those markets where excess renewables are available for longer hours, not necessarily in those with the most renewables.

While our model captures several important dimensions of the storage problem, it is a stylized model designed to capture high-level dynamics, and it thus comes with some limitations. For example, the model is limited to two technologies, it does not include variable energy prices (back-up cost) or additional revenue streams for installed storage capacities like frequency regulation, and it uses simplified assumptions to account for seasonality instead of e.g. empirical patterns or more flexible distributions for demand and solar patterns.

At the same time, these challenges present ample opportunity for future research: Understanding how merit order curves and variable prices impact the results, how a storage portfolio expands if more than two technologies are considered, and how auxiliary services provisions shifts the balance between power and energy limited storage are all relevant, challenging, and open questions.

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A Proofs of Propositions

A.1 Proof of Proposition 1

We first show the optimal capacity investment for batteries, assuming batteries have priority. Following Equation (2), we start with the expected amount of charge. Throughout the appendix, let $q_0 = \sqrt{\frac{2BQ}{L}}$ denote the realization of q beyond which Battery cannot store all excess generation. We furthermore denote $q' = \sqrt{\frac{2BQ}{L}} + H$ as the level of renewable capacity beyond which both technologies can be fully charged.

Note that in diurnal load-shifting energy discharge is never higher than nightly demand - that is, we are always charge-constrained. For this reason, we henceforth focus on charging operations only. As a reminder, $c_{B=1}$ refers to the energy charged in a day when Battery is prioritized.

$$
\begin{aligned}
c_{B=1}(B) &= \Big(\frac{1}{Q}\int_{q_t=0}^{Q} \min[\frac{q_t^2 L}{2Q}, B]dq_t\Big), \\
&= B\Big(1 - \frac{2}{3}\sqrt{\frac{2B}{LQ}}\Big), \qquad (9)\\
\frac{\partial c_{B=1}(B)}{\partial B} &= 1 - \sqrt{\frac{2B}{LQ}}.
\end{aligned}
$$

Since $\pi_{B=1}(B,H) = gc_{B=1}(B) + gc_{H=2}(H|B) - Bc_B - Hc_H$, we have that

$$
\begin{aligned}
B_1^* \Rightarrow \;\; g\frac{\partial c_{B=1}(B)}{\partial B} = c_B \;\Rightarrow\;\; & LQ\Big(\frac{1}{2} - \frac{c_B}{g} + \frac{c_B^2}{2g^2}\Big), \\
&= \frac{QL}{2}\left(\Big(1 - \frac{c_B}{g}\Big)^+\right)^2. \qquad (10)
\end{aligned}
$$

Conditional on the battery capacity B and its operational priority, we then optimize the hydrogen capacity and use $\psi(h, q_t)$ as a shorthand to denote the area of a trapezoid of height h with base Lq_t/Q, which is equal to $(hLq_t)/Q - h^2L/(2Q)$.

$$
\begin{aligned}
c_{H=2}(H|B) &= \frac{e}{Q}\Big(\int_{q_t=q_0}^{q'} \psi(q_t - \sqrt{\frac{2BQ}{L}}, q_t)\ dq_t + \int_{q_t=q'}^{Q} \psi(H, q_t)\ dq_t\Big), \\
&= \frac{eH(-6B - 3HL)}{6Q} + \frac{eH^3L}{6Q^2} + \frac{eHL}{2}, \qquad (11)\\
\frac{\partial c_2(H)}{\partial H} &= -\frac{Be}{Q} + \frac{eH^2L}{2Q^2} - \frac{eHL}{Q} + \frac{eL}{2}.
\end{aligned}
$$

Since: $\pi_{B=1}(B,H) = gc_{B=1}(B) + gc_{H=2}(H|B) - Bc_B - Hc_H$, we have that:

$$
\begin{aligned}
H_2^*(B) : g\frac{\partial c_{H=2}(H|B)}{\partial H} = c_H \Rightarrow\ & Q - \sqrt{2}\sqrt{\frac{BegQ + c_HQ^2}{egL}}, \\
H_2^*(B_1^*) &= Q\Big(1 - \sqrt{2}\sqrt{\frac{c_H}{egL} + (\frac{1}{2} - \frac{c_B}{g} + \frac{c_B^2}{2g^2})}\Big)^+, \qquad (12)\\
&= Q\Big(1 - \sqrt{\frac{c_H}{geL/2} + \Big(1 - \frac{c_B}{g}\Big)^2}\Big)^+.
\end{aligned}
$$

We now turn to the case with the opposite operational priority, where hydrogen has priority and proceed analogously to before.

$$
\begin{aligned}
c_1(H) =& \frac{e}{Q}\Big(\int_{q_t=0}^{H} \frac{q_t^2 L}{2Q}\ dq_t + \int_{q_t=H}^{Q} \psi(H, q_t)\ dq_t \Big), \\
=& \frac{eH^3L}{6Q^2} - \frac{eH^2L}{2Q} + \frac{eHL}{2}, \\
\frac{\partial c_1(H)}{\partial H} =& \frac{eH^2L}{2Q^2} - \frac{eHL}{Q} + \frac{eL}{2}, \\
H_1^* =& Q\Big(1 - \sqrt{\frac{2c_H}{geL}}\Big)^+, \\
=& Q\left(1 - \sqrt{\frac{c_H}{geL/2}}\right)^+.
\end{aligned}
\tag{13}
$$

Conditional on hydrogen capacity H and its operational priority, we optimize battery capacity.

$$
\begin{aligned}
c_2(B) &= g\Big(\frac{1}{Q}\int_{q_t=H}^{Q} \min[\frac{(q_t - H)^2 L}{2Q}, B]dq_t\Big) = B - \frac{BH}{Q} - \frac{2\sqrt{2}}{3}\sqrt{\frac{B^3}{LQ}}, \\
\frac{\partial c_2(B)}{\partial B} &= 1 - \frac{H}{Q} - \sqrt{\frac{2B}{LQ}}, \\
B_2^*(H) &= LQ\Big(\frac{1}{2} - \frac{c_B}{g} + \frac{c_B^2}{2g^2}\Big) - HL(1 - \frac{c_B}{g} - \frac{H}{2Q}), \\
B_2^*(H_1^*) &= \frac{Q}{2eg^2}\Big(\sqrt{2c_H g} - c_B\sqrt{eL}\Big)^2, \\
&= \frac{QL}{2}\left(\Big(\sqrt{\frac{c_H}{geL/2}} - \frac{c_B}{g}\Big)^+\right)^2.
\end{aligned}
\tag{14}
$$

A.2 Proof of Proposition 2

In this section, we analyze under what conditions, hydrogen and Battery would be invested in and compute how such investments change with respect to model parameters of interest. We start with the case where batteries have operational priority.

$$
\begin{aligned}
B_1^* &= LQ\Big(\frac{1}{2} - \frac{c_B}{g} + \frac{c_B^2}{2g^2}\Big)^+ \\
B_1^* &= \begin{cases} 0 \text{ if } g < c_B, i.e., \text{ if } c_B^{adj} < 1. \\ LQ(\frac{1}{2} + \frac{c_B^2}{2g^2}) - \frac{c_B}{g} \text{ if } g > c_B, \end{cases}
\end{aligned}
\tag{15}
$$

Note that because $Q < Q'$, whenever $c_B^{adj} < 1, i.e., g > c_B$, Battery charge will never exceed nightly demand.

$$
\begin{aligned}
H_2^*(B_1^*=0) = H_1^* = Q\Big(1-\sqrt{\frac{2c_H}{geL}}\Big)^+,\\
H_2^*(B_1^*=0) > 0 \text{ if } 1 > \sqrt{\frac{2c_H}{geL}} \Rightarrow \frac{g}{2} > \frac{c_H}{eL} \Rightarrow c_H^{adj} < 1,\\
H_2^*(B_1^*) = Q\Big(1-\sqrt{2}\sqrt{\frac{c_H}{egL} + (\frac{1}{2} - \frac{c_B}{g} + \frac{c_B^2}{2g^2})}\Big)^+,\\
H_2^*(B_1^*) > 0 \text{ if } 1 > \sqrt{2}\sqrt{\frac{c_H}{egL} + (\frac{1}{2} - \frac{c_B}{g} + \frac{c_B^2}{2g^2})} \Rightarrow \frac{c_H}{eL} < c_B - \frac{c_B^2}{2g},\\
\frac{c_H}{eL} < c_B - \frac{c_B^2}{2g} \Rightarrow \frac{c_H}{geL/2} < 2\frac{c_B}{g} - \frac{c_B^2}{g^2} \Rightarrow c_H^{adj} < 2c_B^{adj} - (c_B^{adj})^2.
\end{aligned} \tag{16}
$$

$$
H_2^* > 0 \text{ iff } \begin{cases} c_B^{adj} > 1 \Rightarrow\ B_1^* = 0\ \wedge\ c_H^{adj} = \frac{c_H}{geL/2} < 1, \\ c_B^{adj} < 1 \Rightarrow\ B_1^* > 0\ \wedge\ c_H^{adj} < 2c_B^{adj} - (c_B^{adj})^2, \end{cases} \tag{17}
$$

We now perform the same analysis of the optimal capacity w.r.t. electricity cost g and renewable generation capacity Q for the case where hydrogen has priority.

$$
\begin{aligned}
H_1^* = Q\Big(1-\sqrt{2}\sqrt{\frac{c_H}{geL}}\Big)^+,\\
H_1^* = \begin{cases} 0 \text{ if } g < \frac{2c_H}{eL} \Rightarrow c_H^{adj} > 1, \\ Q(1-\sqrt{\frac{2c_H}{Lge}}) \text{ otherwise} \end{cases}
\end{aligned} \tag{18}
$$

$$
H_1^* = \begin{cases} 0 \text{ if } c_H^{adj} > 1, \\ Q(1-\sqrt{\frac{2c_H}{Lge}}) \text{ otherwise }, \end{cases} \tag{19}
$$

$$
\begin{aligned}
B_2^* = \Big(LQ(\frac{1}{2} - \frac{c_B}{g} + \frac{c_B^2}{2g^2}) - HL(1-\frac{c_B}{g} - \frac{H}{2Q})\Big)^+,\\
B_2^*(H_1^*) = \frac{Q}{2eg^2}\Big(\sqrt{2c_Hg} - c_B\sqrt{eL}\Big)^2,\\
\sqrt{2c_Hg} - c_B\sqrt{eL} > 0 \Rightarrow \frac{c_Hg}{eL/2} > c_B^2 \Rightarrow c_H^{adj} > (c_B^{adj})^2 \Rightarrow c_B^{adj} < \sqrt{c_H^{adj}},\\
B_2^*(H_1^*) \begin{cases} = 0 \text{ if } c_B > \sqrt{c_H^{adj}}, \\ > 0,\ \text{otherwise }. \end{cases}
\end{aligned} \tag{20}
$$

A.2.1 Separating Parameter Space Into cases

After having analyzed the capacity investments, we want to introduce the idea of how different combinations of cost parameters lead to different cases of investments. For subsequent parts of the paper, it will be interesting to study under which circumstances the four capacities $B_1^*, B_2^*, H_1^*, H_2^*$ are positive. We will normalize the back-up cost $g = 1$, so all other costs are expressed relative to the back-up cost.

We repeat the result from Proposition 2 for B_1^* and H_1^*,

$$\begin{aligned}
&B_1^* = LQ(\frac{1}{2} + \frac{c_B^2}{2}),\\
&B_1^* > 0 \text{ if } c_B < 1,\\
&H_1^* = Q(1 - \sqrt{\frac{2c_H}{Le}}),\\
&H_1^* > 0 \text{ if } \frac{c_H}{eL} < \frac{1}{2}.
\end{aligned} \tag{21}$$

To begin, we note that if a technology is not invested in when it has priority, it is also not invested in if it does not have priority. Formally, $B_1^* = 0 \Rightarrow B_2^* = 0$ and $H_1^* = 0 \Rightarrow H_2^* = 0$. Moreover, we know that both technologies will be invested in only if $c_B < 1$ and $\frac{c_H}{eL} < \frac{1}{2}$.

In this space where both technologies can be invested in, it is interesting to distinguish the cases when only one technology is invested in, or both technologies are.

$$\begin{aligned}
H_2^*(B, g = 1) &= Q\Big(1 - \sqrt{2}\sqrt{\frac{c_H}{eL} + \frac{B}{LQ}}\Big)^+,\\
H_2^*(B_1^*, g = 1) &= Q\Big(1 - \sqrt{2}\sqrt{\frac{c_H}{eL} + (\frac{1}{2} - c_B + \frac{c_B^2}{2})}\Big)^+,\\
\text{WTS } H_2^*(B_1^*, g = 1) &> 0,\\
\frac{c_H}{eL} &< c_B - 0.5c_B^2,\\
\frac{c_H}{eL/2} &< 2c_B - c_B^2,\\
c_H^{adj} &< 2c_B^{adj} - (c_B^{adj})^2, \text{ if } g = 1,
\end{aligned} \tag{22}$$

Above, we showed that if the efficiency-adjusted cost of hydrogen $c_H/(eL/2) =$ is higher than $2c_B - c_B^2$, hydrogen is not invested in if batteries have priority. We now perform the same analysis for battery investment when hydrogen has priority.

$$\begin{aligned}
B_2^*(H, g = 1) &= \Big(LQ(\frac{1}{2} - c_B + \frac{c_B^2}{2}) - HL(1 - c_B - \frac{H}{2Q})\Big)^+,\\
B_2^*(H_1^*, g = 1) &= \Big(Q\Big(\sqrt{\frac{c_H}{e}} - \frac{c_B\sqrt{L}}{\sqrt{2}}\Big)^2\Big)^+,\\
\text{WTS } B_2^*(H_1^*, g = 1) &= 0,\\
\frac{c_H}{eL} &= 0.5\ c_B^2,\\
c_H^{adj} &= (c_B^{adj})^2
\end{aligned} \tag{23}$$

If the efficiency-adjusted cost of hydrogen $c_H/(eL/2)$ is lower than c_B^2, batteries are not invested in if hydrogen has priority. Taken together, the conditions we established can be graphically represented in Figure 5 (which we repeat below in Figure 10) and give rise to the following cases:

1. *No Tech* as $B_1^* = 0, B_2^* = 0, H_1^* = 0, H_2^* = 0$,

2. *Battery Only* as $B_1^* > 0, B_2^* > 0, H_1^* = 0, H_2^* = 0$,

3. *Hydrogen Only* as $B_1^* = 0, B_2^* = 0, H_1^* > 0, H_2^* > 0$,

4. *Battery Dominant* as $B_1^* > 0, B_2^* > 0, H_1^* > 0, H_2^* = 0$,

5. *Hydrogen Dominant* as $B_1^* > 0, B_2^* = 0, H_1^* > 0, H_2^* > 0$,

6. *Both Techs* as $B_1^* > 0, B_2^* > 0, H_1^* > 0, H_2^* > 0$.

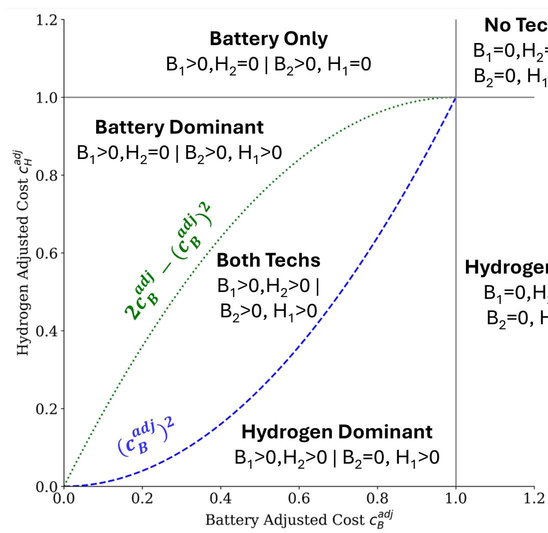


Figure 10: Conditions under which none, one, or both storage technologies are invested in under the different priorities. Backup-cost g normalized to 1.

A.3 Proof of Proposition 3 (and Equation (6))

Depending on the sunshine realization, q_t, we can be in one of two situations. When q_t is large enough that excess renewables exceed both storage technologies' ability to shift energy - see Figure 4, panel (a) - both technologies can be used at their maximum potential: B is fully charged, H uses its full power whenever possible. This happens when $q_t^2 L/(2Q) \geq c(B|q_t) + c(H|q_t) \Rightarrow q_t \geq H + \sqrt{2BQ/L}$ and in these cases, the priority is inconsequential because there is plenty of excess energy. As introduced in Appendix 1, we denote this threshold with $q' \triangleq H + \sqrt{2BQ/L}$ and it will be useful below. By contrast, when the sunshine realization is low ($q_t < q'$) - see Figure 4 b) - excess energy is limited, the technologies are in conflict, and there is contended energy - i.e. energy that could be charged by either technology. In these cases, the priority is consequential, because it decides which technology is charged and which one is not.

We now write the expression for expected charge (hence discharge) for the case when battery has priority, for given positive capacities of B and H. We do isolate the case when there is conflict, i.e. $q_t < q' =$, and then further sub-dividing it into contended and not contended energy. As defined in Appendix A.1, we use $\psi(h, q_t)$ as a shorthand to denote the area of a trapezoid of height h with base Lq_t/Q, which is equal to $(hLq_t)/Q - h^2L/(2Q)$.

$$
\begin{aligned}
E[c_1(B|q_t)] &= \frac{1}{Q}\Big(\int_{q_t=0}^{Q} \min[\frac{q_t^2 L}{2Q}, B] dq_t\Big) = \Big(\int_{q_t=0}^{q_0} \frac{q_t^2 L}{2Q^2} dq_t + \int_{q_t=q_0}^{Q} \frac{B}{Q} dq_t\Big), \\
&= \Big(\int_{0}^{q_0} \frac{q_t^2 L}{2Q^2} dq_t + \int_{q_0}^{q'} \frac{B}{Q} dq_t + \int_{q'}^{Q} \frac{B}{Q} dq_t\Big), \\
E[c_2(H|q_t)] &= \frac{e}{Q}\Big(\int_{q_t=q_0}^{q'} \psi(q_t - \sqrt{\frac{2BQ}{L}}, q_t)\ dq_t + \int_{q_t=q'}^{Q} \psi(H, q_t)\ dq_t\Big).
\end{aligned}
\tag{24}
$$

$$
\begin{aligned}
E[c_1(H|q_t)] &= \frac{e}{Q}\Big(\int_{q_t=0}^{H} \frac{q_t^2 L}{2Q}\ dq_t + \int_{q_t=H}^{Q} \psi(H, q_t)\ dq_t\Big), \\
&= \frac{e}{Q}\Big(\int_{0}^{H} \frac{q_t^2 L}{2Q}\ dq_t + \int_{H}^{q'} \psi(H, q_t) dq_t + \int_{q'}^{Q} \psi(H, q_t)\ dq_t\Big), \\
E[c_2(B|q_t)] &= \Big(\int_{q_t=H}^{Q} \min[\frac{(q_t - H)^2 L}{2Q^2}, B] dq_t\Big) = \int_{q_t=H}^{q'} \frac{(q_t - H)^2 L}{2Q^2} dq_t + \int_{q_t=q'}^{Q} \frac{B}{Q} dq_t.
\end{aligned}
\tag{25}
$$

From here, we use the assumption of $H \leq q_0$ for the bounds of integration. The alternative case, $H \geq q_0$, is analogous and leads to the same simplification.

$$
\begin{aligned}
& c_{B=1}(B, H) = \\
E[c_1(B|q_t) + c_2(H|q_t)] =& \Big(\int_{0}^{H} \frac{q_t^2 L}{2Q^2} dq_t + \int_{H}^{q_0} \frac{q_t^2 L}{2Q^2} dq_t + \int_{q_0}^{q'} \frac{B}{Q} dq_t + \int_{q'}^{Q} \frac{B}{Q} dq_t\Big) + \\
& \frac{e}{Q}\Big(\int_{q_0}^{q'} \psi(q_t - \sqrt{\frac{2BQ}{L}}, q_t)\ dq_t + \int_{q'}^{Q} \psi(H, q_t)\ dq_t\Big).
\end{aligned}
\tag{26}
$$

$$
\begin{aligned}
& c_{H=1}(B, H) = \\
E[c_1(H|q_t) + c_2(B|q_t)] =& \frac{e}{Q}\Big(\int_{0}^{H} \frac{q_t^2 L}{2Q}\ dq_t + \int_{H}^{q_0} \psi(H, q_t) dq_t + \int_{q_0}^{q'} \psi(H, q_t) dq_t + \int_{q'}^{Q} \psi(H, q_t)\ dq_t\Big) + \\
& \int_{H}^{q_0} \frac{(q_t - H)^2 L}{2Q^2} dq_t + \int_{q_0}^{q'} \frac{(q_t - H)^2 L}{2Q^2} dq_t + \int_{q'}^{Q} \frac{B}{Q} dq_t.
\end{aligned}
\tag{27}
$$

We can then rearrange terms to obtain:

$$\int_{H}^{q_0} \frac{(q_t - H)^2 L}{2Q^2} dq_t + \int_{q_0}^{q'} \frac{(q_t - H)^2 L}{2Q^2} dq_t = \int_0^H \frac{q_t^2 L}{2Q^2} dq_t + \int_H^{q_0} \frac{q_t^2 L}{2Q^2} dq_t = \int_0^{q_0} \frac{q_t^2 L}{2Q^2} dq_t \text{ and}$$

$$\frac{e}{Q}\Big(\int_{q_0}^{q'} \psi(q_t - \sqrt{\frac{2BQ}{L}}, q_t) = \int_0^H \frac{q_t^2 L}{2Q}\, dq_t + \int_H^{q_0} \psi(H, q_t) dq_t + \int_{q_0}^{q'} \psi(H, q_t) dq_t + \int_{q'}^{Q} \psi(H, q_t)\, dq_t - \int_{q_0}^{q'} B dq_t. \tag{28}$$

And we can group the terms into three groups - battery, hydrogen, and contended energy, which in principle may go into either storage technology depending on the operational priority chosen, but that in this case goes into (and out of) batteries since they are given priority.

$$c_{B=1}(B, H) = \underbrace{\frac{1}{Q}\Big(\int_0^{q_0} \frac{q_t^2 L}{2Q} dq_t + \int_{q'}^{Q} B dq_t \Big)}_{\text{Battery}} + \underbrace{\frac{1}{Q} \int_{q_0}^{q'} B dq_t}_{\text{Contended}} + \underbrace{e \frac{1}{Q}\Big(\int_{q_0}^{q'} \psi(q_t - \sqrt{\frac{2BQ}{L}}, q_t) dq_t + \int_{q'}^{Q} \psi(H, q_t) dq_t \Big)}_{\text{Hydrogen}}$$

$$\begin{aligned}
c_{\text{Battery}} &\triangleq \frac{1}{Q}\Big(\int_0^{q_0} \frac{q_t^2 L}{2Q} dq_t + \int_{q'}^{Q} B dq_t \Big) \\
c_{\text{Contended}} &\triangleq \frac{1}{Q} \int_{q_0}^{q'} B dq_t \\
c_{\text{Hydrogen}} &\triangleq \frac{1}{Q}\Big(\int_{q_0}^{q'} \psi(q_t - \sqrt{\frac{2BQ}{L}}, q_t)\, dq_t + \int_{q'}^{Q} \psi(H, q_t)\, dq_t \Big) \\
&= \frac{1}{Q}\Big(\int_0^H \frac{q_t^2 L}{2Q} dq_t + \int_H^{q_0} \psi(H, q_t) dq_t + \int_{q_0}^{q'} \psi(H, q_t) dq_t + \int_{q'}^{Q} \psi(H, q_t) dq_t - \int_{q_0}^{q'} B dq_t \Big)
\end{aligned} \tag{29}$$

When hydrogen has priority, expected charge (hence discharge) can be rewritten using the same terms as above - non-contended energy is the same by construction, and contended energy is also the same, except that now is being multiplied by e, due to hydrogen's losing $1 - e$ fraction of energy, inevitably lowering the total amount of demand met through renewables.

$$c_{H=1}(B, H) = \underbrace{\frac{1}{Q}\Big(\int_0^{q_0} \frac{q_t^2 L}{2Q} dq_t + \int_{q'}^{Q} B dq_t \Big)}_{\text{Battery}} + e \underbrace{\frac{1}{Q} \int_{q_0}^{q'} B dq_t}_{\text{Contended}} + \underbrace{e \frac{1}{Q}\Big(\int_{q_0}^{q'} \psi(q_t - \sqrt{\frac{2BQ}{L}}, q_t) dq_t + \int_{q'}^{Q} \psi(H, q_t) dq_t \Big)}_{\text{Hydrogen}} \tag{30}$$

So, conditional on having a certain pair of capacities (B,H), it is always better to run the more efficient technology (battery) first.

A.4 Proof of Proposition 4

We want to analyze under which conditions

$$c_{H=1}(B_2^*, H_1*) > c_{B=1}(B_1^*, H_2^*), \tag{31}$$

that is, hydrogen-first leads to a higher charge - hence higher renewable penetration - than battery-first.

To start, we use the insights from Propositions 1 and 2 (summarized in Figure 5) and distinguish the cases where out of the four capacities $(B_1^*, H_2^*, B_2^*, H_1*)$, at least three are positive. The cases where no technology or only one technology's capacities are positive are not relevant to this analysis as it is trivial to show that in these cases the charge is identical, e.g., $c_{H=1}(B_2^*, 0) = c_{B=1}(B_1^*, 0)$, as $B_1^* = B_2^* | (H_1^* = 0)$.

We proceed in in the following four steps:

1. Step 1 - We differentiate 3 relevant sub-cases of capacity investment for which the expression of the charging difference takes a different form.

2. Step 2 - We show the existence of a set of parameters for which (31) holds.

3. Step 3 - We identify the lowest battery cost under which condition (31) holds, for any other given set of parameters.

4. Step 4 - We identify an upper bound to the highest battery cost under which (31) holds, for any other given set of parameters.

Step 1 - Differentiating three Cases of Capacity Investments

We define $\Delta_B, \Delta_T, \Delta_H$ as the difference in charge between battery-priority and hydrogen-priority across the three different cases as shown in Equation 32. The case Δ_B occurs when hydrogen is only invested if it gets priority, the case Δ_H occurs when battery is only invested in if it gets priority and Δ_T when both technologies are invested in irrespective of their priority. Throughout this analysis we normalize g to 1, hence all costs are expressed relative to that. As derived in Appendix A.2.1, we are only interested in the technology cost space $c_B < 1 (c_B^{adj} < 1)$ and $c_H/e < L/2 (c_H^{adj} < 1)$, as only then at least three of the capacities are positive.

Collectively, the three cases cover the entire cost parameter space of interest as shown in Equation 32. For notational convenience, we write $\Delta_B(c_H, c_B, e, Q, L)$ as Δ_B - all functions are dependent on the model primitives, but not the capacity choices.

$$\begin{aligned}
\Delta_B &= c_{B=1}(B_1^*, 0) - c_{H=1}(B_2^*, H_1^*), \text{ if } c_H/e \geq L(c_B - 0.5c_B^2), \\
\Delta_T &= c_{B=1}(B_1^*, H_2^*) - c_{H=1}(B_2^*, H_1^*), \text{ if } L/2c_B^2 \leq c_H/e \leq L(c_B - 0.5c_B^2), \\
\Delta_H &= c_{B=1}(B_1^*, H_2^*) - c_{H=1}(0, H_1^*), \text{ if } c_H/e \leq L/2c_B^2.
\end{aligned} \tag{32}$$

Step 2 - Show the existence of a set of parameters for which (31) holds.
We start by showing that under a certain condition, hydrogen priority can lead to higher renewable discharge, by studying a particular subset in the parameter space. This subset is $c_H/e = L(c_B - 0.5c_B^2)$, i.e. when $\Delta_B = \Delta_T$ - see Equation 22. This is the set of points where, if hydrogen is not-prioritized, there is no investment in hydrogen, but any marginal cost reduction in will lead to positive investment in hydrogen. Formally, $\frac{\overrightarrow{\partial} H_2^*(c_H = Le(c_B - 0.5c_B^2))}{\partial c_H} = 0$ and $\frac{\overleftarrow{\partial} H_2^*(c_H = Le(c_B - 0.5c_B^2))}{\partial c_H} < 0$. $\overrightarrow{\partial}$ and $\overleftarrow{\partial}$ indicate the directional derivatives from the left and the right respectively.

We start at $c_H/e = L(c_B - 0.5c_B^2)$, because it is the lowest set of values of c_H/e for which H_2^* equals zero, leading to a large difference between H_1^* and H_2^*.

$$
\begin{aligned}
&WTS \Delta_B \le 0, \\
&\frac{1}{6}(c_B - 1)^2(2c_B + 1)LQ - \\
&\frac{Q\left(3\sqrt{2}c_B^2\sqrt{c_H}eL - 2c_B^2 eL\sqrt{c_B^2 eL - 2\sqrt{2}c_B\sqrt{c_H eL} + 2c_H} - 2\sqrt{2}c_H^{3/2}(e-3) + e^{5/2}L^{3/2}\right)}{6\sqrt{e^3 L}} + \\
&\frac{Q\left(-4c_H\left(\sqrt{c_B^2 eL - 2\sqrt{2}c_B\sqrt{c_H eL} + 2c_H} + 3c_B\sqrt{eL}\right) + 4\sqrt{2}c_B\sqrt{c_H eL\left(c_B^2 eL - 2\sqrt{2}c_B\sqrt{c_H eL} + 2c_H\right)} - \right)}{6\sqrt{e^3 L}} \le 0, \\
&\text{Replacing } c_H/e \text{ with } L(c_B - 0.5c_B^2), \\
&\Delta_B(c_H = eL(c_B - 0.5c_B^2)) = \\
&\frac{1}{6}LQ\Big(2c_B\Big(2\sqrt{2c_B - 2\sqrt{-(c_B-2)c_B^3}} + \sqrt{(2-c_B)c_B}e - 3\sqrt{(2-c_B)c_B}\Big) - \Big(\sqrt{-(c_B-2)c_B^5} + 1\Big)e - 4c_B^3 + \\
&\Big(9 - 4\sqrt{2}\sqrt{(c_B-2)\Big(\sqrt{-(c_B-2)c_B} - 1\Big)}\Big)c_B^2 + 1\Big) \le 0, \\
&UL \triangleq 2c_B\Big(2\sqrt{2c_B - 2\sqrt{-(c_B-2)c_B^3}} + \sqrt{(2-c_B)c_B}e - 3\sqrt{(2-c_B)c_B}\Big) - \Big(\sqrt{-(c_B-2)c_B^5} + 1\Big)e - 4c_B^3 + \\
&\Big(9 - 4\sqrt{2}\sqrt{(c_B-2)\Big(\sqrt{-(c_B-2)c_B} - 1\Big)}\Big)c_B^2 + 1 \le 0.
\end{aligned}
\tag{33}
$$

If, for example, $c_B = 0.5$ and $e = 1$, the last expression in Equation 33 (henceforth called UL) is approximately -0.1005, i.e., hydrogen priority results in more demand being met through renewables than battery priority. We have thus shown that the result holds for some parameter combinations. We continue by analyzing where (31) holds in this set of $c_H/e = L(c_B - 0.5c_B^2)$. For that, we take the derivative of UL w.r.t. e to show that it is decreasing in efficiency.

$$\begin{aligned}
\frac{\partial\, UL}{\partial e} &= -1 + 2c_B\sqrt{(2-c_B)c_B} - c_B\sqrt{(2-c_B)c_B^3},\\
\frac{\partial\, UL}{\partial e} &< 0 \text{ if },\\
(2c_B - c_B^2)\sqrt{(2-c_B)c_B} &\leq 1,\\
(2c_B - c_B^2) &\leq 1 \quad \forall 0 \leq c_B \leq 1,\\
\sqrt{(2-c_B)c_B} &\leq 1 \quad \forall 0 \leq c_B \leq 1.
\end{aligned} \tag{34}$$

Clearly, the derivative is negative for any value of $c_B < 1$ - hence the difference in charge is decreasing with e. This means that (31) holds (Δ_B becomes negative) on the considered set of points for a sufficiently high e. We thus try to identify this threshold $\bar{e}$ beyond which (31) still holds.

$$\begin{aligned}
&\text{WTS} \quad UL = 0,\\
&2c_B\Big(2\sqrt{2c_B - 2\sqrt{-(c_B-2)c_B^3}} + \sqrt{(2-c_B)c_B}e - 3\sqrt{(2-c_B)c_B}\Big) - \Big(\sqrt{-(c_B-2)c_B^5}+1\Big)e - 4c_B^3 +\\
&\Big(9 - 4\sqrt{2}\sqrt{(c_B-2)\Big(\sqrt{-(c_B-2)c_B}-1\Big)}\Big)c_B^2 + 1 = 0,\\
&\bar{e} = \frac{c_B\left(4\sqrt{2c_B - 2\sqrt{(2-c_B)c_B^3}} + c_B\left(-4c_B - 4\sqrt{2}\sqrt{(c_B-2)\left(\sqrt{(2-c_B)c_B}-1\right)}+9\right) - 6\sqrt{(2-c_B)c_B}\right)+1}{\sqrt{(2-c_B)c_B^5} - 2\sqrt{(2-c_B)c_B}c_B + 1}.
\end{aligned} \tag{35}$$

If hydrogen's efficiency is higher than $\bar{e}$, at least on the set $c_H/e = L(c_B - 1/2c_B^2)$ (31) holds - i.e., in that case hydrogen priority results in higher overall renewable penetration than battery priority when capacity investments are made taking into account the operational priority.

Step 3 - Identify the lowest battery cost under which condition (31) **holds, for any other given set of parameters.**

After having shown the existence of storage technology parameters under which hydrogen-priority results in a higher renewable penetration (hence charge) than battery-priority, we now want to characterize the range for which (31) holds in more detail. To do this, we study how Δ_B changes as c_B changes and start by looking at $c_B = 0$ - i.e., the left-most area of the Graph in Figure 5.

$$\begin{aligned}
\Delta_B(c_B = 0) = \frac{Q\left(2\sqrt{2}c_H^{3/2}(e-1) + e^{5/2}\left(-L^{3/2}\right) + L\sqrt{e^3L}\right)}{6\sqrt{e^3L}} &\geq 0,\\
-2\sqrt{2}c_H^{3/2}(1-e) + L^{3/2}e^{3/2}(1-e) &\geq 0,\\
L/2 &\geq c_H/e.
\end{aligned} \tag{36}$$

Clearly, at $c_B = 0$, Δ_B is always positive, i.e. (31) never holds. We thus aim to study the derivative of Δ_B w.r.t. c_B, because we know that (31) can hold on the critical line where $c_H/e = L(c_B - 0.5c_B^2)$, which, after rearranging terms is equal to $c_B = 1 - \sqrt{1 - \frac{2c_H}{eL}}$.

$$
\begin{aligned}
\frac{\partial \Delta_B}{\partial c_B} &= \frac{1}{3}(c_B-1)^2 LQ + \frac{1}{3}(2c_B+1)(c_B-1)LQ + \\
&\frac{Q\left(6c_B^2 c_H^{3/2} eL - 2\sqrt{2}c_H^2\left(\sqrt{c_B^2 eL - 2\sqrt{2}c_B\sqrt{c_H eL} + 2c_H} + 3c_B\sqrt{eL}\right) + c_B^3 eL\sqrt{z}\right)}{\sqrt{c_H}e\left(c_B\left(c_B eL - 2\sqrt{2}\sqrt{c_H eL}\right) + 2c_H\right)} + \\
&\frac{Q\Big(-c_B c_H\left(\sqrt{2}c_B eL\left(3\sqrt{c_B^2 eL - 2\sqrt{2}c_B\sqrt{c_H eL} + 2c_H} + c_B\sqrt{eL}\right) - 6\sqrt{z}\right) + 4c_H^{5/2}\Big)}{\sqrt{c_H}e\left(c_B\left(c_B eL - 2\sqrt{2}\sqrt{c_H eL}\right) + 2c_H\right)},
\end{aligned}
\tag{37}
$$

where $z = c_H eL\left(c_B\left(c_B eL - 2\sqrt{2}\sqrt{c_H eL}\right) + 2c_H\right)$.

Despite the expression for Δ_B being simpler than the ones for the other Δ's, the sign of $\partial\Delta_B/\partial c_B$ is not readily discernible - we need to find other ways to study it. We thus analyze $\partial^2\Delta_B/\partial c_B \partial e$.

$$
\begin{aligned}
\frac{\partial^2 \Delta_B}{\partial c_B \partial e} &= \frac{2\sqrt{2c_H}\sqrt{c_B^2 eL - 2\sqrt{2}c_B\sqrt{c_H eL} + 2c_H} + \sqrt{2}c_B\sqrt{c_H eL} - 4c_H}{2e^2}, \\
&= \frac{2\sqrt{2c_H}(\sqrt{2c_H} - c_B\sqrt{eL}) + \sqrt{2}c_B\sqrt{c_H eL} - 4c_H}{2e^2}, \\
&= \frac{-2c_B\sqrt{2c_H eL} + c_B\sqrt{2c_H eL}}{2e^2} < 0
\end{aligned}
\tag{38}
$$

Note that $\frac{\partial^2\Delta_B}{\partial c_B \partial e} < 0$, hence the derivative w.r.t. c_B is decreasing in e. If we set e to its lowest possible value $e = 2c_H/L$ (we need $c_H/e < L/2$ for hydrogen to be invested in) and show that even then the derivative w.r.t. c_B is non-positive, i.e., ($\frac{\partial \Delta_B}{\partial c_B} \leq 0$), then we can conclude that the derivative is non-positive for any $e > 2c_H/L$.

$$
\begin{aligned}
\frac{\partial \Delta_B(e = 2c_H/L)}{\partial c_B} &= (1-c_B)c_B LQ + \frac{1}{3}(1-c_B)^2 LQ - \frac{1}{3}(2c_B+1)(1-c_B)LQ, \\
&= 0.
\end{aligned}
\tag{39}
$$

Thus, even for the lowest possible value of e, the derivative is non-positive and for any lower values of e, we have previously shown that it will be negative. Thus, $\frac{\partial \Delta_B}{\partial c_B} \leq e$ for the entire considered space.

So far we know that $\Delta_B > 0$ when the battery cost is zero $c_B = 0$ and as the battery cost c_B increases, Δ_B decreases. For suitably large values of efficiency, ($e \geq \bar{e}$), Δ_B then becomes negative. We now want to find the value c_B from which onwards, it becomes negative, i.e. the lower bound of battery cost for which (31) holds.

To help with tractability, we combine c_H, e and L terms wherever possible to c_H^{adj}, which as g is normalized to 1 is equal to $c_H/(eL/2)$. With this simplification, we check when Δ_B is zero.

$$WTS\Delta_B(c_H^{adj}(g=1) = \frac{c_H}{eL/2}) = 0,$$

$$\frac{1}{6}LQ\left(3c_B^2\left(\sqrt{c_H^{adj}}-1\right)+(e-1)\left((c_H^{adj})^{3/2}-1\right)\right) = 0,$$

$$\left(3c_B^2\left(\sqrt{c_H^{adj}}-1\right)+(e-1)\left((c_H^{adj})^{3/2}-1\right)\right) = 0,$$

$$\text{We know } c_B > 0,$$

$$\underline{c}_B = \sqrt{\frac{1}{3}\sqrt{e^2c_H^{adj}-2ec_H^{adj}+c_H^{adj}}+\frac{1}{3}(e(-c_H^{adj})-e+c_H^{adj}+1)}. \tag{40}$$

So far, we have shown that $\Delta_B \geq 0$ if $e \leq \bar{e}$ holds, or, if both $e > \bar{e}$ and $c_B \leq \underline{c}_B$ hold. We have also shown that there exists an $\epsilon > 0$ such that $\Delta_B < 0$ if $e > \bar{e}$ and $c_B \in (\underline{c}_B, \underline{c}_B + \epsilon)$. This concludes our proof to identify the lowest battery cost such that (31) holds. However, we can increase that ϵ by noting that Δ_B is defined until $c_H/e = L(c_B - 0.5c_B^2)$. Re-organizing terms, this is equal to $c_B = 1-\sqrt{1-c_H^{adj}}$. Because we know that the derivative of Δ_B w.r.t. c_B is decreasing, this means that $\Delta_B < 0$ if $e > \bar{e}$ and $c_B \in [\underline{c}_B, 1-\sqrt{1-c_H^{adj}}]$.

Step 4 - Identify an upper bound to the highest battery cost under which (31) holds, for any other given set of parameters.

To obtain the result in Step 3, we analyzed Δ_B, which has a simpler expression for charge than Δ_T, as in the Δ_B parameter space hydrogen is not invested in if batteries have priority, i.e., $H_2^* = 0$. To find an upper bound for the range for which (31) holds, we need to investigate the more challenging expression Δ_T, as hydrogen capacity H_2^* becomes positive for values of c_B beyond the critical value of i.e., $c_B > 1-\sqrt{1-c_H^{adj}} \Rightarrow H_2^* > 0$. We know that at the critical point $c_B = 1-\sqrt{1-c_H^{adj}}$ both expressions are the same and are negative i.e., $\Delta_T(c_B = 1-\sqrt{1-c_H^{adj}}) = \Delta_B(c_B = 1-\sqrt{1-c_H^{adj}}) < 0$. However, analyzing Δ_T is intractable due to third/fifth degree polynomial expressions for the optimal capacities.

We thus turn to Δ_H. As shown in Appendix A.2.1, if $c_B \geq \sqrt{c_H^{adj}}$, we are in the parameter space for Δ_H. We now investigate its sign.

In particular, we will show that (31) does not hold if $c_B^2 \geq c_H^{adj}$, i.e., we are in the hydrogen dominant case.

$$
\begin{aligned}
&WTS \Delta_H \geq 0,\\
&c_{B=1}(B_1^*, H_2^*) - c_{H=1}(0, H_1^*) \geq 0,\\
&\frac{Q(c_B-1)^2 eL(2\sqrt{eL((c_B-1)^2 eL + 2c_H)} + 2c_B L + L}{6eL} - \\
&\frac{Q2c_H\sqrt{eL((c_B-1)^2 eL + 2c_H)} + (-3(c_B-2)c_B - 2)e^2L^2}{6eL} - \frac{1}{6}Q(eL - \frac{2\sqrt{2}c_H^{3/2}}{\sqrt{eL}}) > 0.
\end{aligned} \tag{41}
$$

We proceed by showing that at the highest value of battery cost c_B for which the function is defined $c_B = 1$, the difference is 0, and then, by showing that the partial derivative w.r.t. c_B is negative for all values $c_B \in (0, 1)$.

$$
\Delta_H(c_B = 1) = \frac{Q\left(-2c_H\sqrt{eL\,(2c_H)} + e^2L^2\right)}{6eL} - \frac{1}{6}Q\left(eL - \frac{2\sqrt{2}c_H^{3/2}}{\sqrt{eL}}\right) = 0 \geq 0. \tag{42}
$$

Here we have shown that at $c_B = 1$, the difference in charge is exactly zero. Next, we want to show that $\partial\Delta_H/\partial c_B < 0$, to proof that the charge difference for smaller values of c_B is always positive.

$$
\begin{aligned}
&WTS \frac{\partial \Delta_H}{\partial c_B} \leq 0,\\
&\frac{(c_B-1)LQ\left(-e\sqrt{eL\,((1-c_B)^2 eL + 2c_H)} + c_B\sqrt{eL\,((1-c_B)^2 eL + 2c_H)} + (1-c_B)^2 e^2 L + c_H e\right)}{\sqrt{eL\,((1-c_B)^2 eL + 2c_H)}} \leq 0,\\
&\left(-e\sqrt{eL\,((1-c_B)^2 eL + 2c_H)} + c_B\sqrt{eL\,((1-c_B)^2 eL + 2c_H)} + (1-c_B)^2 e^2 L + c_H e\right) \geq 0,\\
&\text{If } c_B > e\text{, this trivially holds, we thus investigate the case } c_B < e,\\
&(1-c_B)^2 e^2 L + c_H e \geq (e - c_B)\sqrt{eL((1-c_B)^2 eL + 2c_H)},\\
&(1-c_B)^4 e^4 L^2 + 2(1-c_B)^2 e^3 L c_H + c_H^2 e^2 \geq (e-c_B)^2\left(e^2L^2(1-c_B)^2 + 2c_H eL\right),\\
&(1-c_B)^4 e^3 L^2 + 2(1-c_B)^2 e^2 L c_H + c_H^2 e \geq (e-c_B)^2\left(eL^2(1-c_B)^2 + 2c_H L\right).
\end{aligned} \tag{43}
$$

To show that this holds we need to separately analyse different cases. For the first case:

$$
\begin{aligned}
&2(1-c_B)^2 e^2 L c_H \geq 2c_H L(e-c_B)^2,\\
&(1-c_B)^2 e^2 \geq (e-c_B)^2,\\
&(e - ec_B) \geq (e - c_B).
\end{aligned} \tag{44}
$$

Where we can take the root, as we know all terms that get squared to be positive and which holds as we know $0 > e > 1$. We continue with the second case.

$$\begin{aligned}
&(1-c_B)^4 e^4 L^2 + c_H^2 e^2 \geq (e-c_B)^2 e^2 L^2 (1-c_B)^2, \\
&(1-c_B)^4 e^4 L^2 \geq (e-c_B)^2 e^2 L^2 (1-c_B)^2, \\
&(1-c_B)^2 e^2 \geq (e-c_B)^2, \\
&(e-ec_B) \geq (e-c_B).
\end{aligned} \tag{45}$$

By showing that (31) never holds for the Δ_H region, we have identified a value of battery cost, $\sqrt{c_H^{adj}}$, beyond which (31) does not hold. Thus, if $e > \bar{e}$, we know (31) holds if $\underline{c}_B < c_B < \bar{c}_B$, for some $\bar{c}_B \in (1-\sqrt{1-c_H^{adj}}), \sqrt{c_H^{adj}})$.

To conclude, we established the existence of a set, identified by a lower bound on efficiency ($\bar{e}$, closed form, tight), and a lower bound ($\underline{c}_B$, closed form, tight) and an upper bound ($\bar{c}_B$, not tight) on the cost of batteries, such that (31) holds - in that set, operating hydrogen with priority increases the amount of demand that is met through renewables (relative to battery priority).

A.5 Proof of Proposition 5

To understand the impact of operational priority on capacity investment, we compare the investments in both technologies under each prioritization - see Appendix A.1 for a derivation of the optimal capacity results.

We start by comparing the capacity results for Battery. From Proposition 2, we now that if $g < c_B$, both capacities are 0 and if $g > c_B$ but $c_H/e < L/2c_B^2$, $B_2^*(H_1^*) = 0$, thus in those cases, the result holds trivially. Hence, we have to check the result for the case of $g > c_B$ and $c_H/e > L/2c_B^2$, for which we know that $B_1^* > 0$ and $B_2^*(H_1^*) > 0$. Lastly, we need $c_H/e < L/2$, so that $H_1^* > 0$, as otherwise both capacities are identical $B_1^* = B_2^*(H_1^* = 0)$.

$$\begin{aligned}
B_1^* &= LQ\Big(\frac{1}{2} - \frac{c_B}{g} + \frac{c_B^2}{2g^2}\Big)^+, \\
B_2^*(H_1^*) &= \frac{Q}{2eg^2}\Big(\sqrt{2c_H g} - c_B\sqrt{eL}\Big)^2, \\
&\text{WTS } B_1^* \geq B_2^*(H_1^*), \\
e(g-c_B)^2 L &\geq \Big(\sqrt{2c_H g} - c_B\sqrt{eL}\Big)^2, \\
e(1-c_B)^2 L &\geq \Big(\sqrt{2c_H} - c_B\sqrt{eL}\Big)^2, \\
\frac{c_H}{e} < \frac{L}{2} &< \frac{c_H}{c_B^2 e}.
\end{aligned} \tag{46}$$

$\frac{c_H}{e} < \frac{L}{2}$ is the condition for $H_1^* > 0$, while $c_B^2 \frac{L}{2} < \frac{c_H}{e}$ is the condition for $H_2^* > 0$, i.e. this holds whenever both battery capacities are positive.

$$
\begin{aligned}
H_1^* &= Q\Big(1-\sqrt{\frac{2c_H}{geL}}\Big)^+, \qquad \text{where } Q' = 120/L,\\
H_2^*(B_1^*) &= Q\Big(1-\sqrt{2}\sqrt{\frac{c_H}{egL}+(\frac{1}{2}-\frac{c_B}{g}+\frac{c_B^2}{2g^2})}\Big)^+,\\
\text{WTS } H_1^* &\geq H_2^*(B_1^*),\\
\frac{2c_H}{geL} &\leq \frac{2c_H}{egL}+(1-\frac{2c_B}{g}+\frac{c_B^2}{g^2}\Big),\\
0 &\leq (1-\frac{2c_B}{g}+\frac{c_B^2}{g^2}\Big),\\
c_B &\leq g.
\end{aligned}
\tag{47}
$$

We know that if $c_B \geq g$, $B_1^* = 0$ in which case H_1^* and H_2^* are identical. Combined with what we showed in Equation 47, $H_1^* \geq H_2^*$ irrespective of the relation between c_B and g.

A.6 Proof of Proposition 6

We present the optimal capacity investment by building on the results from Proposition 1 and Appendix A.1. We use the superscript S to denote the capacity investment under seasonality. We formerly had the following expression for charge and optimal battery investment:

$$
\begin{aligned}
c_{B=1}(B) &= \Big(\frac{1}{Q}\int_{q_t=0}^{Q}\min[\frac{q_t^2L}{2Q},B]dq_t\Big),\\
B_1^* &= LQ\Big(\frac{1}{2}-\frac{c_B}{g}+\frac{c_B^2}{2g^2}\Big),\\
B_1^* &= \frac{QL}{2}\left(\Big(1-\frac{c_B}{g}\Big)^+\right)^2.
\end{aligned}
\tag{48}
$$

As we are now discharge limited if $B > 60$ (i.e., battery capacity exceeds nightly demand), we adjust the optimal battery investment analogously:

$$
\begin{aligned}
c_{B=1}^S(B) &= \Big(\frac{1}{Q}\int_{q_t=0}^{Q}\min[\frac{q_t^2L}{2Q},B,60]dq_t\Big),\\
B_1^S &= \min\Big[\frac{QL}{2}\left(\Big(1-\frac{c_B}{g}\Big)^+\right)^2, 60\Big].
\end{aligned}
\tag{49}
$$

While the investment in hydrogen is not directly impacted by the limitation of the battery, because of the discontinuity of battery capacity investment if $B_1^S = 60$, we have to take into account how this change in battery investment impacts hydrogen capacity. For that, we first check when this condition is met.

$$
\begin{aligned}
B_1^S &= 60,\\
LQ\Big(\frac{1}{2} - \frac{c_B}{g} + \frac{c_B^2}{2g^2}\Big) &= 60, \\
c_B &= g\Big(1 - \sqrt{\frac{120}{LQ}}\Big).
\end{aligned} \tag{50}
$$

Thus, if $c_B > g\Big(1 - \sqrt{\frac{120}{LQ}}\Big)$, the battery capacity investment expression is unchanged and thus the hydrogen capacity expression remains unchanged. If $c_B \leq g\Big(1 - \sqrt{\frac{120}{LQ}}\Big)$ then $B_1^S = 60$ and hydrogen capacity is adjusted. To verify, one can plug-in $c_B = g\Big(1 - \sqrt{\frac{120}{LQ}}\Big) = g\Big(1 - \sqrt{\frac{60}{QL/2}}\Big)$ into the hydrogen capacity equation.

$$
H_2^S(B_1^S) = \begin{cases} H_2^*(B_1^*) = Q\Big(1 - \sqrt{\frac{c_H}{geL/2} + \Big(1 - \frac{c_B}{g}\Big)^2}\Big)^+, \text{ if } c_B > g\Big(1 - \sqrt{\frac{120}{LQ}}\Big), \\ H_2^S(60) = Q\Big(1 - \sqrt{\frac{c_H}{geL/2} + \frac{60}{QL/2}}\Big)^+, \text{ if } c_B \leq g\Big(1 - \sqrt{\frac{120}{LQ}}\Big). \end{cases} \tag{51}
$$

We now turn to the case when hydrogen has priority. As hydrogen is not affected by the seasonality, its expression does not change:

$$
H_1^S = H_1^* = Q\left(1 - \sqrt{\frac{c_H}{geL/2}}\right)^+. \tag{52}
$$

But for the battery we have to check, as before, under which circumstance it reaches the discharge-limit of 60:

$$
\begin{aligned}
B_2^*(H_1^*) &= \frac{QL}{2}\left(\left(\sqrt{\frac{c_H}{geL/2}} - \frac{c_B}{g}\right)^+\right)^2, \\
B_2^*(H_1^*) &= \frac{Q}{2eg^2}\Big(\sqrt{2c_H g} - c_B\sqrt{eL}\Big)^2, \\
\text{Check when } B_2^*(H_1^*) &= 60, \\
\frac{c_H}{e} &= c_B\sqrt{\frac{120L}{Q} + \frac{60g}{Q} + \frac{c_B^2 L}{2g}}.
\end{aligned} \tag{53}
$$

Thus batteries have second priority and if $\frac{c_H}{e} < c_B\sqrt{\frac{120L}{Q} + \frac{60g}{Q} + \frac{c_B^2L}{2g}}$ the battery capacity is the same with and without seasonality $B_2^S(H_1^S) = B_2^*(H_1^*)$. But if, $\frac{c_H}{e} > c_B\sqrt{\frac{120L}{Q} + \frac{60g}{Q} + \frac{c_B^2L}{2g}}$ (while $c_H/e/g < L/2$, so that at least some hydrogen is profitable), $B_2^*(H_1^*) = 60$.

$$
B_2^S(H_1^S) = \begin{cases} B_2^*(H_1^*) = \frac{QL}{2}\left(\left(\sqrt{\frac{c_H}{geL/2}} - \frac{c_B}{g}\right)^+\right), \text{ if } \frac{c_H}{e} < c_B\sqrt{\frac{120L}{Q} + \frac{60g}{Q} + \frac{c_B^2L}{2g}}, \\ B_2^S(H_1^S) = 60 \text{ if } \frac{c_H}{e} \geq c_B\sqrt{\frac{120L}{Q} + \frac{60g}{Q} + \frac{c_B^2L}{2g}}. \end{cases} \tag{54}
$$

A.7 Proof of Proposition 7

We present the comparative statics of the investment amounts w.r.t. the back-up cost g by building on the results from Proposition 6 and Appendix A.6. If not specified otherwise, we assume that $g < c_B(c_B^{adj} < 1)$ and $c_H/e < gL/2(c_H^{adj} < 1)$, i.e., that the first marginal unit of each technology would be profitable.

We commence by analyzing the battery investment that operates with priority for which we have to distinguish the three cases where B_1^S capacity is zero, less than nightly demand and equal to nightly demand:

$$
\begin{aligned}
&B_1^S = \min\Big[LQ\Big(\frac{1}{2} - \frac{c_B}{g} + \frac{c_B^2}{2g^2}\Big)^+, 60\Big],\\
&B_1^S = 0 \text{ , if} g < c_B,\\
&B_1^S = 60 \text{ , if} g \geq c_B/\Big(1 - \sqrt{\frac{120}{LQ}}\Big),\\
&\frac{\partial B_1^S}{\partial g}
\begin{cases}
= 0 \text{ , if } g < c_B,\\
= LQ\frac{c_B(g-c_B)}{g^3} \text{ , if } c_B \leq g < c_B/\Big(1 - \sqrt{\frac{120}{LQ}}\Big),\\
= 0 \text{ , if } g > c_B/(1 - \sqrt{\frac{120}{LQ}}).
\end{cases}
\end{aligned}
\tag{55}
$$

From there, we go to hydrogen if it operates second (H_2^S) and also test, when it is not invested in and also how the investment changes as battery capacity B_1^S reaches nightly demand, i.e., 60.

$$
\begin{aligned}
H_2^S(B_1^S) &= \begin{cases}
0 \text{ , if } g < \frac{c_B^2 eL}{2c_B eL - 2c_H},\\
Q\Big(1 - \sqrt{2}\sqrt{\frac{c_H}{egL} + (\frac{1}{2} - \frac{c_B}{g} + \frac{c_B^2}{2g^2})}\Big)^+ \text{, if } \frac{c_B^2 eL}{2c_B eL - 2c_H} \leq g < c_B/\Big(1 - \sqrt{\frac{120}{LQ}}\Big),\\
Q\Big(1 - \sqrt{2}\sqrt{\frac{c_H}{egL} + \frac{60}{LQ}}\Big)^+ \text{, if } c_B/\Big(1 - \sqrt{\frac{120}{LQ}}\Big) \leq g.
\end{cases}\\
\frac{\partial H_2^S(B_1^S)}{\partial g} &= \begin{cases}
0 \text{ , if } g < \frac{c_B^2 eL}{2c_B eL - 2c_H},\\
\frac{Q(c_B eL(c_B - g) + c_H g)}{g^2\sqrt{eL\Big(eL(c_B-g)^2 + 2c_H g\Big)}} \text{ , if } \frac{c_B^2 eL}{2c_B eL - 2c_H} < g < c_B/\Big(1 - \sqrt{\frac{120}{LQ}}\Big),\\
\frac{c_H Q^{3/2}}{\sqrt{2}g\sqrt{egL(c_H Q + 60eg)}} \text{ , if } c_B/\Big(1 - \sqrt{\frac{120}{LQ}}\Big) \leq g.
\end{cases}
\end{aligned}
\tag{56}
$$

In particular, we want to compare the two derivatives at the point of $g = c_B/\Big(1 - \sqrt{\frac{120}{LQ}}\Big) < g$, where the battery capacity becomes capped.

$$
\frac{\partial H_2^S(B_1^S)(c_B = g\Big(1 - \sqrt{\frac{120}{LQ}}\Big))}{\partial g} = \begin{cases}
\frac{c_H Q - 2eg\big(\sqrt{30}\sqrt{LQ} - 60\big)}{\sqrt{2}g\sqrt{egL(c_H Q + 60eg)/Q}},\\
\frac{c_H Q}{\sqrt{2}g\sqrt{egL(c_H Q + 60eg)/Q}}.
\end{cases}
\tag{57}
$$

We want to show that it is possible for the derivative of hydrogen capacity w.r.t. backup cost

$(\partial H_2^S(B_1^S)/\partial g$ to be higher when batteries become capped, i.e.,:

$$
\begin{aligned}
WTS \frac{c_H Q - 2eg\left(\sqrt{30}\sqrt{LQ} - 60\right)}{\sqrt{2}g\sqrt{egL(c_H Q + 60eg)/Q}} &< \frac{c_H Q}{\sqrt{2}g\sqrt{egL(c_H Q + 60eg)/Q}}, \\
c_H Q - 2eg\left(\sqrt{30}\sqrt{LQ} - 60\right) &< c_H Q, \\
-2eg\left(\sqrt{30}\sqrt{LQ} - 60\right) &< 0.
\end{aligned} \tag{58}
$$

Hence, if back-up cost is sufficiently high, that batteries become capped - the marginal effect of back-up cost on generation is increasing.

From here, we turn to the case where hydrogen has priority and commence with hydrogen priority, which is not affected by the seasonality.

$$
\begin{aligned}
H_1^S &= Q\Big(1 - \sqrt{2}\sqrt{\frac{c_H}{geL}}\Big)^+, \\
H_1^S &> 0 \text{ , if } g < \frac{2c_H}{eL}, \\
\frac{\partial H_1^S}{\partial g} & \begin{cases} = 0 \text{ , if } g < \frac{2c_H}{eL}, \\ = Q\sqrt{\frac{c_H}{2eg^3 L}} \text{ otherwise.} \end{cases}
\end{aligned} \tag{59}
$$

For battery investment without priority, we have to distinguish the three cases where B_2^S capacity is zero, less than nightly demand, and equal to nightly demand:

$$
\begin{aligned}
& B_2^S(H_1^S) = \min\Big[\frac{Q}{2eg^2}\Big(\sqrt{2c_H g} - c_B\sqrt{eL}\Big)^2, 60\Big], \\
& B_2^S(H_1^S) = 0 \text{ , if } \frac{c_H}{e} < \frac{c_B^2}{2g}, \\
& B_2^S(H_1^S) = 60 \text{ , if } \frac{c_H}{e} \geq c_B\sqrt{\frac{120L}{Q} + \frac{60g}{Q} + \frac{c_B^2 L}{2g}}, \\
& \frac{\partial B_2^S(H_1^S)}{\partial g} \begin{cases} = 0 \text{ , if } \frac{c_H}{e} < \frac{c_B^2}{2g}, \\ = -Q\Big(c_B\Big(2c_B eL - 3\sqrt{2}\sqrt{c_H g}\sqrt{eL}\Big) + 2c_H g\Big)/\Big(2eg^3\Big) \text{ , if } \frac{c_B^2}{2g} \leq \frac{c_H}{e} < c_B\sqrt{\frac{120L}{Q} + \frac{60g}{Q} + \frac{c_B^2 L}{2g}}, \\ = 0 \text{ , if } c_B\sqrt{\frac{120L}{Q} + \frac{60g}{Q} + \frac{c_B^2 L}{2g}} \leq \frac{c_H}{e}. \end{cases}
\end{aligned} \tag{60}
$$

A.7.1 Extending the Separation Of the Parameter Space

Here, we expand on the results from Figure 5 and Appendix A.2.1 by also considering the seasonality threshold at which the battery is capped. As before, we normalize all costs so to $g = 1$ so that battery and hydrogen cost are expressed relative to back-up costs.

As shown in Proposition 6, if $c_B < g(1 - \sqrt{\frac{120}{LQ}})$, the battery capacity B_1^S reaches its discharge cap, which in our normalized case equals the case of $c_B < 1 - \sqrt{\frac{120}{LQ}}$ - note that this is a condition irrespective of the cost of hydrogen.

$$
\begin{aligned}
H_2^S(60) &= Q\Big(1-\sqrt{2}\sqrt{\frac{c_H}{eL}+\frac{60}{LQ}}\Big)^+,\\
WTS\ H_2^S(60) &= 0,\\
\frac{1}{2} &= \frac{c_H}{eL}+\frac{60}{LQ},\\
\frac{c_H}{e} &= \frac{L}{2}-\frac{60}{Q}.\\
&\text{Because our y-axis in the graph is } c_H^a dj = c_H/(geL/2)\text{:}\\
\frac{c_H}{e}/\frac{L}{2} &= 1-\frac{120}{LQ}.
\end{aligned}
\tag{61}
$$

Furthermore, if $\frac{c_H}{e} = c_B\sqrt{\frac{120L}{Q}} + \frac{60}{Q} + \frac{c_B^2 L}{2}$, then B_2^S reaches its cap as well.

$$
\begin{aligned}
\frac{c_H}{e} &= c_B\sqrt{\frac{120L}{Q}}+\frac{60}{Q}+\frac{c_B^2 L}{2},\\
&\text{Considering again the y-axis scaling:}\\
\frac{c_H}{e}/\frac{L}{2} &= c_B\sqrt{\frac{480}{LQ}}+\frac{120}{LQ}+c_B^2.
\end{aligned}
\tag{62}
$$

These will be the conditions that further subdivide the parameter space. Subsequently we reintroduce our previously shown case-separation (see Appendix A.2.1), but further split out those cases when batteries are capped:

1. *No Tech* as $B_1^S = 0, B_2^S = 0, H_1^S = 0, H_2^S = 0$.
2. *Battery Only* as $B_1^S > 0, B_2^S > 0, H_1^S = 0, H_2^S = 0$.
3. *Hydrogen Only* as $B_1^S = 0, B_2^S = 0, H_1^S > 0, H_2^S > 0$.
4. *Battery Dominant* as $B_1^S > 0, B_2^S > 0, H_1^S > 0, H_2^S = 0$.
5. *Hydrogen Dominant* as $B_1^S > 0, B_2^S = 0, H_1^S > 0, H_2^S > 0$.
6. *Both Techs* as $B_1^S > 0, B_2^S > 0, H_1^S > 0, H_2^S > 0$.
7. *BD Cap* as $B_1^S = 60, 60 > B_2^S > 0, H_1^S > 0, H_2^S = 0$.
8. *HD Cap* as $B_1^S = 60, B_2^S = 0, H_1^S > 0, H_2^S > 0$,
9. *BT Cap* as $B_1^S = 60, 60 > B_2^S > 0, H_1^S > 0, H_2^S > 0$.
10. B_2^S *Cap* as $B_1^S = 60, B_2^S = 60, H_1^S > 0, H_2^S > 0$.

Graphically, this divides the parameter space as shown and discussed in Figure 6 that we reproduce here in Figure 11. To the right of $1-\sqrt{120/L/Q}$, the capacity results are as before, but we are left with the changes cases to the left of the line - the area where B_1^* reaches the discharge limit.

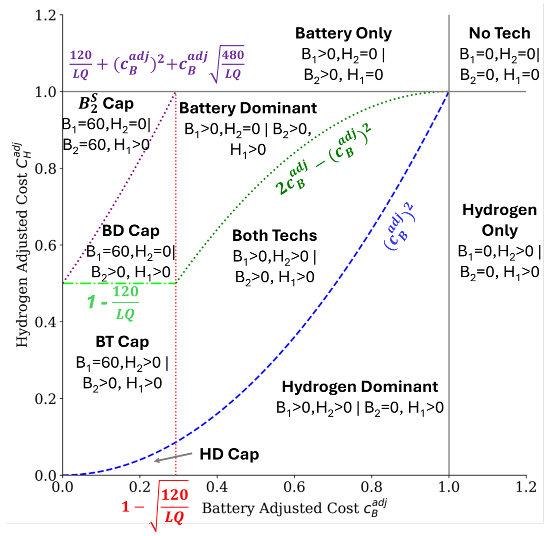


Figure 11: Conditions under which none, one, or both storage technologies are invested in under the different priorities. Backup-cost g normalized to 1.

B Additional Results

B.1 Translating Time-Series Into Model-Parameters

We obtain an hourly time-series $h \in \{1, ..., H\}$ of generation for each technology i in a region, where we denote the hourly generation by technology with $\gamma_{h,i}$ and the vector of all observations of a technology with $\vec{\gamma}_i$. Demand in each period equals the sum of all generation technologies $d_h = \sum_i \gamma_{i,h}$. We require each region to have at least one generation technology but if a certain technology does not exist in a region (e.g. nuclear power) we treat it as if its generation was 0 in each period.

To calculate the excess generation during the day and demand at night, we categorize generation into three types - i) baseload, ii), intermittent, iii) firm. As baseload, we categorize generation technologies that cannot be adjusted quickly in their output - notably nuclear, biogass and run-of-river. We categorize solar and wind as intermittent. All other technologies are firm - i.e. the adjustable fossil fuel technologies like e.g., gas, coal, and oil plants. We proceed in the following steps to calculate the parameters.

1. We scale the technologies' generation and demand to their expected future outputs, by multiplying available generation vectors by the ratio of future capacity estimates with today's

capacity (we denote future values by superscript F), e.g. $\vec{\gamma_i}^{\mathrm{F}} = \vec{\gamma_i} * Cap_i^{\mathrm{F}}/Cap_i$. This step is optional; we use 2030 estimates for future capacities in our empirical section. Implicitly, this assumes that future capacity additions will generate electricity in comparable patterns as currently installed capacity.

2. We obtain residual demand $\vec{d^r}$ by deducting all firm generation and expected wind output from demand $\vec{d^r} = \vec{d}^{\mathrm{F}} - \sum_{i \in \text{firm}} \vec{\gamma_i}^{\mathrm{F}} - \sum_{h \in H} \gamma \vec{Wind}^{\mathrm{F}}/H$. Effectively, this reduces the demand by the baseload generation that is hard to adjust in the short-term and removes the stochastic nature of wind - which has no predictable diurnal pattern like solar.

3. We obtain excess power d_h^x by deducting the residual demand from the solar generation. $\vec{d^x} = \vec{\gamma}_{\text{solar}}^F - \vec{d^r}$.

4. We split $\vec{d^x}$ into sub-periods day d_t^{xd} (7am-7pm) and night d_t^{xn} (7pm-7am), by summing over the hourly demands in each sub-period - $t \in 1, 2, ...T$ indexes days. Let $D_N = \sum d_t^{xn}/T$ denote the average (across all dates in the year) cumulative demand in a nightly-subperiod. Because our model assumes a triangle shape for nightly demand and has a base of 12 (hours), the empirical height of the nightly triangle h_N is equal to $h_N = D_N/12 * 2$.

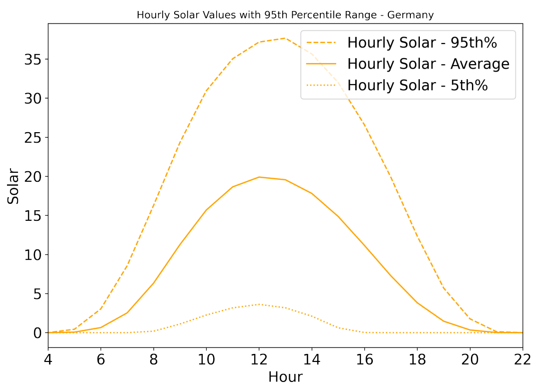
5. We obtain Q as the 99.9th percentile value of $\vec{d^x}$ that we then scale by h_N, to account for the fact that demand and generation in our model is scaled so that average nightly demand is -10. $Q = P_{99.9}(\vec{d^x})/h_N * -10$, where $P_{99.9}$ stands for taking the 99.9th percentile of a series of values.

6. We obtain L by finding the day $t \in T$ that has the maximum number of hours with excess sunshine, i.e., $\mathbb{1} d_t^{xd} > 0$. That maximum is L, i.e., the maximum available duration of excess solar power.

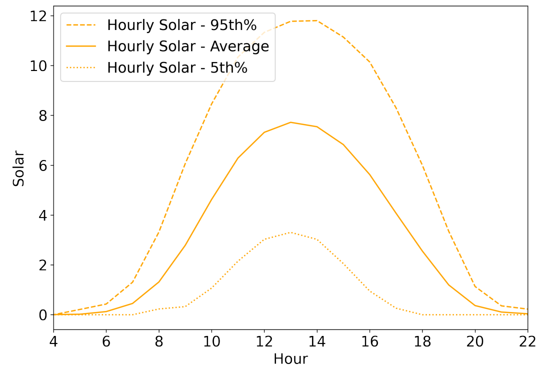
7. Lastly, we calculate the fraction of the year for which our model is applicable - as there may be consecutive weeks/months in winter during which no excess is reached during the day - a fraction of time we want to account for in our model. To do that, for a given year we find $t' = \min_t, s.t. d_t^{xd} > 0$ and $t'' = \max_t, s.t. d_t^{xd} > 0$ for $t = \{1, 2, ...365\}$ starting on January 1 (July 1 on the Southern hemisphere). The fraction of days with excess equals $(t" - t')/365$. We use this fraction to adjust the storage cost accordingly as the technologies can only be used if there is some excess. This way our model can be applied to markets with lower renewable penetration or high seasonality while only requiring the adjustment of storage costs.

B.2 Intraday Solar Generation Patterns

In this Appendix, we plot the intraday pattern of solar generation in Germany and France to support the triangle shaped excess energy profile during the day - comparing sunny (95% percentile of solar generation), average, and dark (5% th percentile of solar generation) days.



(a) Germany



(b) France

Figure 12: Intraday Generation Patterns in Germany (a) and France (b). Mean, 5%th and 95th% values plotted.

As shown in Figure 12, the intraday generation follows a predictable pattern, where it is increasing in the morning, peaks a little after noon and then decreases in the evening - resembling the triangle choice we made for the net energy profile and will subsequently investigate further. Furthermore note that the highest generation days also have more hours of sun-shine, which will translate into more hours of net-energy surplus.

We further compare the empirical pattern with our modelling choice of a triangle by juxtaposing it to the cumulative solar generation across the day. In Figure 13 we plot the cumulative generation per day, averaged across a year of Germany's solar data. We compare this empirical data with the cumulative excess energy that our triangle-based net energy profile model would predict. As we can see, the model approximates the observed patterns well - from the flatter slopes in the morning and evening to the steeper slope in the middle of the day. In combination, these tests make us confident in our choice of a triangle model to capture the first-order effects of solar generation on available net energy.

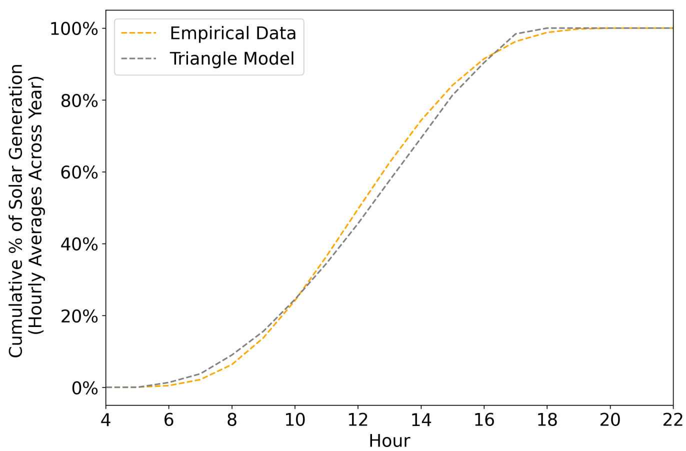


Figure 13: Comparing Solar Generation Pattern Between Empirical Data and Triangle Model

B.3 Seasonality of Solar Generation

In this Appendix, we plot the seasonality of solar generation in Germany and France to support the way we treat seasonality in our model. As shown in Figure 14, the seasonality of solar generation in both countries is such that despite considerable variation across days, the winter days have lower overall generation, while the summer days feature the highest solar generation. This "ordering" of solar generation across the year with concurrent high levels of variability motivated our choice to account for fraction f of days with excess to be able to accommodate low-generation days in winter. The concentration of high-generation days in the summer further motivated our assumption that if excess generation can exceed nightly demand (as in Section 3.4), it does so during the summer.

(a) Germany

(b) France

Figure 14: Seasonality of 2023 Solar Generation in Germany (a) and France (b)

B.4 Additional Results For Section 5.1

We present the same analysis that we discuss in Section 5.1 (Figure 7) for the French data below in Figure 15.

As can be seen, the dynamics are fairly similar to the one discussed for Germany, with joint increases of capacity in the battery-first scenario and an inflection of capacities in the hydrogen-first scenario.

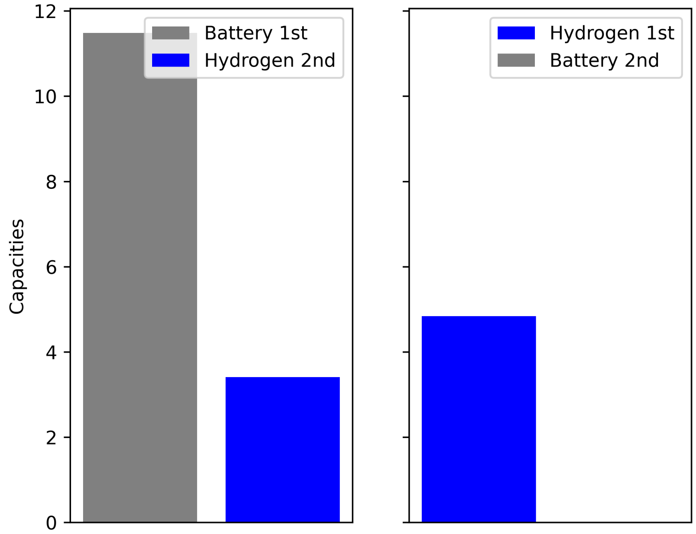
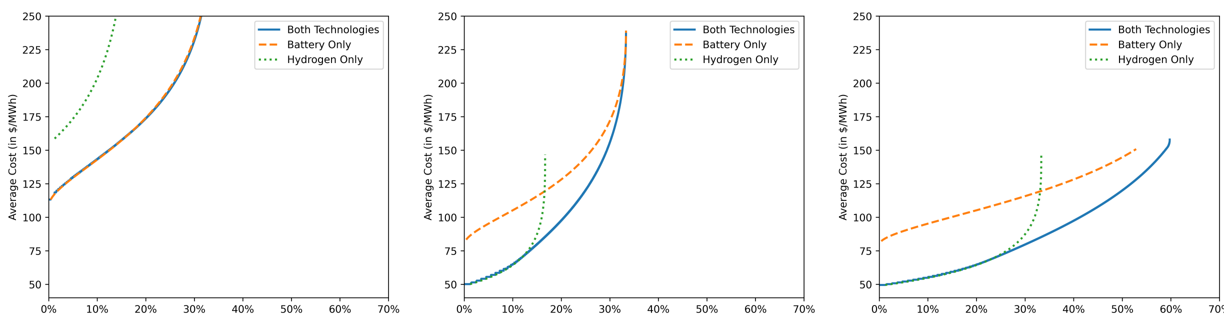


Figure 15: Optimal Capacity Investments In Battery and Hydrogen as Storage Costs Decrease Over Time - France

B.5 Additional Results For Section 5.3

We expand on our analysis from Section 5.3 where we quantified how jointly investing in two storage technologies compared to utilizing only a single technology changes electricity costs at different renewable penetration levels. In this Appendix, we will focus on only the storage investment cost needed to achieve a given target of renewable penetration. This is designed to capture a scenario where the utility aims to reach a certain renewable penetration (e.g., due to a legislated renewable portfolio standard) and tries to determine how much storage investment it will require.

In Figure 16, we plot how much meeting a certain fraction of nightly demand via renewables (x-axis) would cost (y-axis) and distinguish among three investment options: "battery-only", "hydrogen-only", and "both technologies".



(a) Costs of 2024, Q=D **(b)** Costs of 2030, Q=D **(c)** Costs of 2030, Q=2D

Figure 16: Average Storage Cost For A Given Renewable Penetration, Single vs Joint Storage Technologies.

In panel (a), we plot the result at 2024 technology cost and maximum excess generation equal to demand ($Q = D$), the situation many markets are in at the time of writing. We see that battery-only is the dominant choice across the entire feasible renewable penetration range - as it is cheaper and more efficient than the other investment option. Even if both technologies could be combined, the optimal solution is still not to invest in hydrogen.

In comparison, panel (b) plots the results when costs decrease to the expected 2030 level. The presence of cheaper electrolyzers leads to a situation where renewable penetration of up to 15% is best reached by only relying on hydrogen. For renewable levels beyond that, combining both storage technologies is the best choice, with a cost reduction of up to 20-25%, though using only batteries becomes increasingly more cost-competitive, and as good as using both technologies at around 35%. Beyond that level, cost increases too steeply to make it worth it.

Panel (c) considers the same costs as panel (b), but higher excess renewables ($Q = 2D$). The dynamics mimic those from panel (b), with co-investing being the cheapest option for intermediate renewable penetration targets. Two differences with panel (b) should be noted. First, higher renewable penetration levels can be achieved (at a lower cost) due to higher availability of solar energy in excess; and second, with battery-only it is not feasible to target penetration levels higher than 55% due to load-shifting across seasons being prohibitively costly.

Overall, these plots highlight that co-investing in both techs can lead to substantial cost reductions, but also that the future mix of storage technologies will depend on many factors - costs of storage technologies, of course, but also the available renewable power and the policy goals - e.g. desired renewable targets. As such, energy markets with access to the same technologies may invest in drastically different storage technologies, depending on renewable build-out, demand, renewable generation patterns during the day, and the regulatory framework.