Large Scale, Long Duration Energy Storage, and the Future of Renewables Generation

White Paper

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Form Energy, a Massachusetts based startup, is developing and commercializing ultra-low cost (<$10/kWh), long duration (>24hr) energy storage systems that can match existing energy generation infrastructure globally. These systems can reshape the electric system, making renewables fully firm and dispatchable year-round. Form Energy has comprehensively assessed the electrochemical landscape and screened for fundamental cost, abundance, and suitability for long duration applications. The result is two technology platforms under development, an aqueous sulfur (AqS) system, and a proprietary longer duration system. Additionally, the company has developed sophisticated analytical tools to model and identify highest value applications and ensure a tight product-market fit.

Enel Foundation is non-profit organization focusing on the crucial role of clean energy to ensure a sustainable future for all. By developing partnerships with pre-eminent experts and institution across the globe, leveraging on the vast knowledge of its founders, Enel Foundation conducts research to explore the implications of global challenges in the energy domain and offers education programs to the benefit of talents in the scientific, business and institutional realms.

Acknowledgements

Stopping anthropogenic climate change is a major achievement we, individually and collectively, aspire to, and believe is within reach. One of many reasons for hope: our ability to cooperate with others to contribute to something bigger than ourselves, a uniquely human trait that makes us the awesome species we are.

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Table of Contents

1 Note from the authors

Renewables widespread adoption across the globe is at the core of sustainable energy transition just for all.
To effectively manage larger scale of variable renewable energy, power system flexibility is the name of the game and indeed storage is and will be one of the core enablers of decarbonized energy systems.
In the United States Corporate Power Purchase Agreements (PPAs) are a major driving force for renewable power deployment. With deeper renewables penetration, energy intermittency is causing an increase in risks borne by parties to a PPA, and will require effective mitigation to enable the continuation of fast-paced deployments.
In this work, we use FormWare™, a proprietary asset optimization software developed by Form Energy, to explore the impact of increased volume and basis risk on the distribution of returns for long-term contracted windfarms in the Southwest Power Pool (SPP) footprint, under a simple contract for differences and operating in a day-ahead / real-time market environment. Quantitative results demonstrate the ability of storage to effectively manage risk and returns across a variety of potential storage technologies, while currently available short-duration storage technology shows limited impact. We extend the framework to evaluate a range of future renewables scenario and associated risk levels, and offer a methodology to quantitatively assess the risk and return benefits of storage for financially settled, long-term contracted renewable assets.
This work has been carried out considering assets located in the US deregulated markets, and thanks to the methodology and scientific approach can be extended to other locations and markets. In addition, the underlying conditions and risk factors (e.g. intrinsic technology features, variability of renewable sources, limited long distance energy transmission capacity and congestion, supply-demand mismatch etc.) are common across locations and market settings. For this reason, the results of this study have, at least qualitatively, a clear implication for a wide range of geographies.

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2 Introduction

2.1 | Objectives

The objectives of this paper are twofold:

1_ Evaluate the economic rationale for pairing utility scale renewable energy with Long Duration Energy Storage (LODES), by analyzing the conditions that would allow LODES to increase and/or stabilize the market revenues of a renewable energy facility (specifically, a large utility scale wind farm);

2_ Understand how LODES can provide a key technology to add value and bridge the gap between renewables intermittency and predictable, dispatchable renewables, thus overcoming one of the most substantial barriers to 100% adoption of renewable power.

2.2 | Scope

Using real-world examples describing current trends in utility scale wind power generation farms, notably the trend towards private-party power purchase agreements to support climate sustainability goals, the study will assess how LODES can provide a key technology to add value and bridge the gap between renewables intermittency and predictable, dispatchable renewables.

2.3 | Study Overview

Electrical power systems are in the first phases of a profound transformation as the cost competitiveness of renewables puts irreversible pressure on natural gas, coal and nuclear generation, globally. For example, McKinsey anticipates that renewables will reach unsubsidized cost competitiveness with coal and gas in the majority of geographies in the 2025-2030 time-frame[1]. In another study, the Carbon Tracker Initiative finds that 42% of global operating coal fleet is unprofitable in 2018 and 72% will be by 2040, independent of additional climate or air pollution policy[2]. Between 2019 and 2040, renewable energy will be the fastest growing source of energy across the world at an average of 7.1% p.a. (BP Energy Outlook, 2019).

[1] McKinsey, Energy Insight Global Energy Perspective. January 2019

[2] The Carbon Tracker, Powering Down Coal. November 2018

In the US, low cost renewables are putting the $112 billion of gas-fired power plants currently proposed or under construction -- along with $32 billion of proposed gas pipelines to serve these power plants -- at risk of becoming stranded assets. While it is true that extremely low cost of fuel is driving a short-term increase in natural gas-powered generation in parts of the country where coal and nuclear plants have retired, the combination of renewable energy cost declines, environmental concerns, and regulatory and legislative pressure have begun to place the long-term financial viability of natural gas assets in question. According to a recent study by the Rocky Mountain Institute[3], "across a wide range of case studies, regionally specific clean energy portfolios already outcompete proposed gas-fired generators, and/or threaten to erode their revenue within the next 10 years. This has significant implications for investors in gas projects (both utilities and independent power producers) as well as regulators responsible for approving investment in vertically integrated territories."

So what is to stop this powerful march towards a 100% clean, renewable future?

In the same study, McKinsey concludes that natural gas generation will continue to play a critical role in the grid of the future acting as a stable baseload and dispatchable capacity provider in renewable-heavy systems, thereby hindering the objective of a deeply decarbonized grid. In another study specifically focused on the European grid, Eurelectric estimates that ~400GW of dispatchable gas reserves will be required in high decarbonization scenarios (>80%) to provide system flexibility for days with low renewable generation. This gas capacity is in addition to 100GW – 200GW of commercial battery technologies[4].

In theory, utilities could deploy lithium-ion or other commercially available battery technologies in large enough quantities to ride through periods of wind lulls, cloud formations or grid outages and offset the need for carbon emitting gas generation. Lithium-ion batteries in particular offer high energy and power density, high cycling efficiency, low self-discharge rate, fast response time, and low cost of maintenance (Argyrou et al, 2018). Moreover, the cost of lithium-ion packs have come down rapidly, from $1,160/kWh in 2010 to $176/kWh in 2018 (Goldie-Scot, Bloomberg NEF 2019). Correspondingly, lithium-ion has seen a dramatic uptake over recent years, dominating 95% of all new energy storage capacity in the US since 2013 and seeing a 43% increase in installed capacity from 2017 to 2018 (IHS Markit, 2019).

So, why aren't commercially available battery technologies good enough?

In reality, even at the lowest price forecasts for lithium-ion or other commercially available battery technology, the modular nature of lithium-ion technology drives deployment costs linearly higher, making durations greater than 10 hours economically challenging. Lithium-ion and other "short-duration" energy storage

[3] Rocky Mountain Institute, The Economics of Clean Energy Portfolios. 2018

[4] Eurelectric, Decarbonization Pathways, page 62. May 2018

technologies will have an important role in distributed residential, commercial and industrial systems as well as in applications related to electric mobility; however, there is a need and opportunity for long duration electrical storage systems (LODES), which can be broadly defined as electrical storage systems with durations greater than 10 hours.

In a recent review of 40 academic studies of decarbonization pathways, Jenkins et al. observe that, "while [renewable] overgeneration arises during periods of abundant supply, periods of scarce wind or solar production are the flip side of the variability challenge. Prolonged periods of calm wind speeds lasting days or weeks during winter months with low solar insolation are particularly challenging for [variable renewable energy, VRE]-dominated systems. These sustained lulls in available wind and solar output are too long to bridge with shorter-duration batteries or flexible demand. Power systems with high VRE shares consequently require sufficient capacity from reliable electricity sources that can sustain output in any season and for long periods (weeks or longer)"[5]. In acknowledgement of the need, the US Advanced Research Project Agency - Energy (ARPA-E) has launched a federally funded grant program to develop energy storage systems that provide power to the electric grid for durations of 10 to approximately 100 hours with the scope of "opening significant new opportunities to increase grid resilience and performance"[6].

The rest of this paper will focus on a specific use case where the variable nature of renewable generation combined with the limitations of transmission infrastructure are already causing operational and financial risks and threatening the march to high-renewable futures in the US. In particular, the paper will:

1_ Introduce the concept and general structure of commercial power purchase agreements (PPAs), the fastest growing mechanism of contracting and financing new renewable generation infrastructure in the US.
2_ Identify operational and financial risks arising from price volatility and congestion in regions of the grid with excellent renewable resources but slow transmission expansion.
3_ Lay the analytical foundation to investigate how LODES can reduce such sources of risk.
4_ Perform extensive modeling and simulation based on real-world scenarios to drive quantitative conclusions with regard to the value of LODES in said applications.

In conclusion, the last section of the paper will discuss new opportunities for hybrid renewable and LODES products well suited for future grids with majority fractions of renewable generation.

[5] Jesse D. Jenkins, Max Luke, Samuel Thernstrom, Getting to Zero Carbon Emissions in the Electric Power Sector. Volume 2, issue 12, P2498-2510, December 19, 2018.

[6] ARPA-E DAYS

3 Renewable Energy Penetration and Barriers

3.1 | Renewable Energy Development in the USA

According to the Energy Information Administration (EIA), US solar capacity is projected to grow by 17% in 2020. Wind will similarly grow by 14%.[7] Within the ISO territories evaluated for this study, namely the Southwest Power Pool (SPP) and ERCOT, renewable energy development has accelerated rapidly. For example, in 2008, wind energy made up just 3% of SPP's annual energy production. By 2018, wind's share had increased to 23%. Additionally, SPP has reliably met as much as 69% of its load with renewable resources and 64% with wind alone at a given point in time.[8] This momentum is expected to continue: total wind capacity in SPP is expected to leap from 20.5 GW (2018) to 40.5 GW by 2030.[9] Similarly, ERCOT has so far been able to meet as much as 54% of its load with wind alone at a given point in time.[10] More importantly, as of August 2018, 86% of ERCOT's pipeline of new energy projects is either wind or solar, with solar projected to make substantial gains through to 2030.[11]

This rapid growth will be driven by a number of factors; including favorable economic conditions. According to Bloomberg New Energy Finance, by 2050 the cost of an average PV plant will fall by 71% and wind by 58%, the cost per kilowatt hour of lithium ion batteries will fall to roughly $70, global share of coal generation will shrink to 11%, and natural gas will only grow modestly.[12]
With growing concern over climate change, the American policy environment is also increasingly supportive of rapid growth in renewables. For example, 29

[7] Tyler Hodge, Short Term Energy Outlook. January 2019.

[8] Derek Wingfield. As it turns five, Southwest Power Pool's Integrated Marketplace is saving billions and enabling big changes in energy dispatch. Southwest Power Pool Press Release February 28, 2019.

[9] Gary Cate, presentation. SPP's Integrated Marketplace and Renewable Energy Evolution. Southwest Power Pool. October 17, 2017.

[10] Jeff St. John. Texas Grid Operator Reports Fuel Mix is now 30% Carbon Free. Greentech Media, January 23, 2019.

[11] John Weaver. Texas is going green: 86% of future capacity solar or wind, zero coal. PV Magazine USA. August 23, 2018.

[12] Seb Henbest et al. BNEF New Energy Outlook 2018. Bloomberg NEF 2018.

of the 50 states have established Renewable Portfolio Standards (RPS) as of 2018, many of which have undergone multiple iterations to ratchet up renewable generation requirements further.[13] Perhaps the most radical political gesture involves the February 2019 publication of the "Green New Deal" Resolution by Democratic members of the US Congress that called for 100% renewable generation by 2030.

Large American Commercial and Industrial (C&I) entities have also signaled growing appetites for renewable energy, partly out of concern for sustainability, having more than doubled the annual record of corporate off-take renewable power purchase agreements in 2018 by capacity added.[14] In ERCOT alone, corporate PPAs jumped from 292 MW in 2017 to 1.661 GW in 2018.[15]

3.2 | Obstacles to RES development

Despite the widespread interest across the US to rapidly increase renewable energy use, meeting that demand is not without its obstacles. Over recent years, the cost of renewables has achieved parity or even better with more conventional, baseload technologies. Renewables like wind and solar, however, disrupt the conventional methods for planning the daily operation of the electric grid because their output fluctuates depending on the availability of the resources (solar irradiance and wind speed). This variability forces the grid operator to adjust its day-ahead, hour-ahead, and real-time scheduling while also disallowing the renewable power producer to sell at the most ideal times, hindering them from maximizing revenue. Because wind and solar increase the magnitude of sudden power generation shortfalls or excesses, the grid operator requires more reserve power ready to respond at a moment's notice to ensure the grid remains balanced. This process starkly contrasts with the baseload power from fossil-fuel generators such as coal and natural gas, which can reliably produce set quantities of electricity consistently.

Variability manifests in several ways that, without ample availability of storage assets, leads to lost economic value. Price volatility --between morning, midday, and evening energy prices-- can be most commonly reflected through the classic "duck curve", in which solar production hits its peak output during midday, causing demand from other energy sources to be at its lowest. Demand rises rapidly later in the day as solar production falls, placing pressure on grid operators to quickly bring online other generating sources to compensate. With more renewable penetration

[13] Galen Barbose. US Renewable Portfolio Standards: 2018 Annual Status Report. Lawrence Berkeley National Laboratory. Electricity Markets & Policy Group. November 2018.

[14] Emma Foehringer Merchant. The Year of the Corporate PPA. Greentech Media, December 21, 2018.

[15] Sarah Krulewitz. Corporates May Be Leaving Millions on the Table by Procuring Wind Over Solar in ERCOT. Greentech Media. February 27, 2019.

without storage, the duck curve becomes increasingly emphasized. Hawaii has already experienced days where the duck curve has become so pronounced by solar penetration that the load drops below zero at midday, forcing the grid operator to backfeed energy, and as the director of Hawaii's Electro Co's RE planning states, "circuits that send power back up to distribution transformers and substations cause all sorts of technical and operational challenges."[16] In this particular scenario, storage would enable time-shifting of dispatch so that sources like solar and wind would not have to dispatch at the same time that they generate.

Broadening the perspective from solar duck curves to negative wholesale markets presents an even starker picture across the country. According to Greentech Media, multiple regional ISOs have logged patterns of renewable saturation driving down energy prices to negative states. Even at negative prices, renewable plants will often continue to generate when the Production Tax Credit[17] still allows for positive revenues.

Table 1

2017 congestion (negative pricing) in several ISOs in the US. SPP had the largest number of negative hours in 2017.

Negative Wholesales Market Prices by ISO

ISO	Total Negative Price Hours (All Price Nodes /Zone) Nodes /Zone)	Average Negative Price	Total Opportunity (Annulal $/MW, Average Across Price Nodes /Zone)
CAISO	2,044	-$ 4.57	-$ 667
ERCOT	37	-$ 1.11	-$ 41
ISO-NE	59	-$ 2.62	-$ 77
MISO	71	-$ 2.58	-$ 36
NYISO	0	—	—
PJM	38	-$ 1.31	- $ 8
SPP	3,784	-$ 5.36	-$ 1,269

Source: GTM Research, ISO data

[16] Dora Nakafuji. Jeff St. John. Hawaii's Solar Landscape and the "Nessie" Curve. Greentech Media, February 10, 2014.

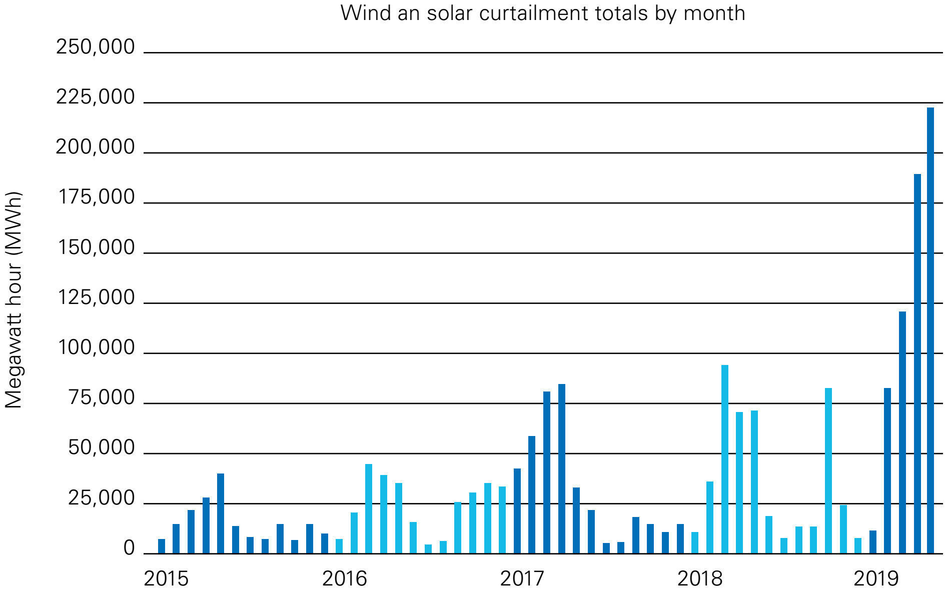
[17] A federal incentive providing financial support for the development of renewable energy.

Here again, pushing the imbalance between generation and load hits such extremes because renewable generators lack control over when they can generate (i.e. when the wind blows and when the sun shines). This economic representation of lost natural resource efficiency can be ameliorated with storage, enabling the discharge of renewable energy to occur when there is more balance between supply and demand.

Finally, in instances where continued dispatch of energy would realize negative returns or is simply prohibited by the grid operator due to congestion, renewable plants may have to curtail production, e.g. go offline, during their finite windows of access to the sun or wind. As Figure 7 demonstrates, the incidence of curtailment has been escalating each year, corresponding with increased renewable penetration.

Figure 1

Curtailment has been growing rapidly in recent years in CAISO, where renewable penetration is only approaching 40%.



The burgeoning C&I market is now coping with the above challenges and their inherent risks largely without long duration storage as an option. While this technology gap continues, C&I off-takers have been turning to increasingly complex and exotic financial instruments in order to minimize these risks. Companies like Microsoft, for example, have partnered with REsurety, Allianz, and Nephila Climate to pioneer the concept of a Volume Firming Agreement (VFA), which moves risk related to weather conditions and the market value of renewables to insurers.[18]

[18] Ibid, Emma Foehringer Merchant.

Storage technology has the potential to change the intermittency drawback of renewables by allowing renewable producers to capture their energy and discharge it at times when they can fetch adequate returns. More generally, pairing storage with renewable generators allows those renewable plants to behave more like dispatchable - guaranteeing fixed quantities of electricity on deliberate schedules, regardless of the wind or sun shine. This opens the way for renewable energy and storage technologies to permeate the market at utility scale, allowing the substitution of fossil fuel-based plants with more renewable plus storage plants that behave like dispatchable generators. Chapters 5 and 6 provide a more detailed discussion of existing storage technologies and their potential role in addressing renewables intermittency.

4 Commercial RES, US Example

4.1 | C&I evolution

As LODES solutions become increasingly commercialized and available, one of the most promising market segments for renewable energy plus storage to quickly penetrate is with a newer brand of customer (off-takers) in Commercial & Industrial (C&I) entities. One of the fastest growing mechanisms of renewable contracting in the United States is the C&I off-taker power purchase agreement. C&I off-takers were responsible for a quarter of new solar and wind capacity in 2018 (Green Tech Media 2018). According to the Rocky Mountain Institute, 2018's volume of corporate off-take agreements reached 6.43 GW of capacity, thereby shattering the 2015 record of 3.22 GW (Rocky Mountain Institute Business Renewables Center 2018).

What has spurred the C&I off-taker phenomenon? From the seller's perspective, C&I off-takers represent a burgeoning market that promises rising opportunity in developing more renewable generation projects. From the C&I buyer's perspective, renewable PPAs are not only beginning to make economic sense but are also enabling corporate entities to achieve sustainability objectives, such as offsetting emissions from electricity consumption, in part by taking ownership of associated Renewable Energy Credits (RECs) from the project. The rise of C&I PPAs provides benefits for both sides. For the developer, it presents a new avenue for renewable energy project development with less risk. For the C&I off-taker, it ensures increasingly economically attractive scenarios for cheaper and cheaper electricity while also achieving sustainability and climate change objectives.

4.2 | Current C&I PPA Structures and Limitations

As the pool of C&I off-takers continues to expand in markets that are seeing increasing penetration of renewables, offtake arrangements will need to further evolve and become more flexible in order to mitigate the associated risks. Currently, C&I PPAs are usually construed as either Physical PPAs or Virtual PPAs.

Physical PPAs: Physical PPAs are most commonly used by organizations that have large concentrated loads. The renewable energy seller builds, owns, and operates the project, and sells the output to the C&I off-taker at a specified delivery point (market hub, etc.). At that point, the off-taker takes ownership of the energy and gains the associated Renewable Energy Credits (RECs), in exchange for the off-taker paying a fixed price. Inherently, the physical PPA requires that the energy can be physically exported through the grid from the seller to the C&I customer. As a consequence, Physical PPAs are not a viable option over considerable distances, even when technically possible, where grid congestion charges and multiple ISOs make them economically unsustainable. For these reasons this study focuses on virtual PPAs, as they represent a more general case.

Virtual PPAs: When Physical PPAs are not possible or not economically viable, Virtual PPAs can be an effective alternative. Like with physical PPAs, the renewable energy seller builds, owns, and operates the project, and delivers the output to a specified delivery point or node. Unlike physical PPAs, the seller liquidates the energy locally (i.e. where power is generated) at the market price; furthermore, the seller and the C&I off-taker enter a contractual arrangement called contract for differences (CfD), whereby the off-taker pays the seller the difference between the market price and a fixed price (the strike price), when such difference is negative, and the payment is reversed, when the difference is positive. Uncertainty in the drivers of that market price and how much it will fluctuate constitutes a considerable risk to potential C&I customers. This is partly what would make shorter-term PPAs more attractive, as that uncertainty is less pronounced the closer the time horizon is. Virtual PPAs most often still allow for the C&I customer to own the associated RECs from the project, allowing them to take credit for using renewable energy.

While Virtual PPAs have in particular opened up vast opportunity for C&I entities to "go renewable" even when not physically receiving the power directly from the renewable energy developer, these contracts do carry risks. The C&I off-taker must have a strong grasp of the various factors that can reduce the local market price so that the fixed price that they pay does not exceed it. Among the myriad factors that drive the market price is the level of local renewable penetration and how much its intermittency can affect the grid.

Despite their many advantages, today's renewables PPAs include a number of risks to both parties involved in the long-term commitment. The PPA is a flexible contract structure that assigns risk across the parties involved in the transaction. Depending on the PPA structure, the risks fall on either or both parties. Although no hard rules exist, commercial trends have converged over time to require parties to typically take on risks they are best positioned to manage, or where the bargaining power favors the counterparty. These risks stem from the intermittency of the resources, the uncertainty of demand and the volatility of prices. The major categories of risk are:

- Basis risk: the spread in prices between where renewable power is generated and where it is delivered (or in the case of virtual PPAs, settled) can be significant. This spread, referred to as "basis", is a function of the transmission capacity between the generation node and, for example, the settlement hub. With many renewable projects co-located and, by nature of the resource, correlated, large bursts of generation can result in locally depressed prices, in contrast with a large settlement hub with much more power liquidity and exposure to a diversified generation pool. Consider the case where the off-taker settles the virtual PPA at the hub: in that case, the asset owner must sell power at the generation node and settle with the off-taker at the hub, incurring a loss if the node prices are lower. This exposure is the essence of basis risk.

- Volume risk: the difference between the forecasted renewable asset volume and its actual production volumes can be a source of downside in a number of ways. In its simplest form and in the context of a virtual PPA, consider an asset owner bidding into the day-ahead market. At the time of the bid, a decision is made based on a resource forecast for the next-day. If actual volumes fall short, any gap between the volumes committed day-ahead and the actual production volumes must be purchased from the market, often at a penalty that captures the cost to the market of suboptimal marginal producer entering the market to cover the shortage. This exposure to forecast uncertainty is one form of volume risk.

- Shape risk: if the output of the renewable asset is drastically different from the load shape of the C&I user, the value of a PPA as a hedge for the buyer against increases in future electricity markets is severely reduced. In the case of high local renewable penetration for a buyer and seller in the same hub, the output of a renewable asset can drive low nodal prices, while the buyer is exposed to high prices in the market where they purchase power coincident with their load. This exposure is a form of shape risk.

In the early days of corporate PPAs, and with relatively low renewables penetration on the grid, the impact of such risks on the profitability and value of these long-term commitments was small. However, with increased renewables penetration and larger price volatility, risk management is, more than ever, a key consideration. As with growing congestion and curtailment (showcased earlier in this paper) renewable PPA risks will increase drastically with deeper renewables penetration, threatening the march towards a decarbonized grid. Corporate procurement of renewables rests on more effective mechanisms for risk management, for both parties.

Although PPAs are inherently flexible in how risk is allocated, general market trends have emerged and evolved over time to reflect the needs of the various parties. Current trends in virtual PPA procurement by corporate off-takers tend to assign basis risk to the project owner / developer. Forecast uncertainty and associated volume risks is again mainly borne by the asset operator & developer, given their deeper understanding of the asset market conditions and control of its scheduling & bidding. Shape risk is at present borne by both parties – the asset operator / developer is exposed to the hub pricing volatility, whereas the off-taker is exposed to the mismatch of their load costs with the

PPA revenue. As renewables penetration drives higher volatility in markets, managing shape risk is likely to become a more central piece of both virtual and physical PPAs. Some recent PPAs have factored in premiums for energy delivered during peak demand hours for off-takers.

One potential approach to PPA risk management is an increased trend towards securitization, financial derivatives and complex financial structures. These structures - by definition - involve the entry of intermediaries and additional overhead costs. In this paper, we focus on a physical storage enabled alternative, which acts to fundamentally reduce risk by addressing the intermittency of renewables.

4.3 | Charting the Pathway for Future C&I Off-taker Agreements

From the perspective of off-takers and developers alike, future long-term off-take agreements must effectively manage risk exposure for both parties.

In general, customers do not want long-run risk exposure, and unless risk factors can be tightly managed, shorter-term off-take commitments will become prevalent. With shorter long-term off-take agreements, more projects will rely in part on future cash flows from merchant revenue which are inherently riskier from a revenue certainty perspective. As a result, the cost of borrowing will increase and equity financing will constitute a larger fraction of the capital stack, increasing the cost of capital for renewable projects. In addition, customers do not want to take on basis risk as the complexity of forecasting and hedging against basis risk requires specialized knowledge, that falls outside the core business for most C&I energy buyers.

Volume and shape risk are arguably inevitable. Renewable assets production will remain uncertain, and the correlation of customer load and prices will always result in some level of risk exposure. These risk factors can be effectively managed through a number of tools, like better forecasting, and, in liquid markets, financial hedges. Customers need a clear and simple formulation that aligns incentives and enables effective exchange of risk & return with developers. Many C&I energy buyers are fairly sophisticated, but ultimately, off-take contract complexity will act to slow down the adoption of corporate PPAs and limit the growth of the segment.

From a developer's standpoint, off-take agreements must match the right level of risk appetite of commercial off-takers, while allowing for sufficient revenue certainty. In markets with capacity value, renewable energy projects can unlock significant value if they are able to provide dispatchable power. Unlocking capacity value can result in higher certainty for at least a portion of the project revenue. In addition, dispatchability can allow for the renewable output to be better matched with customer load and market prices, curbing the sources of risk.

Our perspective in this paper is that dispatchable renewable power enabled by long duration storage can significantly reduce risk for both parties, and enable a more effective and clear exchange that simplifies off-take agreements. With long duration storage, a dispatchable renewable asset can have higher revenue certainty, can be better matched with customer load and structural prices regimes (e.g. peak and off-peak), address volume risk through stored power, and act as a low-cost conduit for power across high congestion times. Quantitative analysis in Chapter 6 will offer a detailed analysis to demonstrate the value of storage in managing both risk and return for long-term contracted renewable assets.

5 Energy Storage Systems

Energy storage is poised to play a critical role in modernizing grids, making them more scalable and resilient, solving emerging energy problems in the burgeoning contexts of climate change and rapid urbanization, as well as recasting the way that we approach the economics of electricity. The grid of the future will require all sorts of storage applications from the micro (home/EV to grid) to the medium/distribution scale to large transmission scale and hybrid applications with utility-scale storage.

To a first order, batteries can be characterized by energy rating, charge and discharge power ratings and charge and discharge efficiencies. Energy rating indicates how much energy can be held by the battery when it's fully charged; charge and discharge power ratings indicate the maximum power that a battery can draw from the grid or supply into the grid; finally, charge and discharge efficiencies measure the power losses while the battery is charging or discharging. A derivative and useful metric often used to characterize batteries is nominal duration, which is the ratio between energy rating and discharge power rating; alternatively, an effective duration metric can be used, which is calculated by de-rating nominal duration by the discharge efficiency. Some technologies, such as flow batteries, allow plant designs where energy and power ratings are independent variables, allowing, in theory, for flexible duration. Other technologies, such as Li-ion cells, impose stringent constraints on battery durations, mostly related to manufacturing processes and cell architectures.

5.1 | Short Duration Storage

Of the battery types that have seen recent growth in the marketplace, lithium-ion particularly stands out as a "yardstick" to compare against for other emerging storage technologies. Lithium-ion offers high energy and power density, high cycling efficiency, low self-discharge rates, fast response times, and low cost of maintenance (Argyrou et al, 2018). While the cost of lithium-ion has historically been prohibitive, limiting their application to high power and energy density ones, such as electric vehicles, these costs have been dramatically decreasing. Vehicle packs, which are currently the highest volume lithium-ion product, have dropped from $1,160/kWh in 2010 to $176/kWh in 2018, with projections of under $100/kWh in 2024 (Goldie-Scot, Bloomberg NEF 2019). In contrast with BNEF's cell and pack level cost estimates, NREL provides plant level cost projections that are nearly twice the energy cost for the pack as forecasted by BNEF. Plant level storage costs include additional overhead such as electrical and structural components as well as land and construction costs which nearly double the pack level energy cost for a 4-hour project and more than triple the pack level cost for a 1-hour system. Driven in part by falling costs, Li-ion has seen a dramatic uptake over recent years, dominating 95% of all new energy storage capacity in the US since 2013 and seeing a 43% increase in installed capacity from 2017 to 2018 (IHS Markit, 2019).

However, lithium-ion storage suffers a number of limitations, such as relatively quick degradation rates, safety concerns tied to high-profile explosions and fire incidents, concerns over the sustainability (and cost) of lithium and other essential material mining, among others. Most importantly, project developers do not typically use lithium-ion for dispatch applications longer than 4 hours in duration because of the modular cost structure of the technology, which today make longer duration projects (>4hrs) economically infeasible. This means that in the near-term (2-5 years), the value of Li-ion technology is maximized in shorter duration applications and especially where the technology really shines such as frequency control response. In this study, we also explore the possibility of future Li-ion costs, using forecasts for 2020, 2030 and 2040 Li-ion batteries to explore longer-duration deployments of the technology.

For renewable energy to fully penetrate electricity markets, supply rapidly growing demand among C&I customers, and supplant the need for fossil-fuel based systems, either significant advances in existing technologies or new long duration storage technologies will be needed to close the gap. LODES will enable renewable energy to provide grid resilience, enable multi-hour time-shifting and arbitrage, as well as replace intermittency with stability, savings, and sustainability and, for C&I customers, to buy utility-scale renewable energy on-demand (specific times of day).

5.2 | Long Duration Storage

LODES can be broadly defined as electrical storage systems with durations greater than 10 hours. For example, LODES would be well in the scope of the recent ARPA-E federally funded grant program to develop energy storage systems that provide power to the electric grid for durations of 10 to approximately 100 hours with the scope of "opening significant new opportunities to increase grid resilience and performance". Because of the long duration, a critical requirement of LODES is a very low $/kWh energy capital cost.

Traditionally, power assets are categorized by their role in serving the supply stack. Baseload assets (like coal & nuclear reactors) are meant to operate at very high capacity factors (>80%) to serve the majority of the load requirements. Mid-merit assets (like modern CCGT plants) are more flexible and can typically provide parts of the baseload function in addition to ramping over days and seasons to match cyclical components of load. Peaker plants (like open-cycle combustion turbines, diesel engines or more modern reciprocating engines) operate at very low capacity factors (<10%) and are primarily intended to address rapid load fluctuations and contribute to higher grid reliability. In a future with deep renewables, asset roles shift as large intermittent low marginal cost assets become the new source of baseload power, while the need for flexible fast-ramping assets increases. This latter role is where long duration storage will be most needed.

An order of magnitude analysis of costs can be instructive here. For example, if the installed capital cost of natural gas plant $1,000/kW was used as a benchmark, a 10-hour LODES would have to have an energy capital cost of less than or equal to $100/kWh and a 100-hour LODES of less than or equal to $10/kWh to respectively provide 10 and 100 hour output services cost competitively. These prices appear to be beyond the most optimistic price projections of currently available technologies at the plant level;[19] in particular, $10/kWh is well below the sole material cost of Li-ion cells.

The only commercially available option of low-cost, long-duration storage today is pumped hydro; unfortunately, as much as the technology is desirable, its deployment is geographically limited because of the very specific site and environmental requirements. A large class of electrochemical systems, which have long been neglected because of their low-rate capabilities and lower than Lithium-ion round-trip efficiencies, may very well become the enabling technology at the heart of LODES. Systems based on cheap, abundant materials such as water, air and certain metals can achieve extremely low $/kWh cost, at the expense of low round trip efficiencies (in the range 40%-70%) and high self-discharge rates (>5%/month). However, these drawbacks should be weighed against emerging grid conditions. If future grids do involve large amounts of inexpensive renewable electricity, low round-trip efficiencies can be tolerated. Moreover, LODES will necessarily have a much smaller yearly cycle count than a short-duration storage system and cycle life requirements can be correspondingly relaxed from the several thousands of a Lithium-ion system to a few hundreds or a few tens for a system with durations between 10 and 100 hours.

Several new classes of electro-chemical, thermal and mechanical LODES are being researched and developed today by academic groups and start-ups across the globe and will reach full commercial bankability by the end of the next decade. Their maturity will be timely with the next phase of large-scale deployment of renewables on the grid. The many cheap hours of storage capacity will allow to store excess renewables and avoid congestion during extended periods of over-generation and to supply market needs and maintain a high quality of electrical service during extended periods of renewable under-generation. The

[19] It is important to note that although cell-level future Li-ion costs can be as low as $70/ kWh, pack and plant total cost of ownership for a 12 year lifetime exceeds $100/kWh in future forecasts.

main question of this study is whether inexpensive LODES can make renewable generation truly dispatchable at a reasonable cost, at the power plant as well as at the grid level, considering here a deregulated market environment. Specifically, the study focuses on quantitatively assessing whether LODES can substantially reduce basis and volume risk of a renewable farm and make its output more dispatchable at a reasonable cost.

The quantitative analysis outlined In Chapter 6 shows how LODES can be conveniently integrated in a renewable rich system to neutralize the intermittency problem, and offer a quantitative framework to evaluate the value of various embodiments of LODES in managing risk in virtual PPAs.

6 Quantitative Analysis

6.1 | Overview

In this section, we explore the value of long duration storage in addressing market risk factors through a quantitative analysis of long-term contracted wind farms on a virtual PPA contract. We explore the effect of basis risk and forecast uncertainty on the asset's revenue distribution, with and without storage. The following sections provide an overview of scope & methodology, followed by a survey of results from the analysis. The quantitative analysis here was performed through FormWare™, Form Energy's proprietary asset management analytics platform.

6.1.1 | Objectives

- Demonstrate the value of more than 4 hours of storage in merchant risk management
- Provide a quantitative framework to assess the value of long duration storage technologies in merchant risk management

6.1.2 | Scope

Virtual PPAs (described above) are one class of long-term contracted renewable assets with large exposure to merchant risks. We focus this quantitative study on wind farms on hub-settled virtual PPAs, operating in the Southwestern Power Pool (SPP) footprint in a day-ahead and real-time market structure. The historical data used for the analysis refer to two years of operations of three wind farms operating in SPP. Day-ahead bidding of the wind farms is based on state-of-the-art weather forecasts, resulting in an average energy output uncertainty of about 15%. The average total energy availability of the farms is 90%, and average energy curtailment for congestions is about 5%, with a maximum of about 24%.

We also limit our focus on risk factors to two primary sources that are most critical today: volume and basis risk. We capture volume risk exposure through wind production and market price forecast uncertainty, and resulting penalties when production falls short of day-ahead commitments. Basis risk is directly reflected in the difference in price between the node and the hub, usually a result of local congestion due to correlated wind production. Basis risk exposure can be managed through physical storage by arbitering dispatch around nodal congestion, effectively smoothing out wind delivery over time. Volume risk exposure is managed through using storage to fill the shortages where wind production is lower than forecasted and resulting DA bids.

In this study, we take a technology-agnostic view to long duration storage. We model a wide range of long duration storage technology specifications (+200 possibilities) as per the permutations from the following table.

Table 2

The full range of energy storage technology specifications modeled in this work. All combinations of these specifications were analyzed in this work.

Roundtrip Efficiency (RTE) [%]	30	40	50	60	70	80	90
Energy CapEx ($/kWh)	5	9	17	31	56	104	190
Power CapEx ($/kW)	100	178	316	562	1000		

Many of the data points on this table are not commercially available today. However, given the novel nature of this asset class and the extensive activity in R&D and venture funding for new long duration storage technologies (e.g. the United States ARPA-E DAYS program), we opted for a broad survey of the design space, with the objective of providing an understanding of the value of various technologies in addressing risk-management challenges. For illustrative purposes, we provide a sample of detailed results for a storage specification that corresponds to pumped-hydro storage, with an energy and power capex of $5/kWh and $562/kW, and 80% RTE.

Finally, with deeper renewables penetration, we expect a rise in intermittency and associated costs. These costs will in part be internalized by the market. In one future trajectory, intermittency costs will manifest in larger basis and higher penalties for missing DA (Day Ahead) commitments. To explore these future scenarios, and given the difficulty of forecasting, we take a simple approach where basis and penalties are increased linearly (i.e. a linear hourly increase across the entire year).

For each case, we analyze the revenue distribution of each farm as is, then contrast with the optimized revenue for the same asset with a co-located storage plant.

6.1.3 | Methodology

To model the wind farms in a hub-settled virtual PPA environment, we use a two-step optimization approach that seeks to mirror the information available to the operator trading the output into the markets, and to replicate the uncertainty around future conditions as decisions are made. Energy storage sizing and operation are focused on managing real-time risk factors only, in particular:

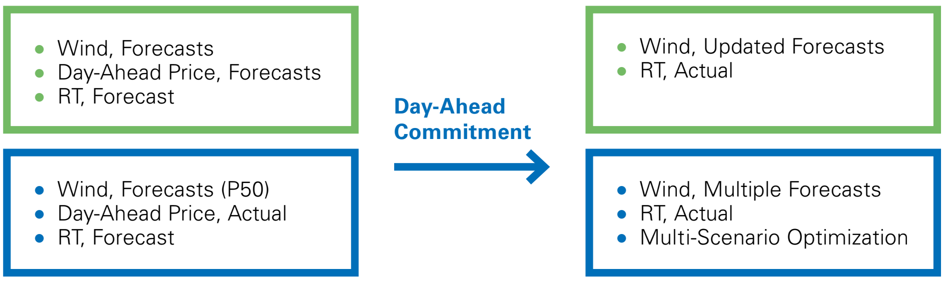
1_ Output shortages corresponding to times when wind generation falls below DA commitments predicated on DA forecasts.
2_ Congestion (basis) and other real-time price dynamics unfavorable correlated with wind generation.

The end-to-end optimization process is implemented in Form Energy's proprietary asset management software, FormWare™, which optimizes asset buildout and dispatch with an hourly resolution for a whole year based on a linear programming framework.

A schematic of the process is shown below in figure 2.

Figure 2

The dynamic scheduling framework used in this work to capture the trader's viewpoint in a day-ahead / Real-time environment, with imperfect foresight.



There are two rounds of optimization with two decision horizons. In the first round, which occurs 12 hours ahead of real time, DA commitments for the wind farm are calculated under limited knowledge of wind production and real-time prices: P50[20] hourly daily forecasts are used for the former and a proprietary regression of real-time prices is used for the latter. The output of that optimization are DA bids for the wind farm. These bids are assumed to be all committed by the market and the corresponding commitments can either be satisfied through available production, or through market purchases with a penalty that reflects DA/RT spreads (DART spread) and potential regulatory imposed penalties.

In the second round of optimization, which occurs in the day of operation, energy storage sizing and dispatch are optimized to minimize penalties from missing wind day-ahead commitments and to maximize real-time price arbitrage value. Energy storage sizing is optimized considering several possible real-time wind and price scenarios to make sure that the storage system deployed is robust across several possible operating conditions.

The distribution of wind farm and storage revenue and costs across possible wind and price scenarios are subsequently used to estimate average revenue and maximum downside, as proxies for risk and return.

[20] Refers to a forecast where the expected volumes have an exceedance probability of 50%.

In detail, the following steps are used:

1_ We first model the wind asset without any storage, and optimize bidding decisions between the DA and real-time market. To simulate forecast uncertainty, we handicap the optimization algorithm by providing as inputs the P50 forecasts for wind volumes and market prices (and not the real data sets) that would be available to a trader bidding for that power plant, so at the time when DA commitments are decided. This approach reflects the fact that operators place bids in the day-ahead market with a necessarily imperfect and limited knowledge of the future production and prices.

2_ The DA commitments computed by the model in the first optimization step are locked in as inputs to the second optimization step. These commitments can either be satisfied through available production, or through market purchases with a penalty that reflects DA/RT spreads (DART spread) and potential regulatory imposed penalties.

3_ We expose the wind farm in the second case to 3 statistically representative wind scenarios that are statistically representative of the volume forecast used in the first optimization step. We explore the distribution of wind farm revenues and compute estimates of average revenue and maximum downside as proxies for return and risk.

When storage is added to the wind farm, an additional set of decision variables are added to the optimization problem, corresponding to the storage build size and hourly dispatch. Steps (1) and (2) of the optimization remain the same, while in step (3), the storage build and dispatch profile are co-optimized across the modelled scenarios. The distribution of wind farm and storage revenue and costs are subsequently used to estimate average revenue and maximum downside, as proxies for risk and return.

While storage could affect DA bid strategy, the present analysis focuses on managing real-time risk factors only, in particular wind shortage and corresponding penalties and real-time price dynamics. Future work may incorporate storage in DA bid decisions.

6.1.4 | Data Sets

The data of the wind farms modeled in this work was provided by the generous courtesy of the Enel Green Power team, and are here anonymized to mask confidential information. They represent different project vintages across the geography of SPP, capturing the growth in the PPA market, increase in wind turbine capacity factor and evolution of contract terms. We model all the farms to be on a simple contract for differences with no hedges, collars or other financial instruments.

6.2 | Results

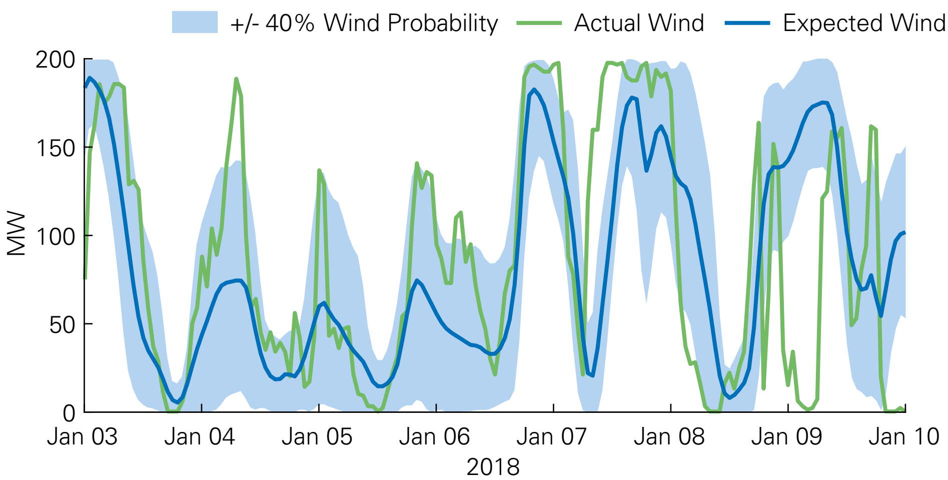
In this section, we explore the quantitative results from the modeling exercise. First, we survey the performance of the wind farms without storage, to understand how forecast uncertainty and congestion act to reduce wind farm revenue. Next, we take a closer look at the temporal results of how storage integrates with wind farms, when specifications correspond to "pumped-hydro like" storage. Finally, we extend our evaluation to survey aggregate results for a variety of storage specifications across a number of scenarios corresponding to future penetration of renewables.

6.2.1 | Results without Storage

Figure 3 contrasts the 24-hour wind forecast available for trading decisions with actual wind production for the same wind farm. The wind forecast tracks production closely on average, in aggregate. However, the hourly forecast's ability to correctly predict hourly production is relatively low, and at times, production is not just at odds with average forecast, but even with the +/- 40% probability envelope (see for example Jan 4th or Jan 9th).

Figure 3

Contrasting wind production with day-ahead forecasts shows the limits of hourly resolution of current weather forecasting data.



Forecast uncertainty manifests in missed day-ahead commitments, which must be covered by market purchases of energy at a premium, or a penalty, that captures the social costs of last-minute activation of expensive marginal producers. We model penalties in the form:

$$P = (Q_{bid} - Q_{DA})\ (P_{RT} + \alpha|P_{RT} - P_{DA}|)$$

where Q_{bid} is the volume bid in day-ahead, Q_{DA} is the volume available for DA at the time of dispatch, P_{RT} and P_{DA} are the real-time and day-ahead prices, and α is a tuning parameter that captures an increase in penalties. The structure of the penalties here is that any shortage in production against day-ahead commitments is covered at the real-time market price and an additional payment capturing the DA-RT spread (the DART), which is a reasonable hourly proxy for the tightness of supply.

In the case of this wind farm with the forecasts and production in figure 3, the mean annual revenue from the farm under the virtual PPA is around $18.6 mn, whereas the worst case scenario revenue is $9.2 mn, and the best case revenue is $26.5 mn.

To capture the impact of storage on the risk & returns for merchant-exposed wind farms, we use the mean and standard deviation of net present value (NPV) as indices of profitability. For two projects with identical mean NPVs, lower volatility of returns would indicate lower risk, and therefore should result in a lower cost of capital. Although investors certainly care about both downside and upside risk, infrastructure developers are generally risk-averse and more focused on downside risk scenarios.

Therefore, we focus in this work on the normalized downside risk spread, which corresponds to the difference in revenue between the mean and worst case scenario, normalized by mean revenue. Given the value of storage in addressing both downside and upside risk, this assumption is conservative. For this farm, this value corresponds to a normalized downside risk of 51%. The caveat is that the downside risk scenario modelled here was an aggressive one that corresponds to a scenario where consistently low wind persists for an entire year. With this context in mind, the results for downside risk can be roughly interpreted to mean that almost half the project's revenue is not guaranteed due to forecast uncertainty and basis risk, under base conditions (current market basis and penalty of ~25% of DART). For the two other wind farms considered in this analysis, the normalized downside risk spread is 52% and 56% under the base conditions.

6.2.2 | The Impact of Storage - Pumped Hydro Storage like Example

As shown in the previous section, a significant amount of revenue from the wind farms is at risk in the virtual PPA environment, when exposed to basis and forecast uncertainty. The co-optimization of energy storage will be shown here to be an effective risk management tool. Before exploring the aggregate results, it may be instructive to showcase an example of how the combined wind plus storage behaves. In the following set of figures, we zoom in on a week in the winter, with a focus on pumped-hydro like storage performance.

Figure 4 shows the dispatch for the wind farm and storage asset. Tracking the DA commitments first, it is clear that they are a complex function of expected production volumes and prices. On the 8th of January for example, large DA commitments are made while production volumes drop significantly almost abruptly (possibly due to a drop in temperature). This "white" gap corresponds to a shortage where a penalty is paid. The storage asset does intervene and provide parts of the shortage, entering the 9th of January with a significantly reduced state of charge.

In addition to covering missed commitments, the storage asset also actively arbiters around congestion and prices. For example, the storage asset charges up during the 7th of January when there is excess wind production over committed in DA, accompanied by a drop in real-time prices. A similar but shorter cycle can be tracked between January 3rd and January 5th, with a series of charge & discharge cycles corresponding to congestion and price arbitrage activity.

Figure 4

Sample results for 1 week of dispatch from a wind farm in SPP, operating in a day-ahead / real-time market structure, with a co-optimized storage asset (specifications corresponding to a pumped-hydro-like energy storage asset).

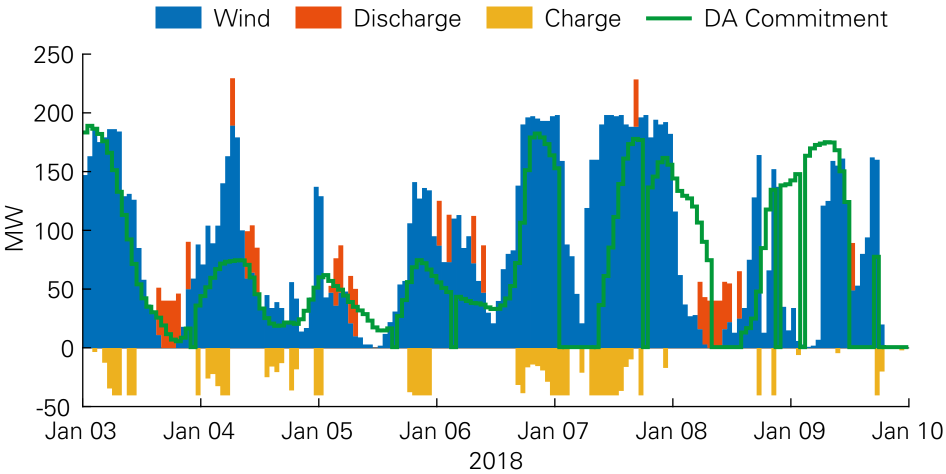
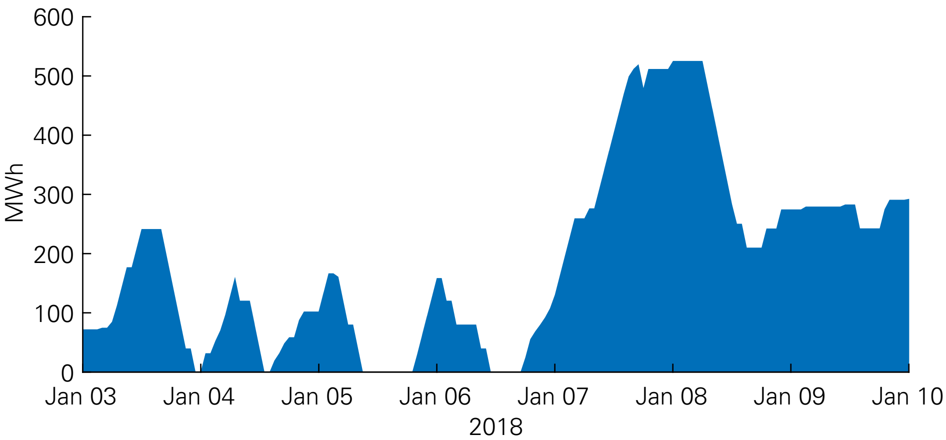


Figure 5

Sample results for 1 week showing the state of charge evolution of a co-optimized storage asset (specifications corresponding to a pumped-hydro-like energy storage asset) attached to a wind farm in SPP, operating in a day-ahead / real-time market structure.



Given the rich and multi-faceted nature of the wind-plus-storage co-optimization, we switch gears to tracking the mean and downside risk management impact of adding storage. Table 3 summarizes the results with and without storage for the three wind farms. Pumped hydro-like storage results in a modest impact of risk and return for farm (1), a sizeable impact on farm (2), and a significant impact on farm (3).

Table 3

Summary of results for three wind farms in SPP, operating with and without a storage asset (whose specifications correspond to a pumped-hydro like storage technology), demonstrating the impact of storage on the risks and returns of the projects.

Wind Farm	Storage technology	Optimal Duration (hrs)	Optimal Power (MW)	Mean virtual PPA NPV (MM USD)	Worst Case NPV (MM USD)	Downside risk	Downside risk variation
1	No Storage	N/A	N/A	18.6	9.2	51%	-
	Pumped Hydro	13	36	19.2 (+3%)	9.7	49%	-2%
2	No Storage	N/A	N/A	16.9	8.2	51%	-
	Pumped Hydro	17	108	19.0 (+12%)	10.2	46%	-6%
3	No Storage	N/A	N/A	13.9	6.1	56%	-
	Pumped Hydro	23	106	20.7 (+49%)	11.1	46%	-10%

For comparison, we also modeled one version of short duration storage technology using state-of-the-art Lithium ion, with costs estimated for 2025. We estimate the costs to be around $190/kWh and $178/kW at a 90% round-trip efficiency (based on NREL's plant-level cost estimates). As expected, the optimal durations were short (<1.5 hrs) while the impact on mean returns and downside risk was minimal for all farms, except for farm 3, where a short cycle arbitrage unlocked 27% in mean returns though had a limited impact on risk. These findings are consistent with our hypothesis that wind farm merchant risk management requires longer durations of storage because of the fundamental structure of forecast uncertainty and wind correlated congestion patterns.

Table 4

Summary of results for three wind farms in SPP, operating with a storage asset whose specifications correspond to currently available short duration storage technology using state-of-the-art lithium ion technology, demonstrating the limited impact of this storage technology on the risks and returns of the projects.

Wind Farm	Storage technology	Optimal Duration (hrs)	Optimal Power (MW)	Mean virtual PPA NPV (MM USD)	Worst Case NPV (MM USD)	Downside risk
1	2020 Li	1	2	18.9 (+2%)	9.2	51% (-0%)
2	2020 Li	1	13.5	17.0 (+1%)	8.3	51% (-1%)
3	2020 Li	1.4	137	17.7 (+27%)	8.5	52% (-6%)

6.2.3 | Sensitivity Analysis

The results above represent for the most part the current state of the world, where wind farms are subject to relatively moderate congestion conditions and market penalties for missing commitments. To explore how these results might change as more renewables come online, we repeat the same analysis for a variety of scenarios capturing a linear increase in basis over time (i.e. with the same shape, the difference in prices between hub and node goes up by a linear fraction across all hours). We also model scenarios with larger penalties, one mechanism markets may use to price-in the externalities of intermittency onto market players.

Figure 6

Sensitivity analysis contrasting the impact of a pumped-hydro like storage technology (solid triangles) to without storage (hollow triangle) on the risk and returns of a wind farm in SPP, operating in a day-ahead / real-time market structure under a contract-for-differences arrangement. Results show the impact of storage across a range of scenarios of penalties and basis risks, corresponding to potential future scenarios of renewables deployment.

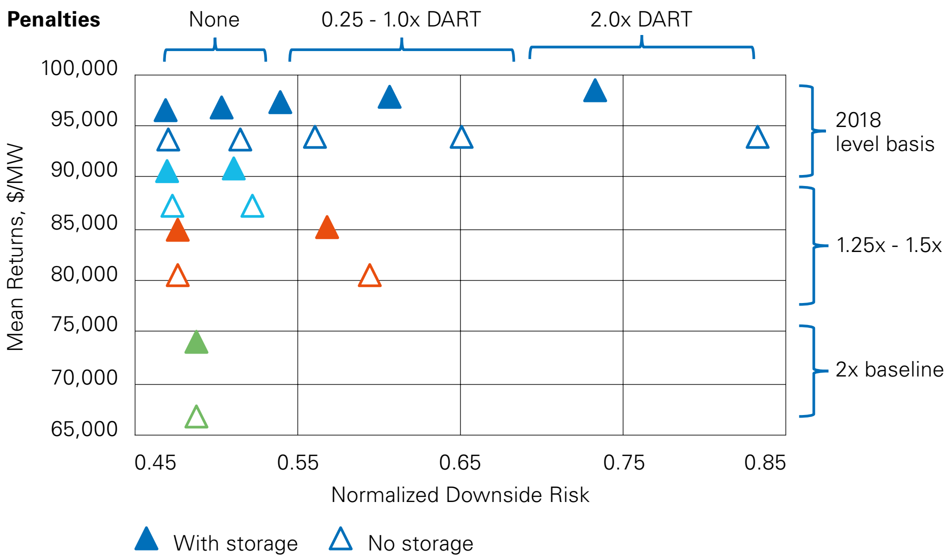
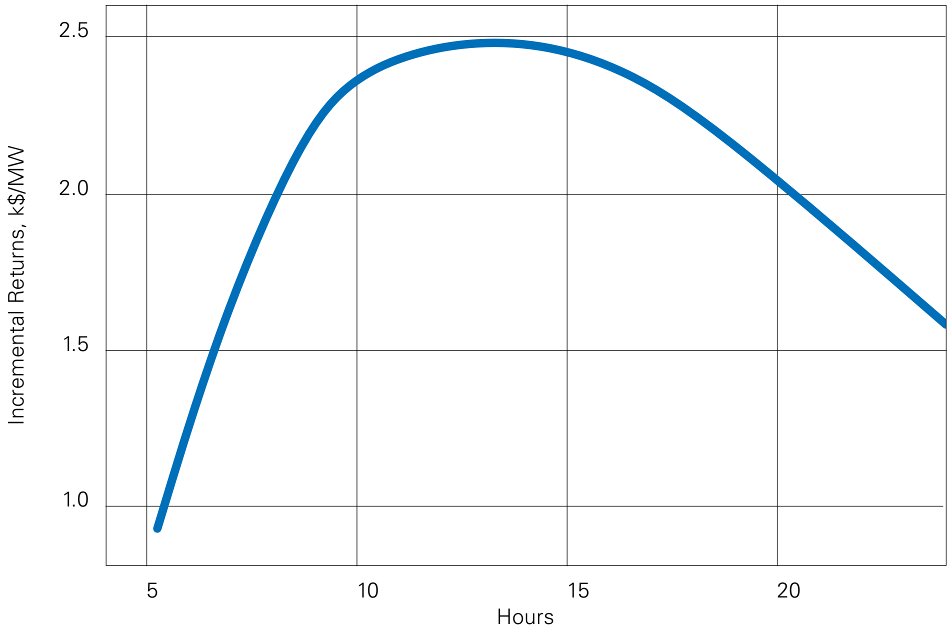


Figure 6 shows the sensitivity of the mean returns and normalized downside risk to an increase in basis and penalties for wind farm (1). The impact of higher penalties is clear: they act to increase the cost of forecast uncertainty, and therefore, increase risks. On the other hand, the primary impact of basis is to reduce mean profits by eating at wind production revenue. Storage (solid labels) consistently improves mean returns over baseline and reduces downside risk. Here, storage provides backup energy to mitigate forecast errors when they are most expensive, and provides a time-shifting mechanism for production to circumvent high congestion costs. Across the data points shown in this figure, the optimal duration of storage is between 13 and 14 hours, with a strong and positive monotonic relationship between penalty levels and total energy storage required (in MWhs of capacity).

The impact of duration on returns can be further highlighted by computing the returns for a range of durations, while fixing other cost and efficiency variables. Figure 7 shows how incremental returns (the improvement in returns through the addition of storage) are impacted by duration for a merchant-risk exposed wind farm. For durations less than 5 hours, the impact of storage on returns remains limited, then increases linearly to around 10 and plateaus at around 13 hours. Beyond 15 hours, incremental returns drop linearly, reflecting the limited marginal value of additional storage and the pressure the storage CapEx imposes on returns. In the simulations shown in this paper, the optimization algorithm automatically determines the optimal duration that maximizes returns, and we report results based on this optimal configuration.

Figure 7

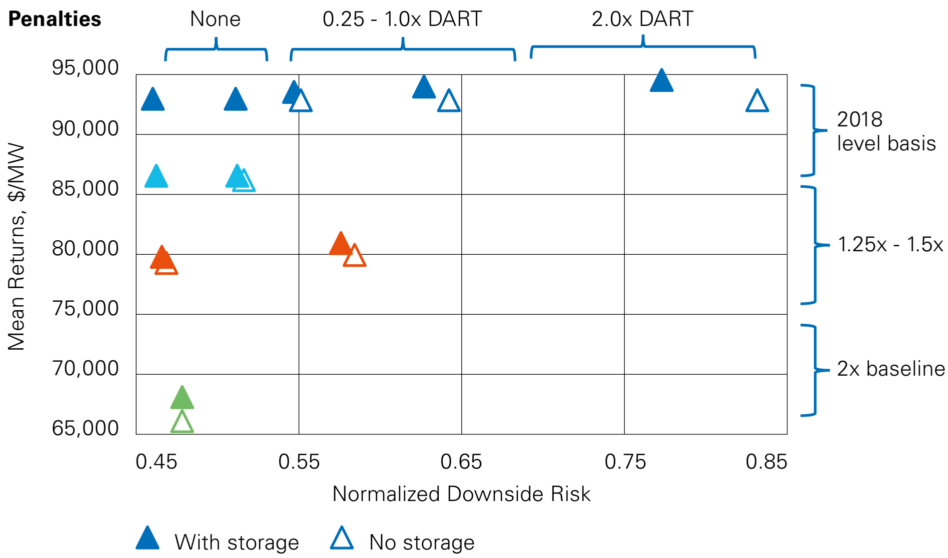
Incremental returns fall off rapidly when more than ~10% away from the optimal ESS size.



It is instructive here to contrast the above results with those of short duration storage, exemplified by 2025 Lithium ion technology, shown in figure 8. The impact of basis and penalty on the baseline results remains the same. However, it is evident in this case storage has a weaker impact on both mean returns and downside risk. The optimal duration of storage deployed across the cases here is around 1 hour. The long duration nature of these applications is well captured by the difference in impact on both risk and returns by the "pumped-hydro like" storage as compared with 2025 Lithium ion technology.

Figure 8

Sensitivity analysis contrasting the impact of today's lithium ion short duration storage technology (solid triangles) to without storage (hollow triangle) on the risk and returns of a wind farm in SPP, operating in a day-ahead / real-time market structure under a contract-for-differences arrangement. Results show the limited ability currently available short duration to manage volume and basis risks, corresponding to potential future scenarios of renewables deployment.



To explore whether these findings were consistent across potential storage technologies, we repeat the above analysis for all the combinations explored in section 6.1.2 In each case, we optimize the wind farm dispatch in day-ahead and real-time, accounting for penalties and the basis risk arising from price differences between the settlement hub and the production node, computing the optimal storage duration (if any) in the process. We run this analysis for the current state of a wind farm in SPP, as well as an extrapolated future case where basis risk increases by 50% and penalties for missing forecasts rise to 0.5 DART. Figures 9 and 10 show the variation of returns and risks versus optimal durations for a variety of energy capex levels. Two clear trends emerge. The first trend is that longer duration storage is correlated with an improvement in both returns and risks, with a tendency for the impact to be maximized around 9-11 hours. The second trend is that longer durations are optimal when energy capex costs are lower, as one might expect.

Figure 9

The correlation between optimal duration and incremental profits and risks, as well as the underlying energy capex costs (in $/kWh) and resulting project size (in MW), for an SPP wind farm under today's conditions of basis risk and penalties.

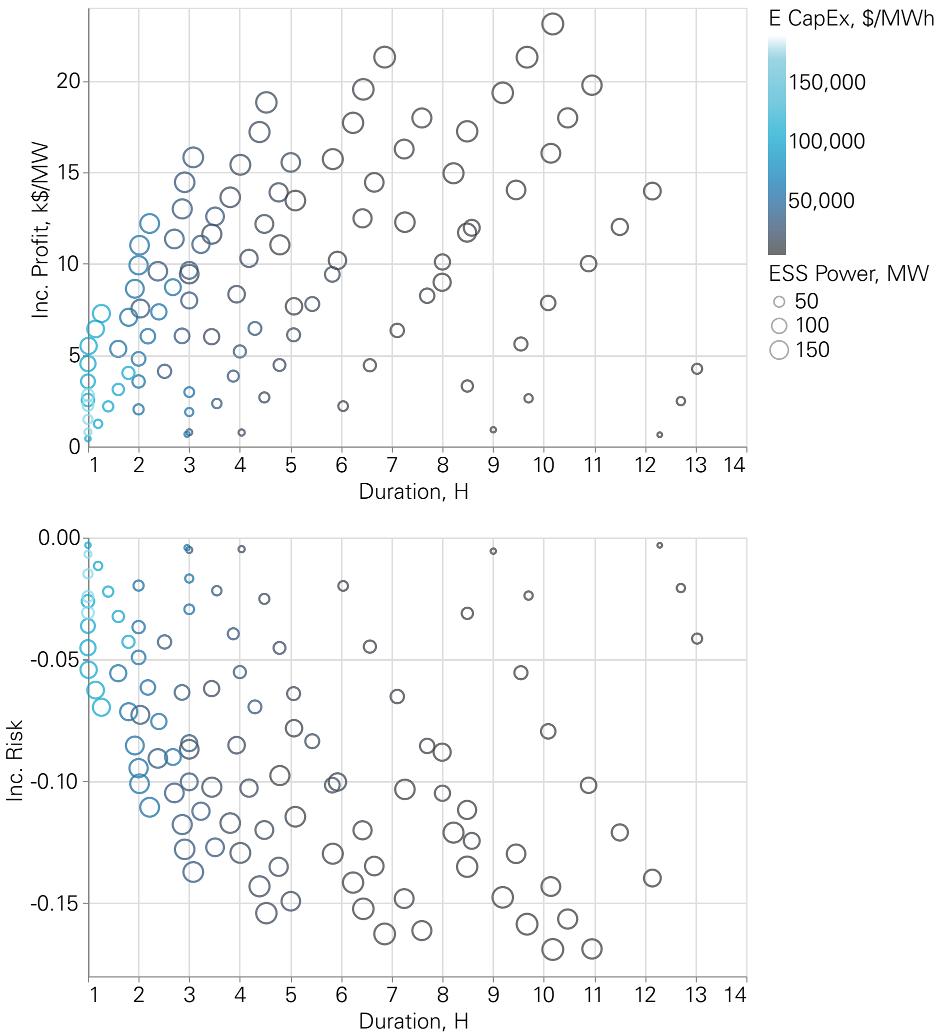
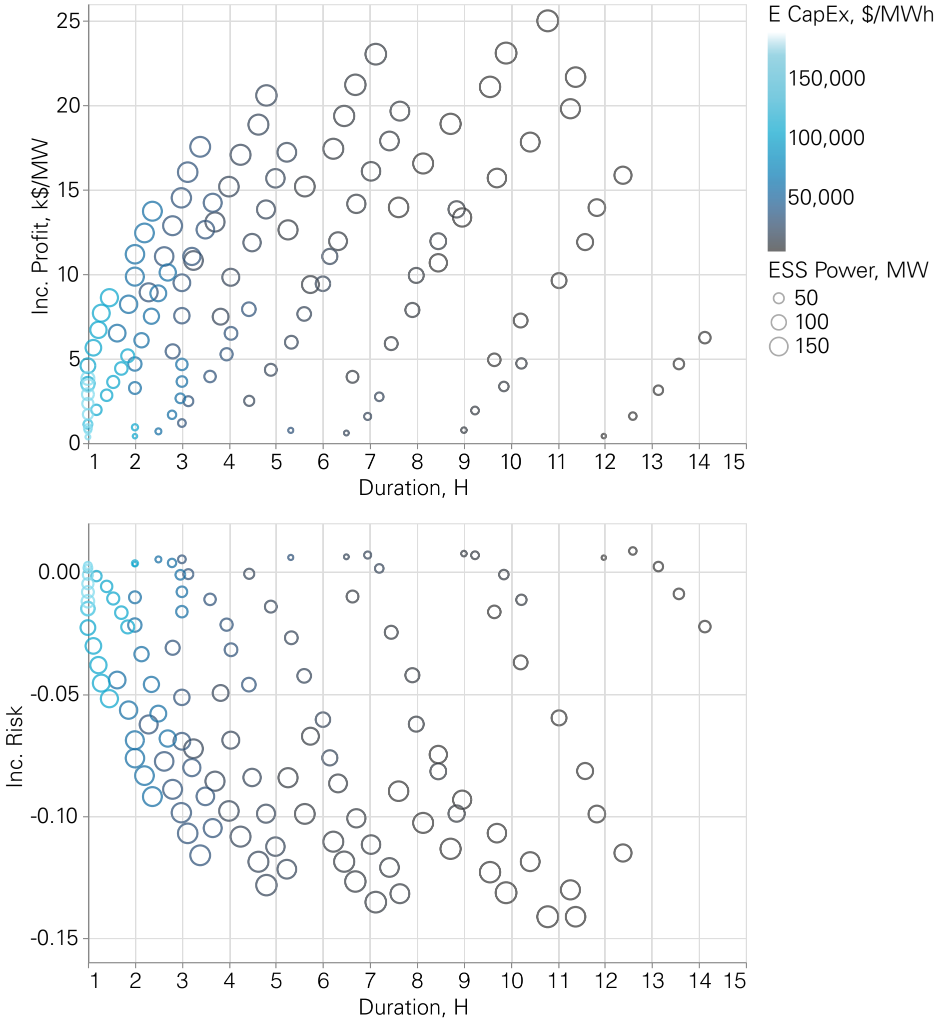


Figure 10

The correlation between optimal duration and incremental profits and risks, as well as the underlying energy capex costs (in $/kWh) and resulting project size (in MW), for an SPP wind farm under future conditions of basis risk and penalties.



To further resolve the value of storage in risk management, and the design trade-offs involved, the following set of surface plots provide a different view of energy capex, roundtrip efficiency, again for the same wind farm under current and future basis & penalty trajectories, with depth of color representing the incremental profits and risks associated with combining storage with a merchant risk exposed wind farm. The contours plots show results corresponding to the lowest power capex level included in the design space, $100/kW. Consistently, the results show a clear relationship between lower energy capex costs (which drive longer optimal durations) and higher incremental profits as well as lower incremental risks, with roundtrip efficiency contributing on the margin. This trend is consistent for current and future scenarios of basis risk & penalties.

Figure 11

Contour plot of the impact of energy capex costs (in $/kWh) and roundtrip efficiency on incremental profits for an SPP wind farm under current conditions of basis risk and penalties.

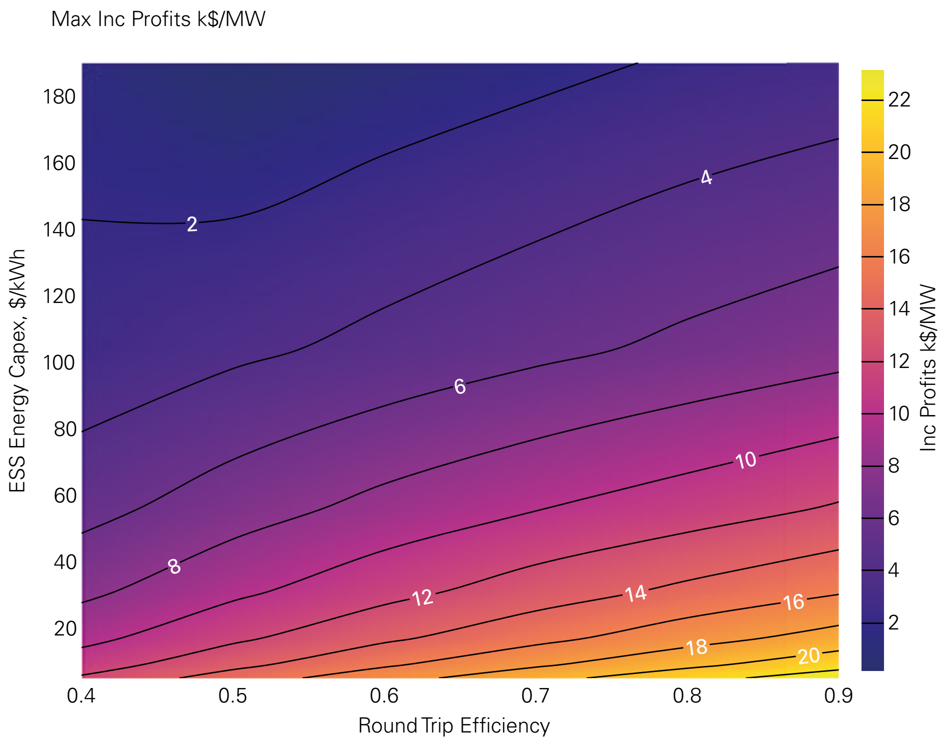


Figure 12

Contour plot of the impact of energy capex costs (in $/kWh) and roundtrip efficiency on incremental risks for an SPP wind farm under current conditions of basis risk and penalties.

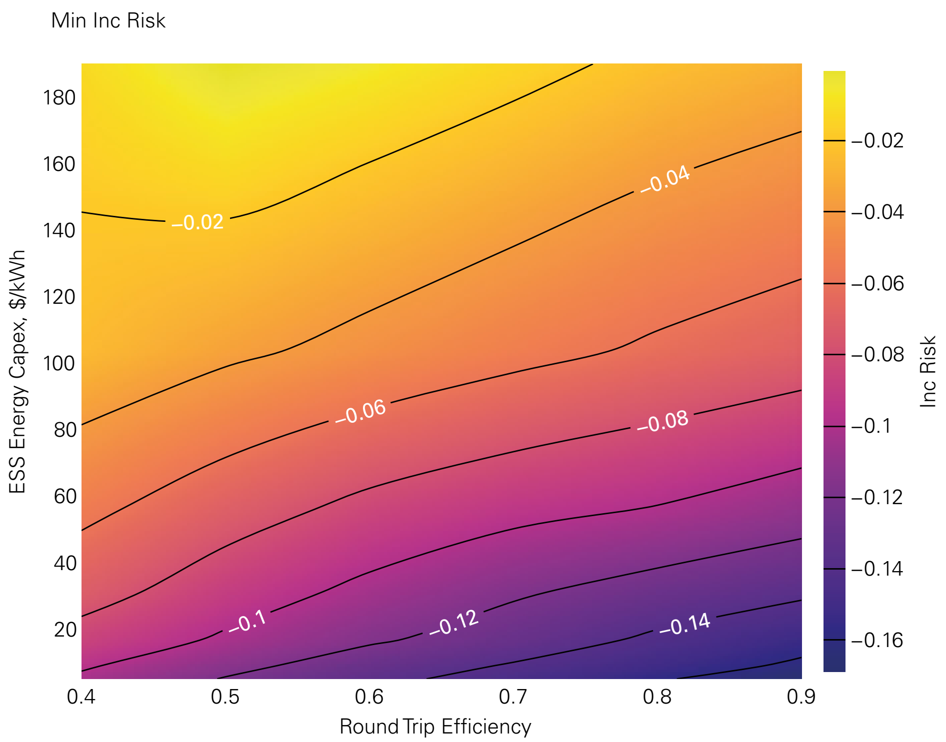


Figure 13

Contour plot of the impact of energy capex costs (in $/kWh) and roundtrip efficiency on incremental profits for an SPP wind farm under future conditions of basis risk and penalties.

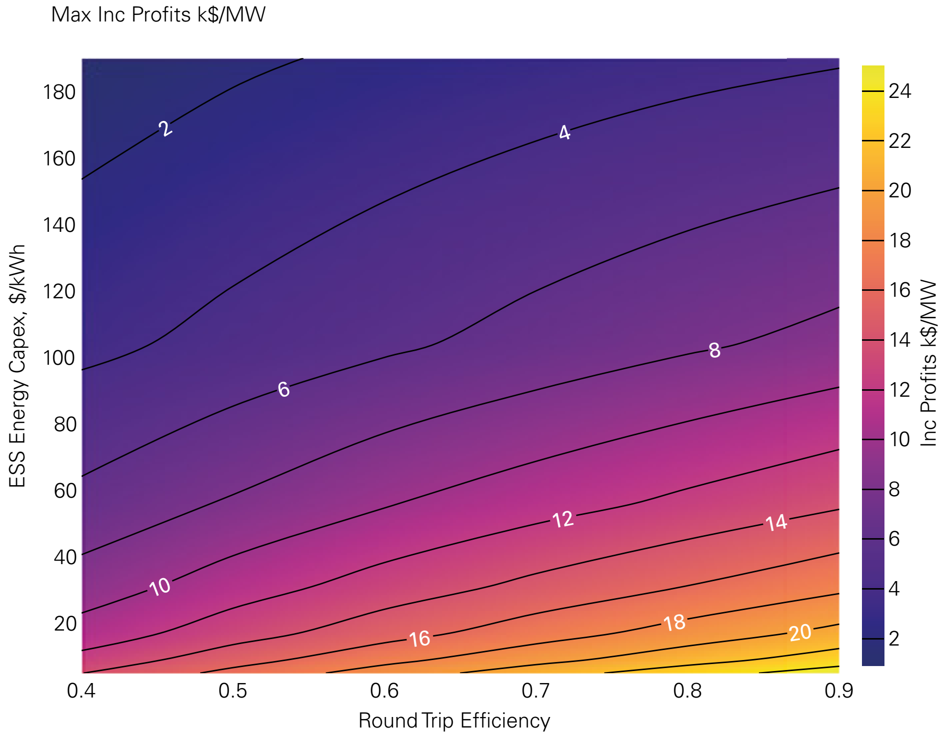
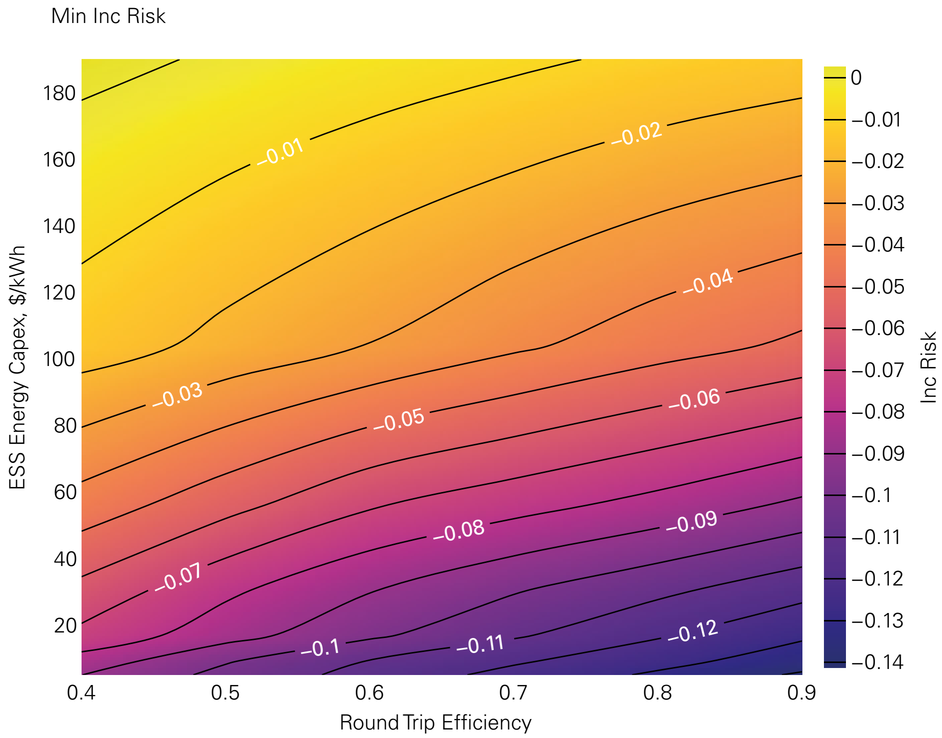


Figure 14

Contour plot of the impact of energy capex costs (in $/kWh) and roundtrip efficiency on incremental risk for an SPP wind farm under future conditions of basis risk and penalties.



The trends are also consistent when higher power capex surfaces are showcased in the contour plots. Figures 15 and 16 show the contour plots selected for a specific power capex level, \$562/kW. As expected, the impact on incremental profits and risks is much less pronounced given the higher total cost of the storage embodiments highlighted in this surface slice.

Figure 15

Contour plot of the impact of energy capex costs (in \$/kWh) and roundtrip efficiency on incremental profits for an SPP wind farm under current conditions of basis risk and penalties, with a surface slice at the \$562/kW power capex level.

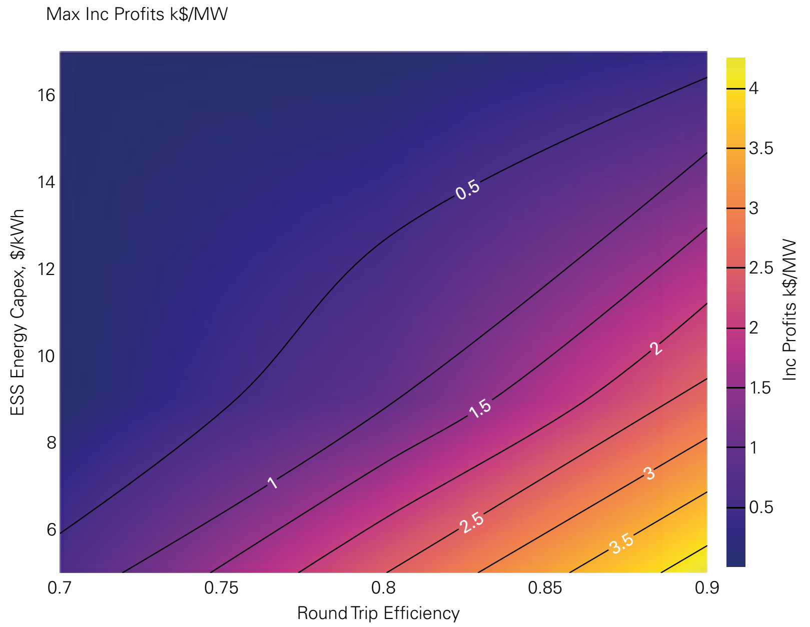
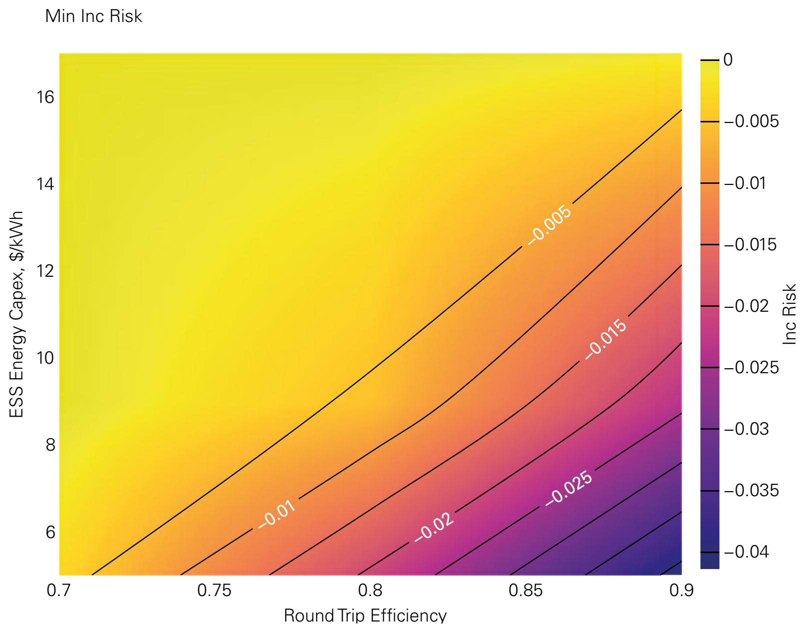


Figure 16

Contour plot of the impact of energy capex costs (in \$/kWh) and roundtrip efficiency on incremental risks for an SPP wind farm under current conditions of basis risk and penalties, with a surface slice at the \$562/kW power capex level.



The results are persistent for the other wind farms modeled in this work, although the optimal durations, the risk / return trends and their exact levels vary with the price signal, the strike price of the virtual PPA and the correlation of wind production with the basis and price signals. Figures 17 – 20 show the results for the other two wind farms across the storage specification space demonstrating similar trends, with varying risk and return levels, depending on the wind farm conditions.

Figure 17

Contour plot of the impact of energy capex costs (in $/kWh) and roundtrip efficiency on incremental risks for SPP wind farm (2) under current conditions of basis risk and penalties.

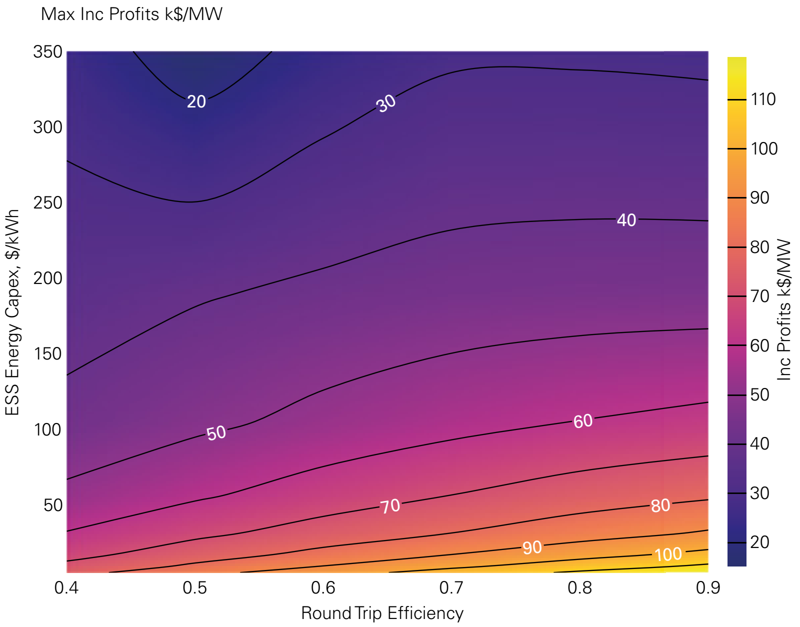


Figure 18

Contour plot of the impact of energy capex costs (in $/kWh) and roundtrip efficiency on incremental risks for SPP wind farm (2) under current conditions of basis risk and penalties.

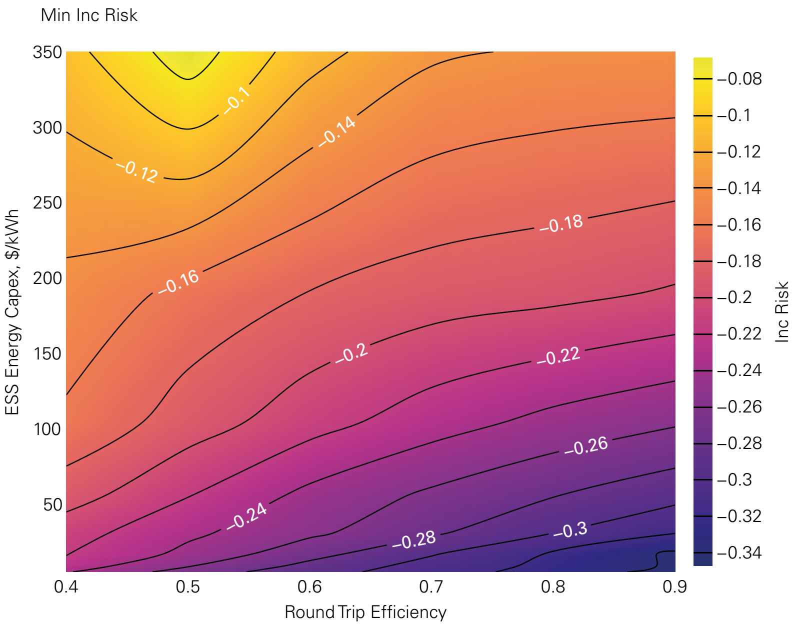


Figure 19

Contour plot of the impact of energy capex costs (in $/kWh) and roundtrip efficiency on incremental returns for SPP wind farm (3) under current conditions of basis risk and penalties.

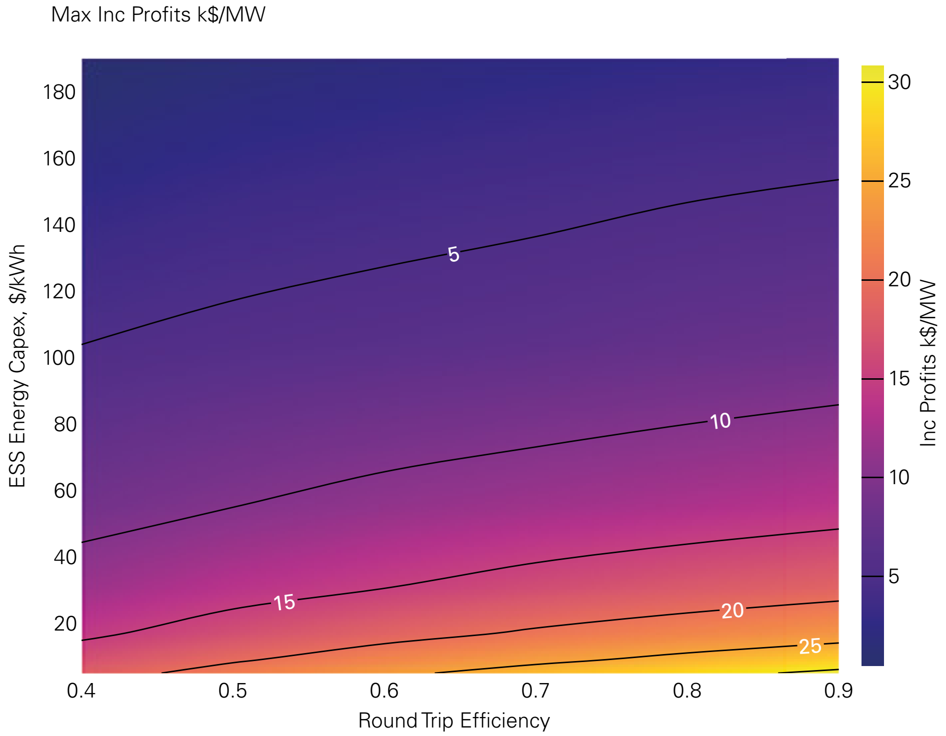
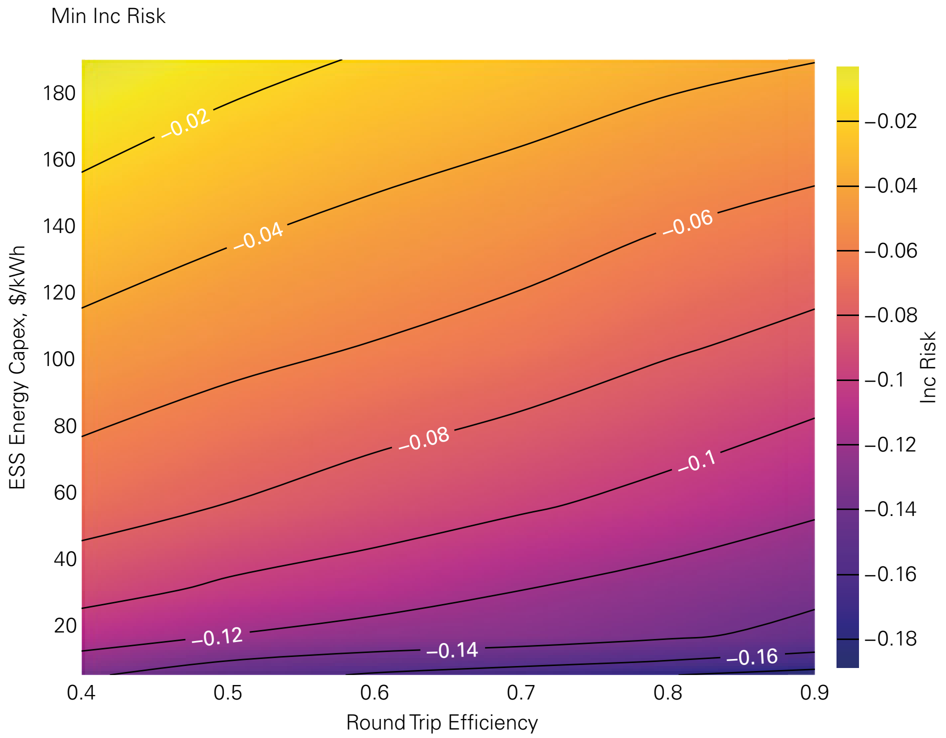


Figure 20

Contour plot of the impact of energy capex costs (in $/kWh) and roundtrip efficiency on incremental risks for SPP wind farm (3) under current conditions of basis risk and penalties.



6.3 | Summary of Storage Impact

In summary, the quantitative analysis presented in this section provides a methodology for dispatch optimization for real-time and day-ahead operation and quantifies asset exposure to volume risk (due to forecast uncertainty) and basis risk. Building on this methodology, we provide a quantitative framework to evaluate the ability of storage to improve utility scale project risk and return, across a variety of storage technologies. We use this framework to understand storage specifications necessary to achieve target levels of risk management for a variety of wind farms. We show how a pumped-hydro like storage technology will result in optimal durations between 13 and 23 hours and offer a significant improvement in risk and returns, in contrast with today's short duration storage which results in 1-2 hours of optimal durations and much more limited ability to modulate risk and returns. The specific target performance criteria for storage will depend on a specific investor's risk and return preferences.

7 Conclusions

In this work, we highlight the impact of corporate PPAs as a major driver for renewables penetration, and their value in reducing the cost of capital for new projects. With deeper renewables penetration, the costs of intermittency are increasing. In a deregulated market environment, these costs manifest as increased volume and basis risks that are borne by developers and off-takers. Effective management of increased intermittency risks is critical, if we are to see continued expansion of corporate PPAs as a driving force for renewable deployment.

We focus here on the use of physical storage technologies for risk management; specifically, we look at effective risk management via novel long duration storage technologies. We utilize Form's asset optimization software, FormWare™, to offer a flexible and technology-agnostic methodology to simulate financially-settled and long-term contracted wind farms operating in a day-ahead / real-time market structure and we explore the distribution of asset returns, using real data from anonymized wind farms owned and operated by Enel Green Power.

Through this analysis, we provide a quantitative framework to demonstrate the ability of storage to manage risk and return for wind farms exposed to volume and basis risk factors. We explore a range of representative storage specifications, using a pumped-hydro like storage technology to showcase the risk management capabilities of this emerging asset class. The results are persistent across the wind farms modeled and demonstrate the impact of bulk energy storage technologies to effectively manage risks and maximize returns. While general trends emerge, the specific performance thresholds for storage will vary by project configuration and technology. To our knowledge, this paper represents the first attempt in the literature to jointly quantify risk and return of renewable and storage assets operated in a realistic day-ahead and real-time market structure with imperfect foresight, in an attempt to more accurately capture the trader's perspective.

The future of renewable energy is bright and windy, and though the rising variability risks present a roadblock on the path to complete decarbonization, we are confident that the next wave of innovation in storage technologies, and specifically in ultra-low-cost, long duration technologies, will address emerging concerns and enable the rapid pace needed to manage the greatest challenge of our generation: matching economic prosperity and environment protection.

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