Hydropower Value Drivers

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HydroWIRES

U.S. DEPARTMENT OF ENERGY

Foreword

This project was funded by the United States Department of Energy's (DOE's) Water Power Technologies Office (WPTO) under its HydroWIRES initiative and carried out by a collaborative consisting of three DOE National Laboratories led by Argonne National Laboratory. In addition to Argonne, the Project Team members included National Renewable Energy Laboratory (NREL) and Pacific Northwest National Laboratory (PNNL).

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HydroWIRES

In April 2019, WPTO launched the HydroWIRES Initiative* to understand, enable, and improve hydropower and pumped storage hydropower's (PSH's) contributions to reliability, resilience, and integration in the rapidly evolving U.S. electricity system. The unique characteristics of hydropower, including PSH, make it well suited to provide a range of storage, generation flexibility, and other grid services to support the cost-effective integration of variable renewable resources. The U.S. electricity system is rapidly evolving, bringing both opportunities and challenges for the hydropower sector. While increasing deployment of variable renewables such as wind and solar have enabled low-cost, clean energy in many U.S. regions, it has also created a need for resources that can store energy or quickly change their operations to ensure a reliable and resilient grid. Hydropower (including PSH) is not only a supplier of bulk, low-cost, renewable energy but also a source of large-scale flexibility and a force multiplier for other renewable power generation sources. Realizing this potential requires innovation in several areas: understanding value drivers for hydropower in evolving system conditions, describing flexible capabilities and associated tradeoffs associated with hydropower meeting system needs, optimizing hydropower operations and planning, and developing innovative technologies that enable hydropower to operate more flexibly.

HydroWIRES is distinguished in its close engagement with the DOE National Laboratories. Five national laboratories—Argonne National Laboratory, Idaho National Laboratory, National Renewable Energy Laboratory, Oak Ridge National Laboratory, and Pacific Northwest National Laboratory—work as a team to provide strategic insight and develop connections across the HydroWIRES portfolio as well as broader DOE and National Laboratory efforts such as the Grid Modernization Initiative.

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* Hydropower and Water Innovation for a Resilient Electricity System ("HydroWIRES")

Research efforts in the HydroWIRES Initiative are designed to benefit hydropower owners and operators, independent system operators, regional transmission organizations, regulators, original equipment manufacturers, and environmental organizations by developing data, analysis, models, and technology research and development that can improve their capabilities and inform their decisions.

More information about HydroWIRES is available at https://energy.gov/hydrowires.

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Executive Summary

Key takeaways:

- Conventional hydro resources generate the majority of their value by providing *energy* under most conditions, but the relative fraction of value generated by providing ancillary services and capacity increases with increasing penetration of resources with zero fuel costs.
- Pumped storage hydropower resources generate the majority of their value by providing *capacity* under most conditions, but the relative fraction of value generated by providing energy increases with increasing penetration of resources with zero fuel costs.
- The total value of conventional hydropower generally decreases in systems with increasing penetration of resources with zero fuel costs; this is largely due to the associated decrease in average energy prices.
- The total value of pumped storage generally increases in systems with increasing penetration of resources with zero fuel costs, largely due to opportunities to operate in pumping mode when energy prices are low or even negative.
- Energy storage representation must be enhanced to ensure that models accurately capture system value streams for these resources.
- Current power system models have a limited ability to capture the price dynamics of ancillary services, and it is still challenging to assess the role and magnitude of ancillary service value streams in future systems.

Power systems are currently in a state of rapid and dramatic evolution due to a number of different factors, including the increasing penetration of variable renewable energy (VRE) sources, such as wind and solar, and battery energy storage systems (BESS). This evolution will change the way power systems are fundamentally planned and operated. Some of these changes may be incremental, while others may be more significant, but the result will likely be parallel evolution in the definition and requirement of different grid services and therefore a subsequent shift in their relative values.

This report presents a framework developed to identify such system **value drivers** and quantify their relative impact on several different **value streams**, with a specific focus on implications for conventional hydropower and pumped storage hydropower (PSH) resources. This value drivers framework (VDF) encompasses five core analytical steps:

1. Identify potential drivers and develop scenarios
2. Execute production cost models
3. Calibrate prices
4. Optimize hydropower operations
5. Quantify value drivers

Because a wide variety of different methods, models and tools can be used to complete the associated analytical processes, we first take a generic look at the VDF. We then present a set of case studies in which the VDF is used to compute the value provided by conventional hydropower resources in 164 combinations of system and plant conditions, and PSH resources in 297 combinations of system and plant conditions, in five locations in the U.S. For these case studies, we develop and implement standardized plant designs (not intended to represent any one specific real-world resource) and then conduct a range of parameter sensitivity analyses. This enables us to control the variations in resource parameters that impact value and to isolate and quantify the magnitude of specific value drivers.

Two different commercial production cost models (PCMs) are used to generate hourly energy prices for this analysis: GridView in the Western Interconnection (WI) and PLEXOS in the Eastern Interconnection (EI). A statistical calibration method is then applied to these prices as needed to generate more realistic distributions that better capture the occurrence of high price periods. Hourly prices for ancillary services are also derived from historical market data and applied to each scenario. These collective price signals are then provided as inputs to the Conventional Hydropower Energy and Environmental Systems (CHEERS) model and the Pumped Storage Hydropower Market Analysis Tool (PMAT) to optimize hourly provision of both energy and ancillary services, with the objective of maximizing the value these resources provide to the system under various operational conditions and constraints. Through this process we are able to establish a number key findings related to how the system values of both conventional hydropower and PSH resources are influenced by their physical characteristics and the dynamics of the system in which they are located.

We first analyze the relative magnitude of value that each type of resource generates through the provision of three types of products, energy, ancillary services, and capacity. Conventional hydropower resources generate the majority of their value through the provision of energy, as opposed to ancillary services and capacity, in most scenarios, but the total magnitude of value they generate decreases with increasing the penetration of resources with zero fuel cost (ZFC). Conversely, energy accounts for a minority of the value generated by PSH resources, with capacity generating the largest share in most scenarios. Also in contrast to conventional hydropower, the total value of PSH resources increases with increasing penetration of ZFC resources.

We also find that the value generated by conventional hydropower becomes more concentrated across relatively few high-value periods as VRE penetration increases, whereas the opposite effect is observed with PSH; value becomes more uniformly distributed across time periods. In the case of both conventional hydropower and PSH, the high-value periods that do occur are distributed more evenly across months of the year and hours of the day in systems with higher VRE penetration, occurring sporadically in both mornings and evenings and across summer, fall and winter. In systems with lower VRE penetration, individual high-value periods tend to occur primarily on summer evenings.

We then conduct a series of single- and multi-variable regression analyses across the entire set of scenarios to identify the system- and resource-level factors that are mostly closely associated with changes in hydropower value. We find that the energy value generated by conventional hydropower is more closely associated with higher annual price percentiles (i.e., the 75^{th}) than lower percentiles (i.e., the 25^{th}). This means that periods with high energy prices have a greater positive impact on conventional hydropower value than the corresponding negative impact of low price periods. On the other hand, the energy value generated by PSH is explained more by the spread between minimum and maximum energy prices each day rather than the distribution of prices across an entire year. This suggests that such daily price spread metrics are broadly indicative of diurnal arbitrage opportunities. Corresponding multivariate analyses show that energy price distributions, annual water availability, and capacity prices collectively explain the large majority (80%) of total conventional hydropower value, whereas capacity prices, daily price spread metrics, and quantity of AS provision collectively explain the large majority (92%) of total PSH value. These results suggest that if these system and resource factors are known, it may be possible to roughly identify value opportunities for conventional hydropower and PSH respectively without running detailed operational models. We also show that PSH value is highly sensitive to the amount of capacity that the resource is able to allocate to providing AS without influencing prices, and that longer-duration storage (12 hours or more) has much greater value in systems where energy prices are negative with some frequency.

Table **ES-1** summarizes the full set of 16 key findings that have been identified from our case study analyses of standardized conventional hydropower and PSH resources. These findings are all reviewed in more detail in Sections 3.1 and 3.2. Table ES-2 summarizes four key findings that relate more generally to the interaction between system conditions, price signals, and value realization. These findings are reviewed in more detail in Section 3.3. Table ES-3 summarizes four additional findings with implications for power system models and electricity market design. These findings are reviewed in more detail in Section 3.4. We conclude the report by noting several important paths forward and directions for future work that could be pursued to further improve the understanding and quantification of how hydropower value might evolve in different future system and operating conditions. These are summarized in Table ES-4 and detailed in Section 4.0.

Table ES-1 Key findings related to value drivers for conventional hydropower and PSH

Category	Conventional Hydropower	PSH
Value allocation across grid services	1. *Energy* provision accounts for the majority of conventional hydropower value under most conditions, but this fraction decreases with the increasing penetration of ZFC resources.	9. *Capacity* provision accounts for a majority of PSH value under most conditions, but this fraction decreases with the increasing penetration of ZFC resources.
Total value	2. The total energy, ancillary service, and capacity value of conventional hydropower *decreases* with increasing ZFC penetration.	10. The total energy, ancillary service, and capacity value of PSH *increases* with increasing ZFC penetration.
Ancillary service (AS) prices and market participation	3. In most cases, doubling AS prices is not sufficient to recover the value lost to decreasing energy prices in high-VRE systems unless ramp rates also increase.	11. AS market participation is a key driver of PSH value.
Energy price correlation	4. Reservoir hydropower value is more close correlated with the 75th and 95th percentile of annual energy prices than the 25th and 5th percentile.	12. PSH value is more closely correlated with the average daily electricity price spread than the average annual electricity price.
Multivariate correlation	5. Regression analysis finds that changes in energy prices, annual inflow, and capacity prices account for 80% of variation in reservoir value.	13. Regression analysis finds that changes in capacity price, daily energy price spread, and AS market participation levels account for 92% of the variation in PSH value.
Concentration of value	6. Reservoir value is more concentrated with 1) fast ramping, 2) high VRE penetration, 3) high electrification, 4) high AS prices, and 5) low water availability.	14. PSH value is less concentrated with high VRE penetration and more concentrated with higher electricity demand.
Temporal clustering of value	7. High reservoir value periods are less temporally clustered with fast ramping and high VRE.	15. High PSH value periods are less temporally clustered with high VRE and more temporally clustered with high electrification.
Ramping capability	8. Fast ramping is more valuable in systems with high VRE penetration and higher AS prices	
Storage capacity		16. The marginal value of additional PSH storage capacity above 12 hours is low unless negative prices are frequent.

Table ES-2 Key findings related to interactions between system conditions, price signals, and resource value.

Key Findings: System Conditions
17. System composition impacts energy prices and therefore drives resource value.
18. Increasing the duration of all new storage resources from 4 hours to 10 hours decreases combined annual wind and solar curtailment from 32.7 TWh to 28.5 TWh (13%).
19. Natural gas is the primary substitute for hydropower generation when water availability is low.
20. Power flow patterns change substantially at higher VRE penetration.

Table ES-3 Key findings related to power system models and wholesale electricity markets.

Key Findings: Markets and Modeling
21. Energy storage representation must be enhanced to ensure that models accurately capture system value streams.
22. Energy prices produced by production cost models are not predictions of the future but can be valuable for comparative analysis.
23. Current power system models have limited ability to capture AS price dynamics.
24. The value of capacity depends on the value of energy and ancillary services.

Table ES-4 Potential paths forward and next steps.

Paths Forward
1. Assess the value impacts of increasing VRE penetration in greater detail.
2. Analyze the value impacts of new and proposed policies.
3. Conduct additional targeted case study analyses of real-world hydropower resources that are located in different systems and have different characteristics.
4. Consider the ability of a targeted resource to influence prices.
5. Analyze hydropower value in zero-carbon systems.
6. Assess value impacts of new and proposed competitive wholesale market designs.
7. Consider evolving climate conditions and extreme weather events as potential value drivers.

Acronyms and Abbreviations

The following acronyms and abbreviations are used in this document.

AS	Ancillary services
BESS	Battery energy storage systems
BPA	Bonneville Power Administration balancing area
CAISO	California Independent System Operator
CEM	Capacity expansion model
CHEERS	Conventional Hydropower Energy and Environmental Systems model
CIPV	California Pacific Gas & Electric balancing area
CONE	Cost of new entry
DBNN	Dual-headed Bayesian neural network
EI	Eastern Interconnection
ERCOT	Electric Reliability Council of Texas
GW, GWh	Gigawatt, gigawatt hour
hr	Hour
kW, kWh	Kilowatt, kilowatt hour
LDES	Long duration energy storage
MW, MWh	Megawatt, megawatt hour
NERC	North American Electric Reliability Corporation
NG	Natural gas
NYISO	New York Independent System Operator
PCM	Production cost model
PMAT	Pumped Storage Hydropower Market Analysis Tool
PSH	Pumped storage hydropower
PWLC	Piecewise linear curve
ReEDS	Regional Energy Deployment System
RTM	Real-time market
TW, TWh	Terawatt, terawatt hour
VDF	Value drivers framework
VRE	Variable renewable energy
WACM	Western Area Power Administration Colorado-Missouri Region balancing area
WAT	Water allocation tool
WECC	Western Electricity Coordinating Council
WI	Western Interconnection
ZFC	Zero fuel cost

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Target Audience

This report summarizes 18 months of research collectively intended to provide insight into 1) the primary mechanisms through which hydropower resources provide value to power systems, i.e., *value streams*, and 2) the system- and plant-level factors and characteristics that impact the magnitude of this value, i.e., *value drivers*. The report will likely be of interest to a wide range of stakeholders throughout the hydropower community as well as the power sector more broadly. Hydropower operators may be able to draw upon the findings presented in this report to inform operational strategies and prioritize operational enhancements and/or to provide direction for more detailed plant-specific studies. Policy makers and regulators may benefit from better understanding how different policies or operational constraints impact the value that hydropower resources are able to provide to the power system because of the way in which value streams for hydropower and other generation resources may evolve in the power system's transformation to low-carbon generation. This work may also raise awareness throughout the broader power system community of the unique capabilities of hydropower resources, as well as the unique operational constraints that they face.

1.0 Introduction

1.1 Value Streams

The goal of modern power systems in the U.S. and around the world is to deliver reliable and affordable electricity to consumers while also meeting various policy or regulatory objectives. While energy is the ultimate product that is delivered to consumers, there is a variety of additional power system elements that help maintain operational reliability and stability and therefore provide value. These are often referred to as “grid services,” and to the extent that they provide value to a power system we refer to them in this report as **value streams**.

Conventional hydropower and pumped storage hydropower (PSH) can provide many different grid services and therefore are able to access a number of value streams. In *Pumped Storage Hydropower Valuation Guidebook: A Cost-Benefit and Decision Analysis Valuation Framework*, Koritarov et al. (2021) present a valuation guide with a cost-benefit analysis framework specifically centered on PSH resources. Services that provide power system value and the associated valuation metrics are shown in Table 1-1 . The framework and analysis presented in this report focus on the value streams shown in boldface type in Table 1-1 , as these can be quantified through the application of traditional production cost models (PCMs) and hydropower dispatch tools.

Table 1-1 Taxonomy of hydropower value streams adapted from Koritarov et al. (2021)

Hydro owner or operator	Bulk energy services	**Energy and energy arbitrage**
		Bulk power capacity
	Ancillary services	**Frequency regulation**
		Spinning reserve
		Non-spinning reserve
		Supplemental reserve
		Voltage support & reactive power
		Black start service
Power system	Power system stability (dynamic performance)	Inertial response
		Governor response
		Flexibility
	Power system reliability and resilience	Reduced sustained power outages & restoration costs
	Power system indirect benefits	Reduced electricity generation cost
		Reduced cycling and ramping (wear & tear costs) of thermal units
		Reduced curtailments of variable generation
	Transmission infrastructure benefits	Transmission upgrade deferral
		Transmission congestion relief
Society	Non-energy services	Water management services
		Socioeconomic impacts
		Environmental & health impacts
	Energy security benefits	Fuel availability, savings, and diversification
		Major blackouts avoided

1.2 Value Drivers

Power systems are dramatically evolving due to a number of different factors:

- Increasing penetration of variable renewable energy (VRE) sources such as wind and solar
- Increasing penetration of battery energy storage systems (BESS)
- Increasing penetration of distributed resources
- Increasing participation of demand side resources, such as responsive demand
- Changing load profiles due to end-service electrification, such as electric vehicles
- New policy and regulatory paradigms reflecting the societal benefits of reducing carbon emissions

This evolution will lead to fundamental changes in the way power systems are planned and operated. Some of these changes may be incremental while others may be more significant, but the result will likely be parallel evolution in the definitions and requirements of different grid services and therefore a subsequent shift in their relative values. In this report, we define the different factors—system, macroeconomic, policy, regulatory, climate, and technological—that as **value drivers** influence the relative magnitude of different power system value streams**.** These drivers can impact value streams in diverse ways, and these impacts can be challenging to capture and quantify due to the myriad complex interactions that define the power system.

The remainder of this report outlines the development and application of a **value drivers framework (VDF)** designed to identify and quantify the impact of these value drivers on different value streams across a range of system conditions and hydropower plant characteristics. We present a number of case study analyses to demonstrate how it can be used to understand how different elements of a power system will drive the value of hydropower resources in the future.

1.3 Value Paradigms

Power systems typically operate within one of two broad paradigms:

1. Traditional, vertically integrated systems that rely on a centralized planning mechanism to produce energy and grid services to balance long-term cost and reliability tradeoffs and drive the system towards socially optimal outcomes
2. Restructured systems that rely on competitive market mechanisms to procure energy and the grid services needed to operate the system reliably, thereby utilizing market forces to drive the system towards optimal outcomes

In each case, various grid services provide value to the system, but the manifestation and monetization of this value may differ. Regulatory and market structures also differ across regions, which may lead to different valuation mechanisms even for systems that operate in the same general paradigm.

More specifically, in a vertically integrated system, a centralized system operator plans and operates all elements of the power system, including generation, transmission, distribution and retail services. The goal of the system operator is to minimize the cost of providing service to consumers in its territory while also meeting a set of reliability, regulatory and policy objectives. To this end, the system operator typically determines system requirements for different grid services and procures them from resources in the system through a series of bilateral contracts or other arrangements. Each grid service provides value in its ability to minimize the cost of serving electricity demand while maintaining system reliability.

In restructured markets, on the other hand, many grid services are procured through competitive market clearing processes that determine the intersection of supply and demand curves for each service. The result is a clear price signal for each competitively procured grid service in each region (e.g., a reserve zone) and at each market clearing time interval (e.g., hourly). Supply curves are determined by competitive offers made in the market by profit-seeking market participants. These offers may be subject to market monitoring to mitigate their exertion of market power. Demand curves are determined based on the needs of specific load-serving entities as well as requirements that are established by the system operator to ensure that system reliability targets are met.

In either paradigm, the price or value of a grid service at a particular location and time can be determined through marginal-cost based pricing mechanisms. These mechanisms are employed to form prices in competitive electricity markets, but they may also be applied in regulated regions to indicate the relative value of different services.

Throughout our analysis, we assume that the *value* a grid service provides to the power system is equal to its *price*, as determined through this marginal-cost based pricing mechanism. For simplicity, we use the market-oriented term “price” as shorthand for *the marginal system cost incurred by increasing the requirement for a particular service by one unit in a given time period*, as this is how prices are determined in most market clearing processes. However, this “price” can also represent the instantaneous value of a service in a non-market framework.

Mathematically, the price of a service is obtained by taking the shadow price of the corresponding system constraint in a centralized least-cost optimization problem. In simpler language, the price is defined as the additional cost that the system would face if one additional unit of that service were to be procured at a given location and time. The framework and analysis presented in this report are focused on identifying the value of different grid services in different system conditions.

1.4 Determining Capacity Value

Capacity is a grid service that provides system value by contributing to resource adequacy and reliability, and its value can be challenging to quantify (Koritarov et al., 2021). We utilize two different methods, dictated by the structures of the two different modeling frameworks used, for quantifying capacity value.

Capacity values in the Eastern Interconnection (EI) are determined through a cost-based approach that calculates the shadow price of the zonal capacity constraint implemented in the Regional Energy Deployment System (ReEDS) capacity expansion model. This value therefore equals the marginal system cost of increasing the zonal capacity constraint by one megawatt. Utilizing this approach is possible because ReEDS conducts centralized least-cost capacity expansion planning.

We utilize GridView to model system operations in the Western Electricity Coordinating Council (WECC), specifically the WECC 2030 Anchor Dataset (ADS) model. GridView simulates system operations but does not optimize investment decisions; the generation portfolio for each scenario is a user-defined input. Therefore, we use an alternative method for determining capacity values in the Western Interconnection (WI) based on plant revenue requirements.[*] This approach is intended to approximate outcomes that would result in a competitive capacity market with a vertical demand curve at the regional planning reserve margin, where all units offer their full credited capacity at their true revenue requirement in the market. With this method, the capacity value is set at the intersection of the capacity supply and demand curves or the revenue requirement of the last unit that is needed to meet the target planning reserve margin in a given region.

1.5 References for Section 1

Koritarov, V., P. Balducci, T. Levin, M. Christian, J. Kwon, C. Milostan, Q. Ploussard, et al. 2021. *Pumped Storage Hydropower Valuation Guidebook: A Cost-Benefit and Decision Analysis Valuation Framework* ANL-21/10. https://doi.org/10.2172/1770766.

[*] A revenue requirement is defined as the additional revenue that a plant requires to achieve zero net profit after consideration of the costs incurred and revenues received from providing energy and ancillary services. If the plant has a positive net profit then the revenue requirement is zero.

2.0 Methods

2.1 Value Drivers Framework

The development of the VDF was motivated by the fact that no single model or tool has all the capabilities that are needed to capture and quantify the value of hydropower resources in evolving power system conditions:

- Provide a detailed representation of an existing generation fleet
- Provide a detailed representation of the transmission system and its associated power flows
- Quantify changes in grid service requirements as generation portfolios evolve
- Determine high-fidelity, nodal prices for energy and other grid services
- Track reservoir inflows and volumes
- Capture complex operational constraints and strategies for hydropower resources

While there are many separate models that do some or even many of these things well, it was determined that a set of interconnected models, tools, and processes was needed to quantify the full impacts of different hydropower value drivers across a wide range of system scenarios and plant characteristics. The VDF therefore encompasses the following five-step process:

1. Identify potential drivers and develop scenarios
2. Execute production cost models
3. Calibrate prices
4. Optimize hydropower operations
5. Quantify value drivers

Figure 2-1 depicts the set of interconnected processes that were developed for the VDF presented throughout the remainder of this report. However, many of these components could be replaced with different specific models or tools that satisfy the same objectives.

We first reviewed historical data from the California Independent System Operator (CAISO) in an attempt to identify the root system factors that influence different types of price events, i.e., periods of intermediate, high, or extreme energy prices. The findings from this analysis were used to inform our scenario design for the PCMs as well as our development of a statistical calibration method and its application to the prices generated by PCMs. We then executed two different PCMs—GridView and PLEXOS—that leverage data from the WECC 2030 Anchor Data Set and the NREL Standard Scenarios respectively. GRAF-Plan was also used to revise the system requirements for different grid services in GridView for different future generation portfolios.

Next, we applied a statistical price calibration tool to augment the hourly energy prices generated by PLEXOS in order to improve the fidelity of the modeled price distributions. PCMs often underestimate price volatility and may not appropriately represent periods of intermediate or high prices due to their inability to capture net load uncertainty and the impacts of unforeseen events. This statistical calibration was ultimately not applied to the prices generated by GridView, as the nodal resolution of GridView enhances its ability to capture temporal and locational price volatility.

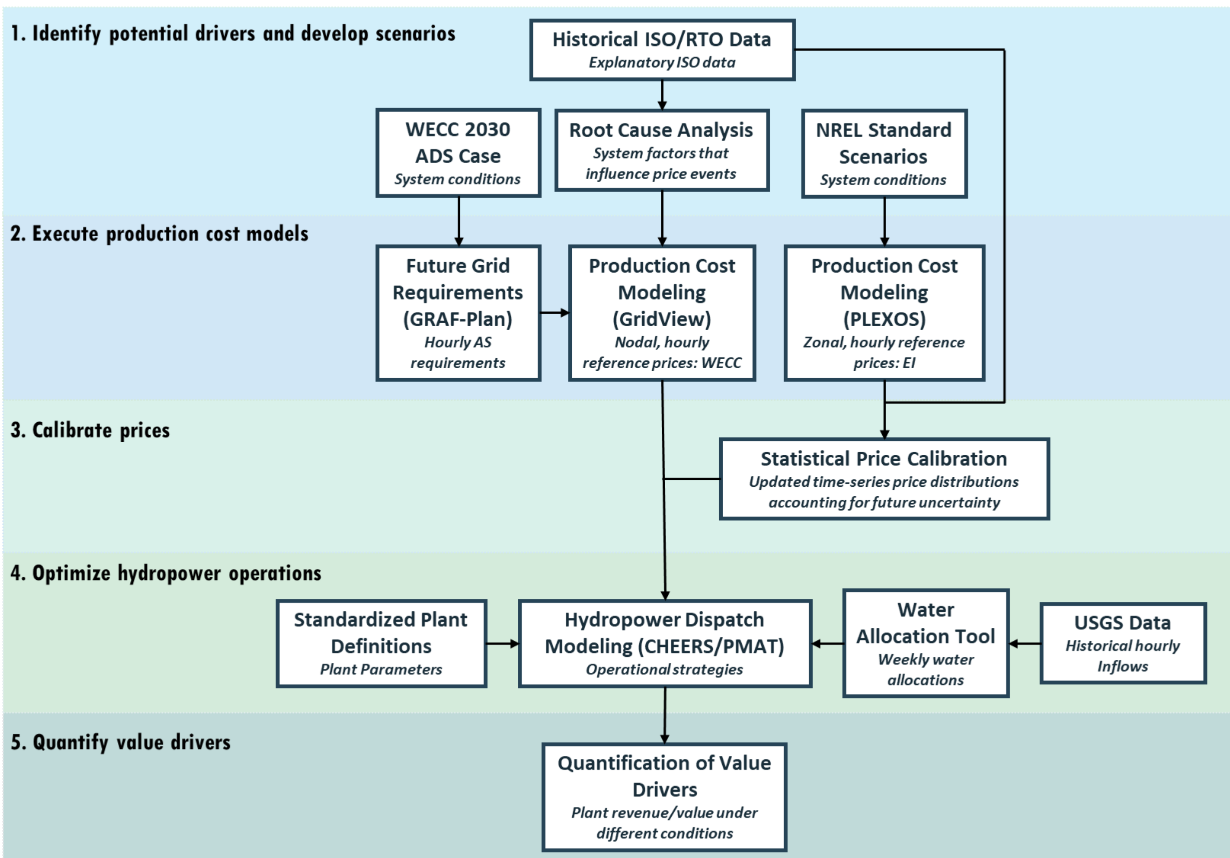

Figure 2-1 The application of the VDF utilized for the analysis presented in this report

These final prices were then used in two different hydropower optimization models to determine optimal operational strategies for conventional hydropower and PSH. For conventional hydropower, we used the Conventional Hydropower Energy and Environmental Systems (CHEERS) model, which has the ability to simulate operational strategies of hydropower resources subject to a variety of operational constraints. In this application, CHEERS was operated as a profit-maximizing price-taker model; i.e., operational strategies are selected to maximize the profit of the resource, and it is assumed that resource's operations do not impact system prices.

Rather than developing case studies based on specific real-world hydropower resources, we defined a set of *standardized plants* for both conventional hydropower and PSH to demonstrate the VDF. This approach enabled us to explore the value impacts of changes in individual key resource parameters in a controlled setting. Historical USGS data were utilized to develop a median inflow scenario for each standardized plant configuration as well as high and low water availability sensitivity cases. A separate water allocation tool was developed and applied to provide CHEERS with weekly water allocations based on smoothed price forecasts to strategically allocate more water during high-value weeks without assuming perfect price foresight over an entire year. Finally, the hourly provision of energy, regulation, spinning reserves, and non-spinning reserves produced by CHEERS was multiplied by the hourly prices for those services to determine total operating value over an entire year. This value was then added to annual capacity value to determine the total value for each standardized plant configuration in each location and grid scenario considered.

For PSH, we used the Pumped Storage Hydropower Market Analysis Tool (PMAT) to optimize the market participation strategy and scheduling of a closed-loop PSH plant based on potential revenue streams from various grid services. PMAT is also a price-taker model, and, as in our analysis of conventional hydropower, we considered value streams from providing energy, regulation, spinning reserves, non-spinning reserves, and capacity. We also analyzed a set of standardized plant configurations that were combined with a number of sensitivity scenarios to isolate and analyze the value impacts of changes in two key plant characteristics: storage capacity and ancillary service (AS) market participation level. More detailed methodologies for each of these processes are provided in Appendix A.

2.2 Grid Scenarios

We first generated hourly energy prices for five different regions using two different production cost models. GridView was used to model the nine WI grid scenarios, and PLEXOS was used to model three different EI grid scenarios. These scenarios are detailed in Table 2-1 .

Table 2-1 Grid scenarios analyzed

Name	Detail
GridView (WI)	
Reference Case	Generation portfolio and parameters based on WECC 2030 ADS. AS prices based on historical prices from the CAISO real-time market (RTM) in 2020.
Wet Hydro	Hydro year 1997 (+4.0% total hydro generation vs. Reference case)
Dry Hydro	Hydro year 2005 (-4.6% total hydro generation vs. Reference case)
High Electrification	+30 million EVs by 2030 (+2.7 % increase of total WECC demand, concentrated in California)
High Gas Price	+50% natural gas fuel price ($4.20/MMBtu vs. $2.80/MMBtu WECC average in Reference case)
Moderate VRE	30% of installed coal capacity (4.5 GW) is replaced by 14.3 GW of wind and 3.5 GW of solar
High VRE	100% of installed coal capacity (15.0 GW) is replaced by 46.5 GW wind and 13.4 GW solar plus 20.3 GW of 4 hr energy storage

Name	Detail
GridView (WI)	
High VRE with LDES	100% of installed coal capacity (15.0 GW) is replaced by 46.5 GW wind and 13.4 GW solar plus 20.3 GW of 10 hr energy storage
High VRE with High AS	High VRE + all AS prices are doubled in each hour
Standard Scenarios (EI)	
Reference	2020 NREL Standard Scenarios Mid Case for 2030
High VRE	2020 NREL Standard Scenarios Low Renewable Energy Cost case for 2030
High VRE with High AS	High VRE + all AS prices are doubled in each hour

GridView was used with associated data from the WECC 2030 ADS version 2.3, which is an industry vetted case study commonly used to represent potential system evolution in the WI. We elected to utilize GridView, and the associated WECC ADS, for our analysis in the WI because it provides nodal system resolution rather than the zonal resolution provided by the NREL Standard Scenarios. It therefore provides a more detailed representation of transmission congestion and localized price impacts. We were also able to develop a number of customized scenarios to analyze the impacts of specific value drivers.

GridView was executed with hourly timesteps to simulate system operations in 2030 across the entire WI with a fixed generation portfolio. Prices for energy and AS were determined each hour and at each node based on marginal-cost based pricing. It was determined that the GridView ADS has limited ability to capture realistic AS prices (see Section 4.0). Therefore historical data from the CAISO RTM in 2020 were used to establish AS prices for our Reference scenario. We also added a manual high AS price sensitivity in combination with the High VRE scenario.

The WECC 2030 ADS generation capacity portfolio provides the basis for our Reference, Wet Hydro, Dry Hydro, High Electrification, and High Gas Price scenarios. To study the impacts of higher penetration of variable renewable energy (VRE) resources on hydropower value streams, we developed four additional scenarios with higher VRE penetration. In each scenario, VRE penetration was increased by replacing coal generation capacity with an equivalent capacity value of wind and solar as well as some complementary battery storage capacity. The equivalent capacity value and relative allocation of wind and solar capacity in each region was determined through a heuristic that is outlined in more detail in Appendix A. We considered two primary VRE scenarios:

1. A Moderate VRE scenario in which 30% (4.5 GW) of the 2030 coal capacity in the WI is retired and replaced with 14.3 GW of wind, 3.5 GW of solar capacity and zero additional storage capacity

2. A High VRE scenario in which 100% (15.0 GW) of the 2030 coal capacity in the WI is replaced with 46.5 GW of wind, 13.4 GW of solar, and 20.3 GW 4-hour energy storage.

We also considered two additional sensitivities in the High VRE scenario:

1. A High VRE with long duration energy storage (LDES) scenario in which the 4 hr energy storage is upgraded to 10 hr energy storage
2. A High VRE with High AS scenario that retains the 4 hr energy storage and doubles all AS prices in each region and each hour.

These WI portfolios are detailed in Figure 2-2.

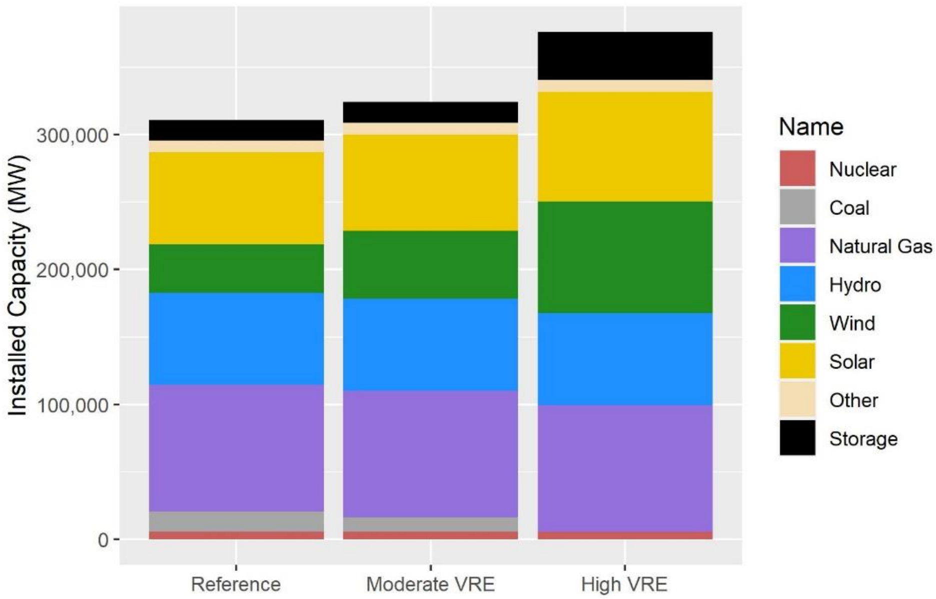

Figure 2-2 Generation capacity by fuel type for the Western Interconnection.

ReEDS and PLEXOS were used to model the EI with scenarios and generation portfolios defined by the 2020 NREL Standard Scenarios projections for 2030 (Cole et al., 2020). Our Reference scenario uses prices generated by the Mid case, while our High VRE and High VRE High AS scenarios utilize prices generated by the Low Renewable Energy Cost scenario. As was the case with the WI, we used historical AS price data from the New York Independent System Operator (NYISO) in 2020 for our Reference scenario and added a manual high price sensitivity in combination with the High VRE scenario. These EI portfolios are detailed in Figure 2-3.

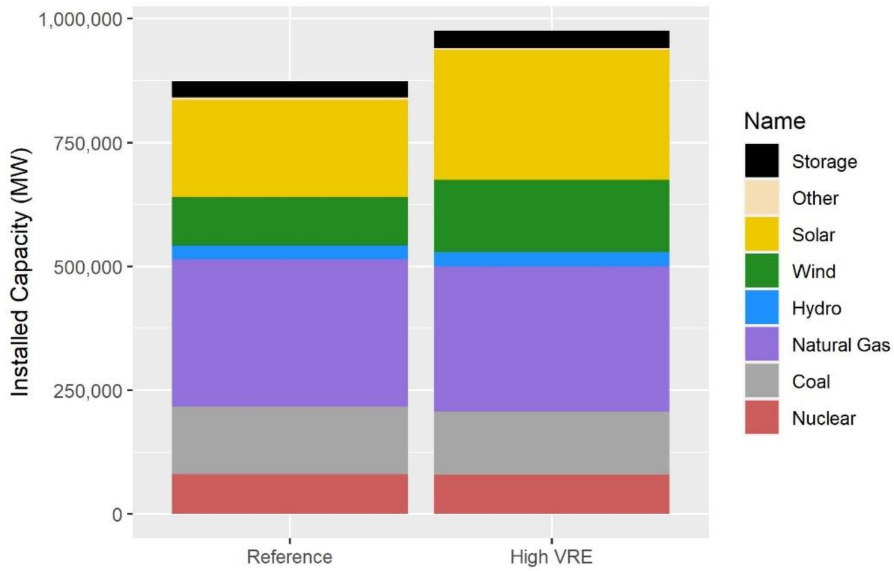

Figure 2-3 Generation capacity by fuel type for the Eastern Interconnection.

It was beneficial to apply the VDF to two different PCMs to help ensure the robustness of our approach. However, because two different production cost models were used, some care must be taken when attempting to directly compare results across the EI and WI. We therefore express most of our key findings in terms of the trends that are observed as system or plant parameters are changed *within* individual regions rather than across regions. Similarly, the objective of this work is to identify and quantify broad value driver trends; this work is not intended to provide detailed financial analyses of any specific real-world resources. All findings and results must therefore be interpreted in the full context of all assumptions and methods that were employed.

It is also worth noting that the Standard Scenarios have evolved since 2020 and now encompass a suite of more aggressive decarbonization scenarios. Similarly, the WECC ADS case will be revised in the future and may become more reflective of new techno-economic developments and federal decarbonization objectives. In addition, the passage of the Inflation Reduction Act in 2022 is expected to impact future power system investments in ways that are also not reflected in either the 2020 Standard Scenarios or the WECC ADS 2030 case. Therefore, we again stress that our analysis focuses on identifying and quantifying *value drivers*, and therefore results should be interpreted directionally, i.e., how much a relative shift in VRE generation impacts value in different conditions. Our results should not be interpreted as an attempt to concretely predict the size of different value streams in the future, as this will depend on the specifics of how electricity systems actually evolve.

2.3 Standardized Plants and Sensitivities

As discussed previously, we developed a standardized plant configuration for both conventional hydropower and PSH and analyzed the value streams for this standardized plant in the following regions: Conventional reservoir plants were modeled in New York, Tennessee, Oregon, and Colorado, while pumped storage hydropower (PSH) plants were modeled in these four regions as well as in California. For each of these locations, we consider energy and AS prices generated by GridView and the Standard Scenarios as well as location-specific river inflow profiles derived from historical USGS data. Our New York and Tennessee plants utilize data from ReEDS zones p127 and p92, respectively, our Oregon plants utilize data from the Bonneville Power Administration balancing area (BPA), our Colorado plants from the Western Area Power Administration Colorado-Missouri Region balancing area (WACM), and our California plants from Pacific Gas & Electric balancing area (CIPV). For convenience we will refer to these plant locations in terms of the state in which they are located throughout the rest of the report.

Table 2-2 shows the fraction of generation provided by VRE resources (i.e., wind and solar) and zero-fuel-cost (ZFC) resources (i.e., wind, solar and hydropower). These percentages reflect the VRE or ZFC generation within the localized zone or balancing authority that we consider in each state and are not necessarily reflective of the generation mix across the entire state. Both resource classes have the potential to greatly impact price formation as penetration increases due to their low marginal costs, although it should be noted that hydropower resources may not always have zero *marginal* cost due to the opportunity costs that they face (Zhou et al., 2022).

Colorado shows the greatest relative change in VRE and ZFC generation when transitioning from the Reference scenario to the High VRE scenario, due to the large quantity of coal capacity in the region in the Reference conditions. California, Oregon and New York exhibit small relative changes due to the correspondingly small amount of coal in these regions in the Reference case.

Table 2-2 The fraction of annual generation from VRE and ZFC resources in the Reference and High VRE scenarios for each location considered

	% VRE		% ZFC	
Location	**Reference**	**High VRE**	**Reference**	**High VRE**
OR	13.2%	13.7%	75.5%	78.3%
CO	10.3%	78.8%	34.3%	97.8%
NY	42.4%	43.1%	63.5%	64.7%
TN	10.4%	18.2%	18.8%	27.3%
CA	45.5%	46.0%	70.8%	72.0%

We further analyzed a range of different sensitivity cases across a number of key plant characteristics in each location. For conventional hydropower, we analyzed a high and low sensitivity case for three different parameters—ramp rate, storage capacity, and water availability—resulting in seven total cases for each grid scenario and location. For PSH, we considered all nine combinations of low, mid, and high values for both storage capacity and AS market participation level for each grid scenario and location. The details of these plant sensitivities are detailed in Table 2-3 and Table 2-4. In total, we optimized hourly dispatch strategies and calculated the annual value provided by hydropower plants for 164 different conventional hydropower scenarios and 297 different PSH scenarios as shown in Figure 2-4. These hourly and corresponding aggregate annual results informed the key findings that are presented in the following section.

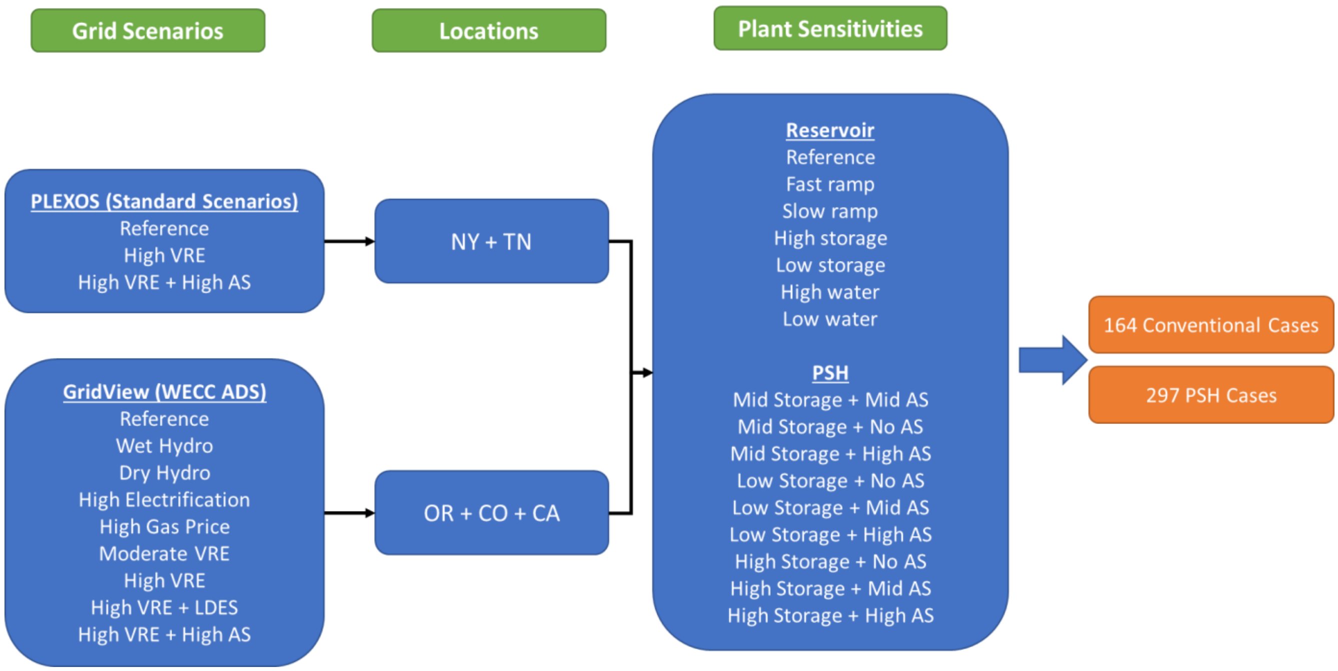

Figure 2-4 Scenario tree used for our case study analysis.

Table 2-3 Conventional hydropower plant sensitivity parameters

Name	Detail
Reference	100 MW plant, 25 MW/hr ramp rate, 1000 hr of storage, ~40% capacity factor
Fast ramp	100 MW/hr ramp rate
Slow ramp	12.5 MW/hr ramp rate
High storage	2000 hr of storage
Low storage	100 hr of storage
High water	~60% capacity factor
Low water	~20% capacity factor

Table 2-4 PSH plant sensitivity parameters

Name	Storage Capacity (hours)	AS Participation (%)
Reference	10	10
Mid Storage + No AS	10	0
Mid Storage + High AS	10	20
Low Storage + No AS	5	0
Low Storage + Mid AS	5	10
Low Storage + High AS	5	20
High Storage + No AS	20	0
High Storage + Mid AS	20	10
High Storage + High AS	20	20

2.4 References for Section 2

Cole, W., S. Corcoran, N. Gates, T. Mai, and P. Das. 2020. *2020 Standard Scenarios Report: A U.S. Electricity Sector Outlook*. https://doi.org/10.2172/1721757.

Zhou, Z., A. Botterud, and T. Levin. 2022. *Price Formation in Zero-Carbon Electricity Markets: The Role of Hydropower* ANL-22/31. https://doi.org/10.2172/1877029.

3.0 Key Findings

3.1 Conventional Hydropower

3.1.1 System Conditions

Finding 1 Energy provision accounts for the majority of conventional hydropower value in most conditions, but this fraction decreases with increasing penetration of ZFC resources.

Figure 3-1 shows that in most scenarios, more than 50% of the value provided by conventional hydropower is derived from the provision of energy. In the Reference scenario with Reference plant characteristics, this fraction varies from 55.1% in Colorado to 77.0% in New York. Capacity accounts for the largest share of remaining value, while the fraction of value derived from providing AS is less than 12% in Reference conditions in each of the four regions.

The relative contribution from AS increases when 1) AS prices are higher, 2) the system has more VRE generation, and 3) when the plant has faster ramping capabilities. The most extreme instance of these conditions is the High VRE High AS scenario in Colorado, where VRE generation reaches 78% of the total. Combined with the faster ramping plant sensitivity, the relative value contribution from energy provision drops to 22.6%, while AS provision accounts for 50.8% of value.

The system driver with the highest impact on the relative share of value derived from energy provision is the fraction of generation in the system provided by ZFC resources, i.e., wind, solar, or hydropower. Such resources have a zero or near-zero marginal cost of generation, and therefore, when they provide the marginal unit of generation in a region, the price or instantaneous value of energy in that zone also tends towards zero. As the penetration of ZFC resources increases, they also increasingly provide the marginal unit of generation, which accordingly drives down average energy prices—a process known as the merit order effect. As shown in Figure 3-2, the result is a reduction in the fraction of value derived from energy provision and a corresponding increase in the fraction of value derived from capacity and AS.

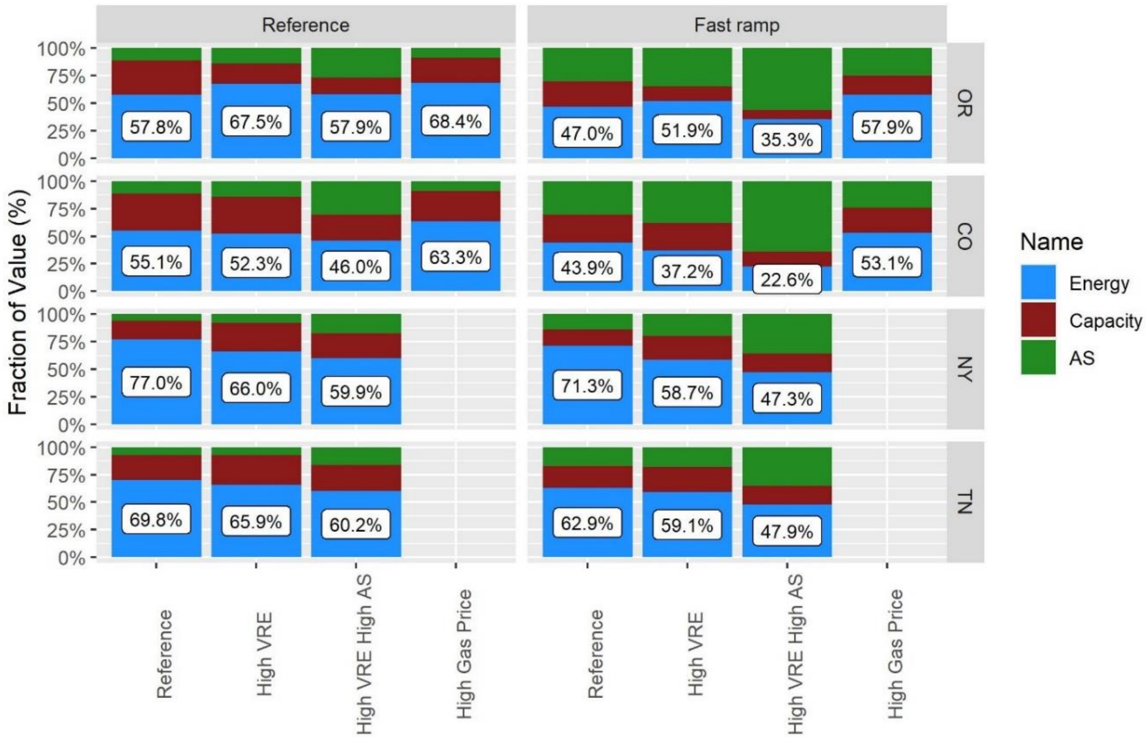

Figure 3-1 Fractions of conventional hydropower value derived from provision of energy, AS, and capacity.

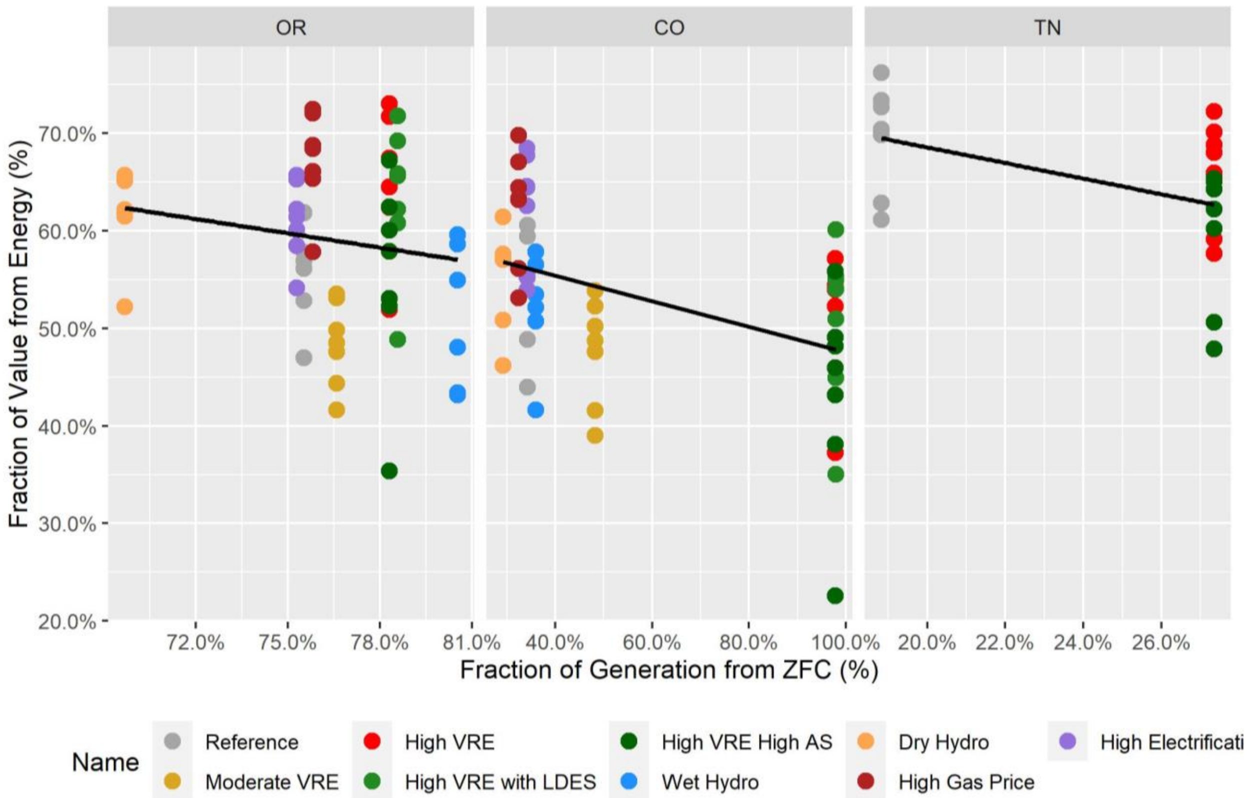

Figure 3-2 Fraction of conventional hydropower value derived from energy provision as a function of the fraction of system generation from ZFC resources.

Finding 2 Conventional hydropower value decreases with increasing ZFC penetration.

As the fraction of value derived from energy provision decreases with increasing ZFC penetration (Section 3.1.3), so too does the *total* value provided by conventional hydropower. This general downward trend is observed in each of the four regions that were analyzed, although magnitudes differ as shown in Figure 3-3. This indicates that in most cases, the reduction in energy value caused by the merit order effect is larger than any corresponding increase in value from AS and capacity.

This decline in total value is largely driven by the merit order effect. It is therefore a system-wide phenomenon and not specific to hydropower resources. In fact, thermal resources with higher marginal costs and less ability to adjust generation levels in response to short-term signals may be even more affected. This decline in total value may be mitigated if AS and capacity value streams increase more than was assumed and determined through our analysis, which was guided by current market and operational frameworks. Such increases may result from changes in system requirements or new market designs and valuation frameworks to ensure that the full system value created by a given resource is accurately quantified and captured. However, more advanced modeling capabilities and additional analyses are needed to better understand the extent of this potential transition to reliance on non-energy value streams.

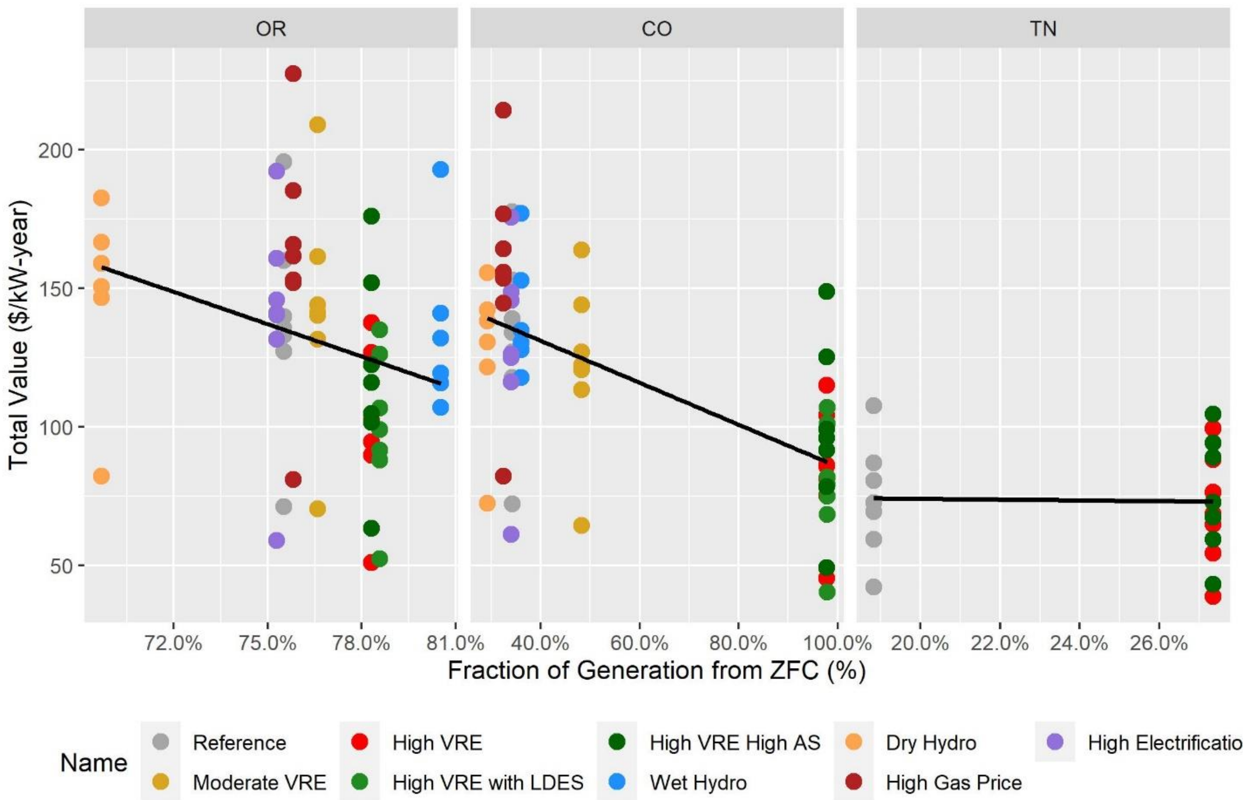

Figure 3-3 Total conventional hydropower value as a function of the fraction of system generation from ZFC resources.

3.1.2 Market Conditions

Finding 3 In High VRE scenarios, AS prices would need to increase by at least a factor of two to counteract the merit order effect.

While AS value does increase modestly with increasing ZFC penetration, this increase is smaller than the corresponding decrease in value from energy. As a result, total value decreases. Both the Moderate VRE and High VRE scenarios assume that there are no changes in AS prices relative to the Reference scenario. However, as VRE penetration increases, AS requirements are expected to increase, and thermal retirements may eliminate a primary source of AS supply. A number of modeling analyses have analyzed this combination of increased demand and reduced supply and determined that AS prices are likely to increase in High VRE systems (Wiser et al., 2017). We therefore explore a manual High VRE sensitivity scenario where the price of each AS is also doubled in each hour of the year.

Figure 3-4 shows that in most cases, AS prices would have to more than double in order for plants to fully recover their lost energy value. For example, in Colorado, where the relative increase in VRE penetration between the Reference scenario (10%) and the High VRE scenario (78%) is the most dramatic, the standardized reservoir plant generates 64.1% as much value in the High VRE scenario as it does in the Reference scenario. In the High VRE High AS scenario, value increases—but only to 72.1% of the Reference scenario. Conditions are different in Tennessee, where the relative increase in VRE penetration between scenarios is much smaller (10% and 18% VRE penetration respectively), as doubling AS prices does result in just over 100% of the Reference value. Increasing the ramping capability of plants also magnifies the relative value impact of doubling AS prices in a high VRE system: In all four regions value reaches at least 90% of the Reference value.

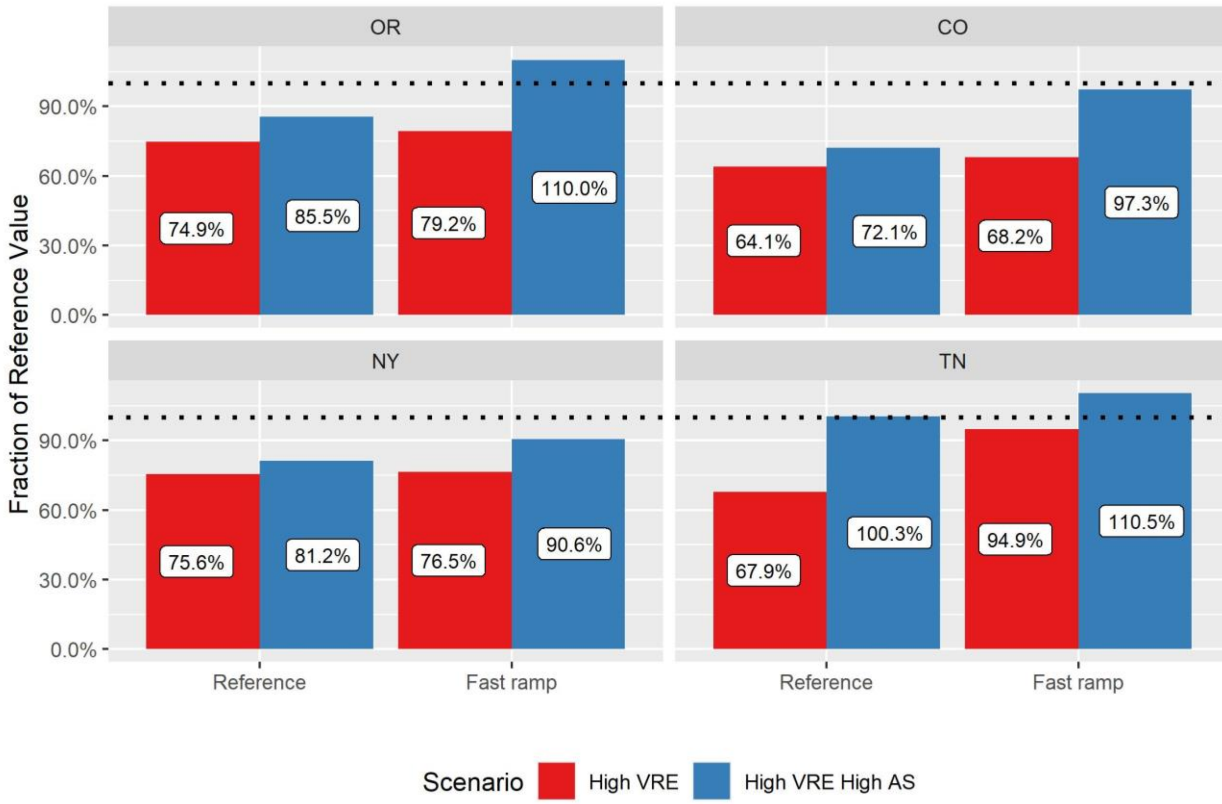

Figure 3-4 The total value generated by conventional hydropower in the High VRE and High VRE High AS grid scenarios as a percentage of the value generated in the Reference grid scenario.

Finding 4 Conventional hydropower energy value is closely correlated with the mean and upper percentiles of hourly energy prices.

Figure 3-5 shows the correlation among mean annual energy price, seven different price percentiles, and the total value created through energy provision in all five regions with Reference plant characteristics. It is clear that higher energy price percentiles have greater explanatory power for predicting hydropower value than lower percentiles. This is largely because hydropower resources are able to store water and concentrate their energy generation within periods where energy prices are higher than average, so they are relatively less exposed to lower price periods.

It is noteworthy that the explanatory value diminishes for the 99th percentile; however, this reduction is largely driven by one apparent outlier from the Reference grid scenario in New York. In this scenario the 99th energy price percentile exceeds $100/MWh, but the total value from energy provision is only moderately higher than other New York scenarios with a much lower 99th energy price percentile. This is because most of these high price periods occur in the late winter and early spring when reservoir levels are relatively low, and therefore the plant does not have sufficient operational flexibility to take full advantage of the high price. Removing this single scenario from the regression model does increase the R^2 value to 0.78.

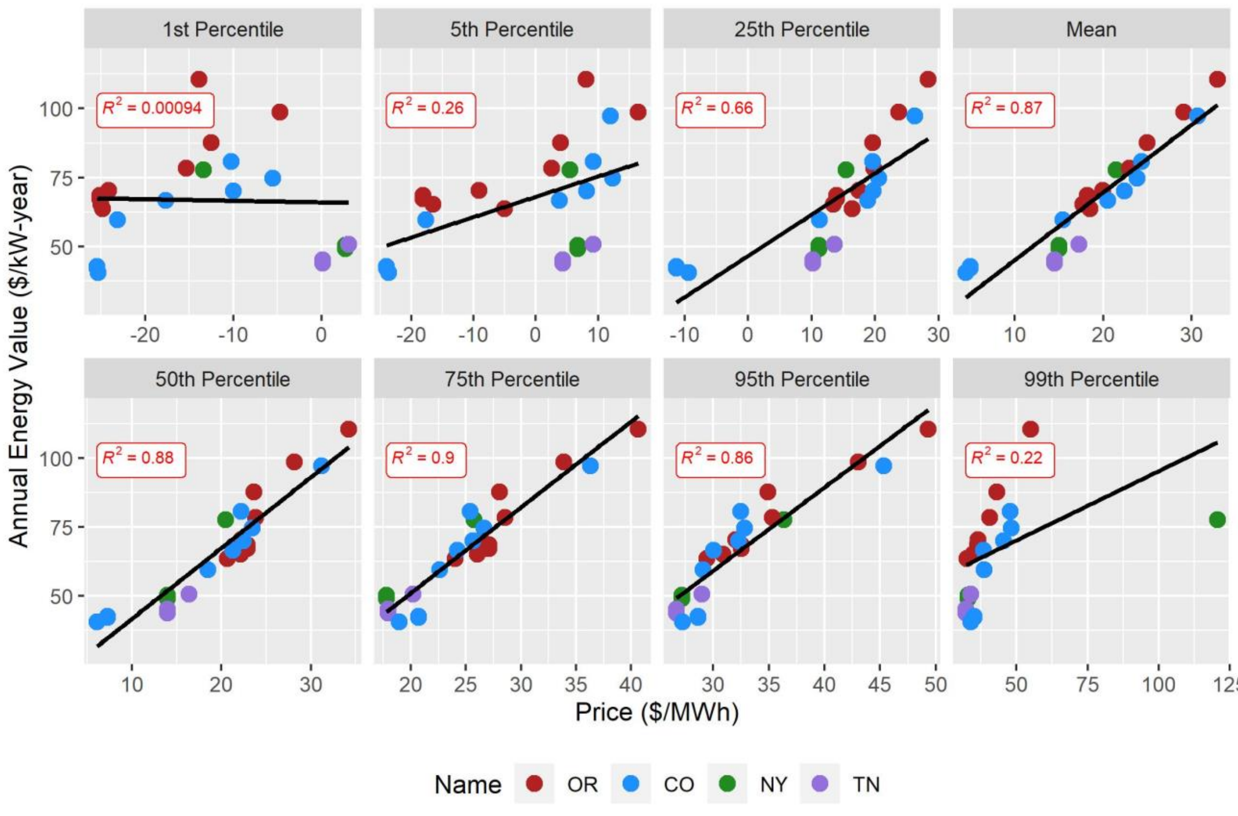

Figure 3-5 The correlation among mean annual energy price, seven different price percentiles, and the total conventional hydropower value derived from energy.

Finding 5 Energy prices, annual inflow, and capacity prices explain 80% of the variation in conventional hydropower value.

Table 3-1 shows the results of a multivariate regression analysis of several explanatory factors of total value from conventional hydropower. The adjusted R^2 metric represents the fraction of the total variation in value that can be explained by variations in the factors that are considered in each successive regression model. For example, the 75th percentile of the hourly energy price alone explains 36.6% of the variation in value across all different scenarios, locations and plant sensitivities. Also taking annual water availability and the capacity price into account increases this value to 80.4%, and adding an indicator for faster or slower ramping further increases this value to 84.9%. The mean regulation up price and the conventional hydropower storage capacity do not add much additional explanatory power, as the impacts from changes in these factors are either small or already explained by changes in the other factors included in those models.

Table 3-1 The impact of adding successive explanatory variables to a multivariate regression model of conventional hydropower value.

Reservoir Value						
	Dependent variable:					
	Annual Value					
	(1)	(2)	(3)	(4)	(5)	(6)
Energy 75^{th} Percentile	4.214***	4.382***	3.494***	3.494***	3.533***	3.532***
	(0.436)	(0.287)	(0.265)	(0.232)	(0.231)	(0.231)
Annual Water (kAF)		0.103***	0.102***	0.102***	0.102***	0.101***
		(0.007)	(0.006)	(0.005)	(0.005)	(0.005)
Capacity Price			0.471***	0.471***	0.478***	0.478***
			(0.057)	(0.050)	(0.050)	(0.050)
Ramp Rate (Indicator)				15.868***	15.868***	15.868***
Mean Reg Up Price				(2.270)	(2.250)	(2.249)
					0.962*	0.962*
					(0.490)	(0.490)
Storage Capacity (Indicator)						2.352
						(2.251)
Constant	7.654	-101.108***	-108.595***	-108.595***	-118.094***	-117.841***
	(11.172)	(10.485)	(8.867)	(7.780)	(9.101)	(9.102)
Observations	164	164	164	164	164	164
R^2	0.366	0.726	0.808	0.853	0.856	0.857
Adjusted R^2	0.362	0.723	0.804	0.849	0.852	0.852
Residual Std. Error	32.341 (df = 162)	21.309 (df = 161)	17.925 (df = 160)	15.727 (df = 159)	15.587 (df = 158)	15.583 (df = 157)
F Statistic	93.435*** (df = 1; 162)	213.699*** (df = 2; 161)	223.831*** (df = 3; 160)	230.308*** (df = 4; 159)	188.331*** (df = 5; 158)	

Note: *p<0.1; **p<0.05; ***p<0.01

Finding 6 Conventional hydropower value is more concentrated with 1) fast ramping, 2) high VRE penetration, 3) high electrification, 4) high AS prices, and 5) low water availability.

Figure 3-6 shows the fraction of total operation value—value from energy and AS —that is generated during the 100 highest-value hours in each scenario. This figure shows results only for

Colorado, where the relative increase in VRE penetration is most pronounced across scenarios. In the Reference scenario and plant configuration, 9.5% of annual value is generated during just 100 hourly periods. This fraction increases with 1) faster ramping capabilities, because the plant is more able to respond to brief periods with high prices, 2) high VRE penetration, because the frequency of zero or negative energy price periods increases, and value must be captured during the relatively few moderate or high price periods, 3) increased electricity demand, as this creates a small number of periods with extremely high energy prices, 4) higher AS prices, because value opportunities become more concentrated over fewer hours, and 5) lower water availability, because plants have to conserve their limited water supply to generate energy over relatively few periods.

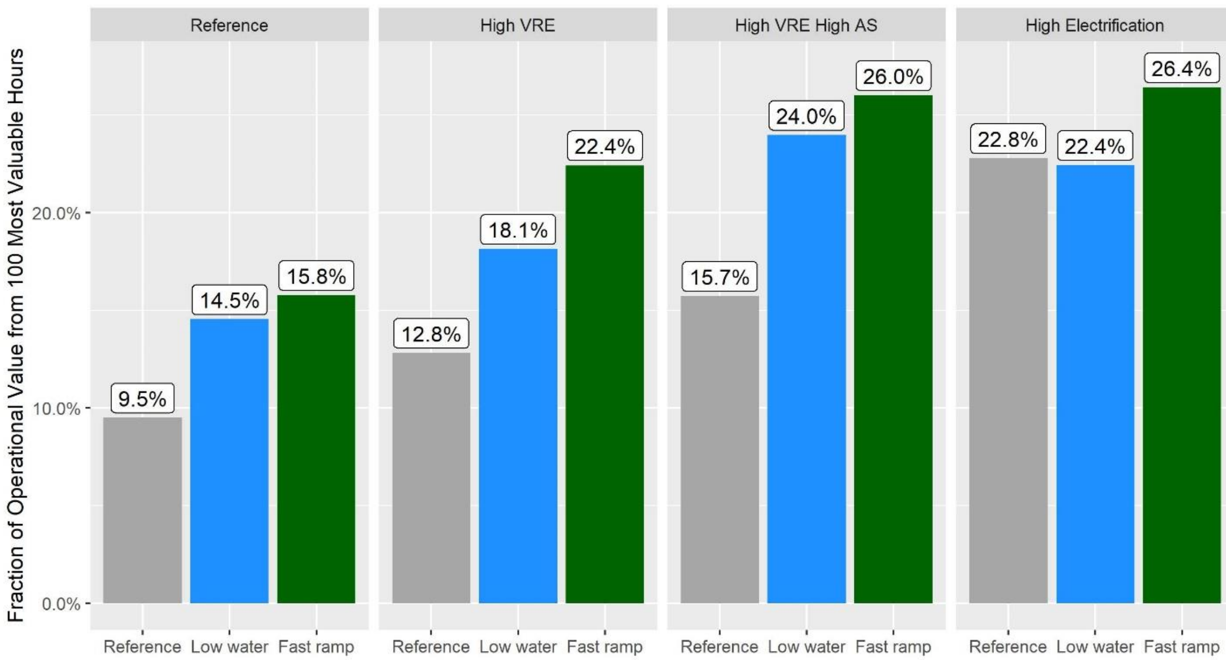

Figure 3-6 The fraction of operational value generated during the 100 most valuable hours in Colorado across several scenarios and plant configurations.

Finding 7 High value periods are less temporally clustered with fast ramping and high VRE.

While Finding 6 shows that as VRE penetration increases, value generation becomes more concentrated over the 100 most valuable hours of the year, the temporal distribution of these high-value periods becomes more dispersed on both a daily and annual basis. Figure 3-7 shows that in the Reference scenario in Colorado, the highest value hours tend to occur on summer evenings when electricity demand is highest. As VRE penetration increases, these high value periods start to occur more frequently in other months and early mornings. This suggests that net load (demand less wind and solar generation) or other factors may be a stronger driver of hourly hydropower value than total demand. Increasing the ramping capability of the plant has a similar effect, as the plant becomes more flexible in its ability to respond to value signals over short timescales throughout the year.

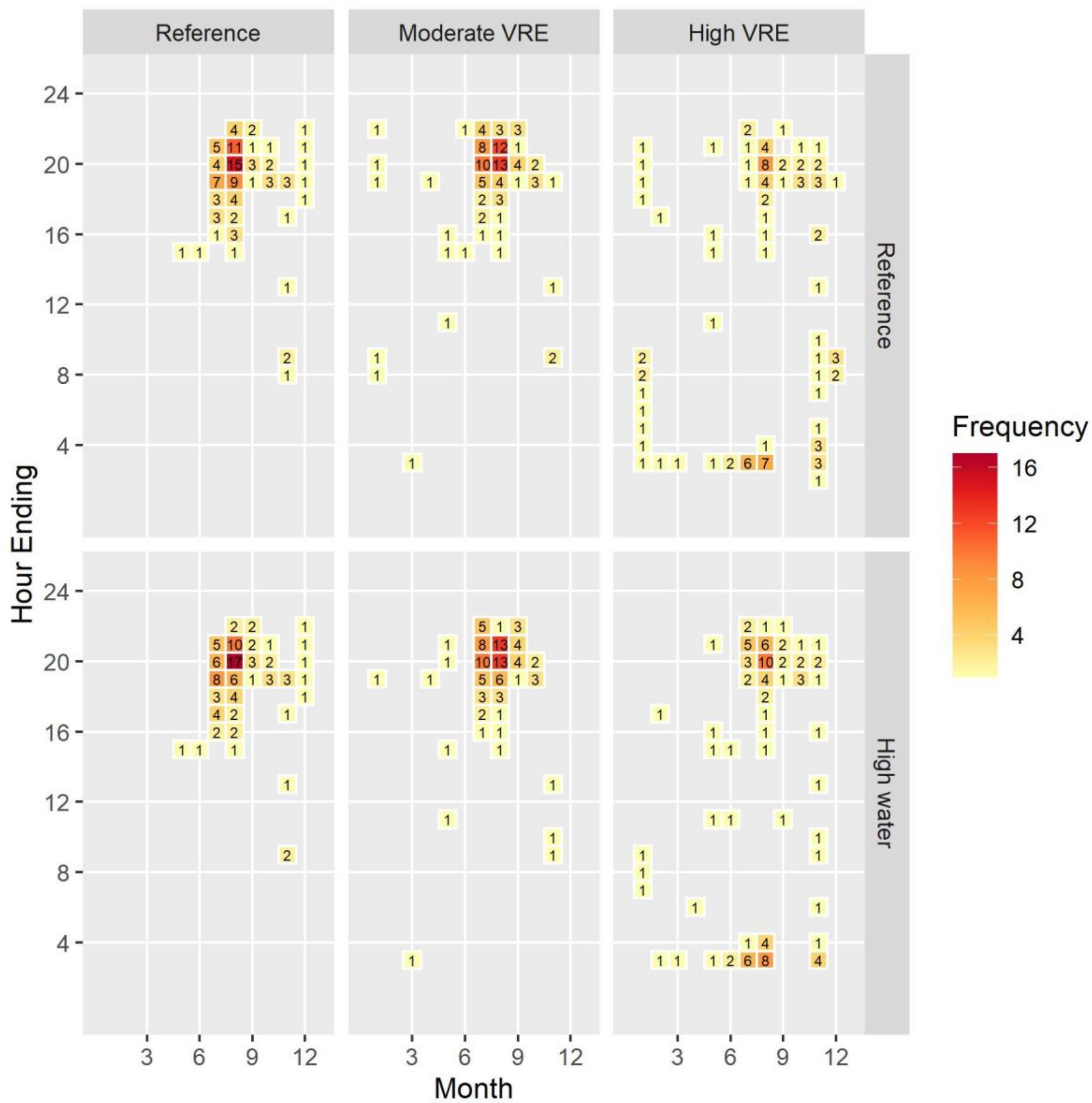

Figure 3-7 A heat map indicating the temporal distribution of the 100 most valuable hours throughout the year. Each data point depicts the occurrence frequency of a high value period during the specified month and hour.

3.1.3 Technology

Finding 8 Fast ramping is more valuable in systems with high VRE penetration and higher AS prices.

As might be expected, increasing the ramping capability of a plant also increases its value. This stems from both its ability to adjust output more quickly to capture high-value energy generation opportunities and its ability to provide more ancillary services. Figure 3-8 shows the increase in value relative to the Reference plan configuration that is created by faster ramping capabilities in several scenarios and regions. These results indicate that this relative increase in value is even larger in systems with high VRE penetration and high AS prices. For example, in Colorado, adding fast ramping capabilities to the standardized plant increases value by 20.3% in the Reference grid scenario. In the High VRE scenario, this increase grows to 28.0%, and when AS prices are also doubled, the increase grows to 62.4%. Similar trends are seen in the other regions as well.

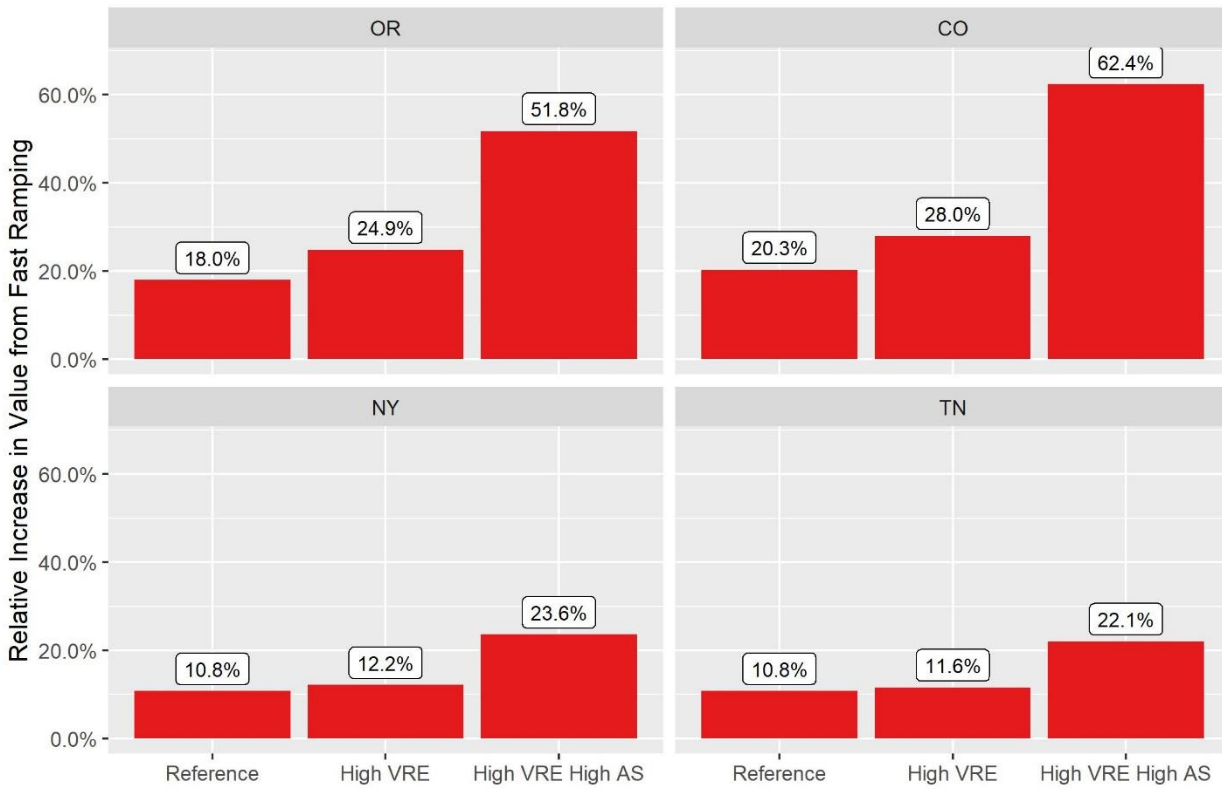

Figure 3-8 The relative increase in value from increasing ramping capabilities from 25% of installed capacity per hour to 100% of installed capacity per hour.

3.1.4 Implications for Industry

- Energy will likely remain the primary source of value for conventional hydropower, unless or until there is a dramatic shift in system composition.
- As power systems decarbonize and transition towards higher ZFC penetration, AS and capacity provision will become a more important source of value.
- Either capacity and AS prices will need to increase more than anticipated in higher ZFC futures, or market design and planning paradigms will have to evolve to more explicitly value the services that hydropower can provide.
- AS prices will have to increase if they are going to make up for all the value lost due to the merit order effect in systems with very high VRE penetration. Alternatively, new services and associated value streams will have to be identified and formalized.

- Collectively, these results indicate that it is important to consider distribution prices throughout a year rather than any one single metric when analyzing implications for value.

- These results suggest that relative differences in value across locations and scenarios can be predicted reasonably well with these parameters, even without running a detailed optimization model.

- As VRE penetration increases, plants will need to be more flexible to capture brief high value periods, as a larger fraction of total value will be concentrated in those periods.

- Fast ramping capabilities will become increasingly valuable in systems with higher VRE penetration and higher AS prices.

3.2 Pumped Storage Hydropower

3.2.1 System Conditions

Finding 9 Capacity provision accounts for a majority of PSH value in most conditions, but this fraction decreases with increasing penetration of zero fuel cost resources.

In contrast to conventional hydropower plants, energy provision generally accounts for a minority of the value produced by PSH plants. Figure 3-9 shows that capacity typically accounts for the largest share of value in many of the Reference grid scenarios exceeding 80% of total value. There are some exceptions in which energy provision accounts for a larger share of value. For example, the High Electrification scenario in California leads to a number of hours with energy scarcity pricing that creates valuable arbitrage opportunities for PSH plants.

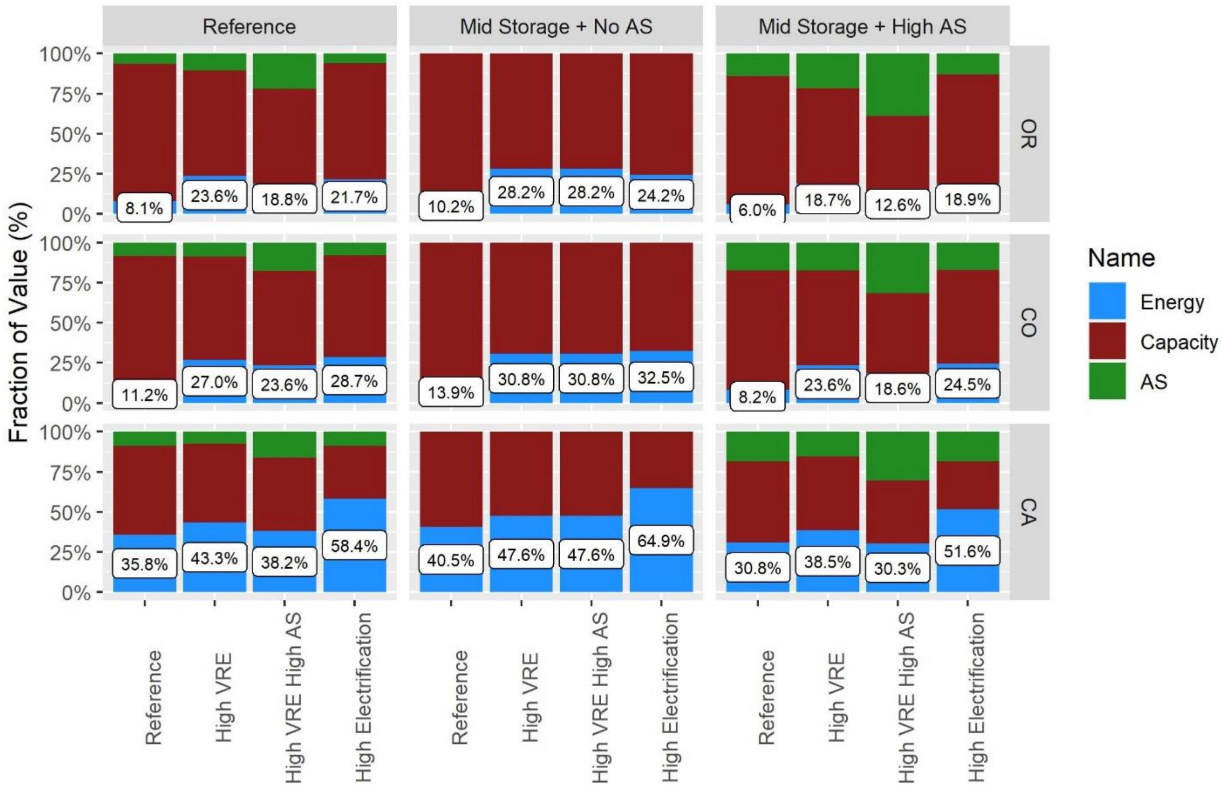

Figure 3-9 Fractions of PSH value derived from provision of energy, AS and capacity.

Finding 10 PSH value increases with increasing ZFC penetration.

Again in contrast to conventional hydropower plants, Figure 3-10 shows that the fraction of value derived from energy provision generally increases with increasing ZFC penetration. This is because energy value opportunities for PSH plants are based on price spreads rather than just the average energy price. The overall reduction in energy prices can therefore increase value, as the PSH plant is able to pump at very low cost when prices are low and still capture value by generating during high price periods—even if they are less frequent. PSH plants can also generate value simply by pumping while energy prices are negative, an occurrence that becomes more frequent in high ZFC systems.

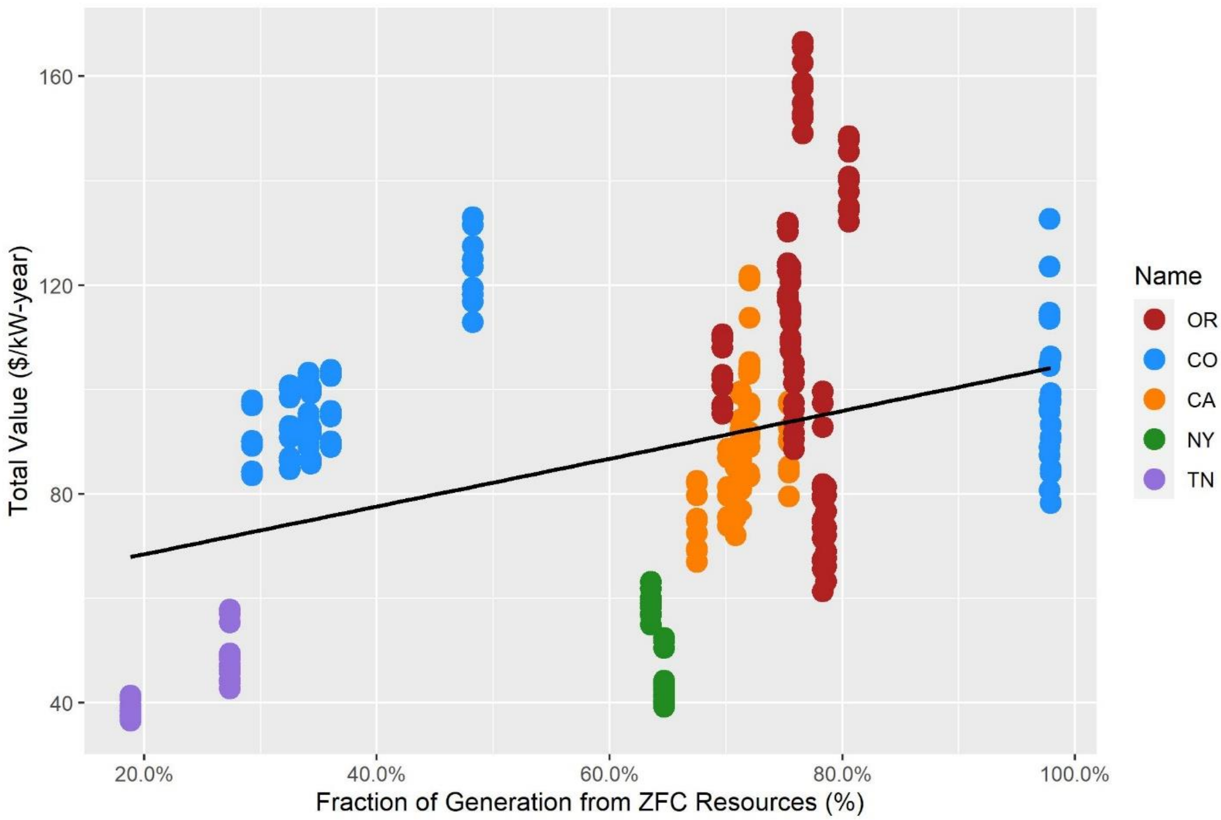

Figure 3-10 Total PSH value as a function of the fraction of system generation from ZFC resources.

Figure 3-11 shows that the fraction of value derived from energy provision tends to increase with increasing ZFC penetration. However, in most scenarios and sensitivity cases, the relative contribution of energy provision to total value is still less than 50%. This value is higher in California, where average energy prices and price spreads are also higher than in other regions, particularly in the High Electrification scenario, which leads to brief periods of very high electricity prices due to scarcity conditions and therefore a corresponding increase in the fraction of value from energy.

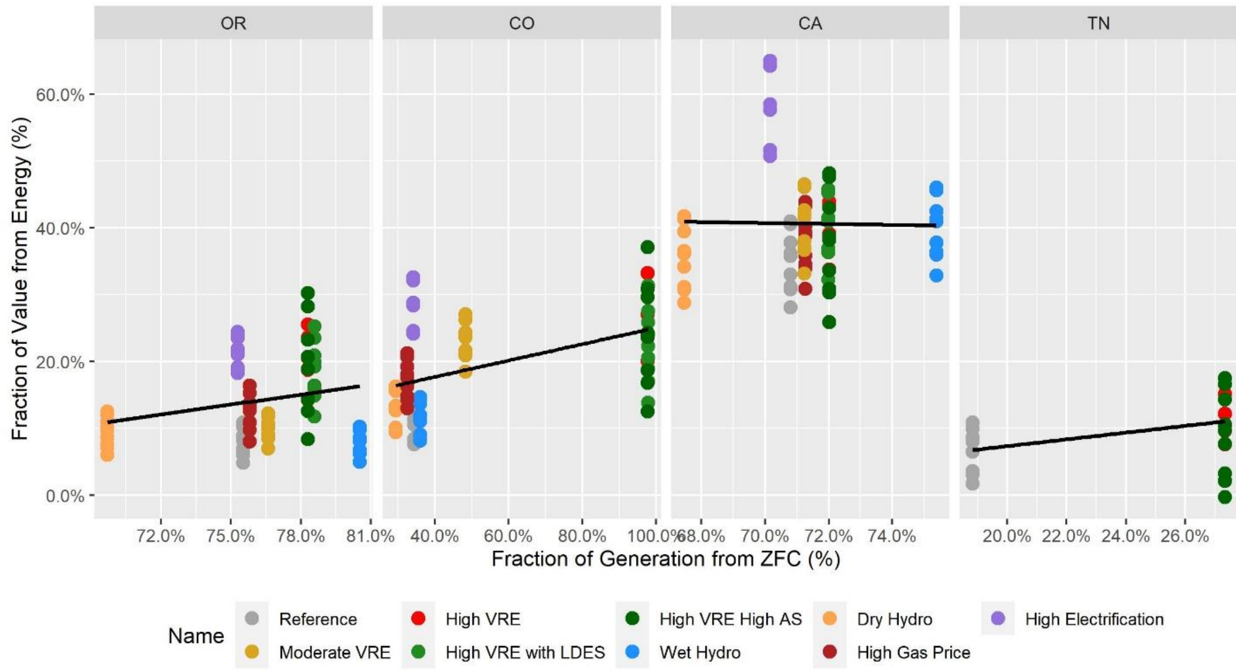

Figure 3-11 Fraction of PSH value derived from energy provision as a function of the fraction of system generation from ZFC resources.

3.2.1 Market Conditions

Finding 11 Ancillary service market participation is a key driver of PSH value.

Our Reference plant configuration assumes that a PSH plant can allocate up to 10% of its capacity to providing AS in any given hour. This restriction is based on an analysis of historical PSH participation in AS markets as well as the fact that in some balancing areas a single large PSH plant could potentially provide more AS than the region needs (Somani et al., 2021). Because specific conditions may lead to a wide variation in AS market participation for PSH plants, we pick a reasonable reference value and examine two broad sensitivity scenarios based on 0% and 20% market participation. The value impacts of market participation levels that we do not explicitly consider can be approximated by interpolating or extrapolating based on these two sensitivities.

Figure 3-12 makes it clear that the AS market participation level is an important driver of PSH value, and the ability to provide more AS is even more valuable in systems with high VRE penetration and high AS prices. For example, increasing the participation level from 10% to 20% in Oregon increases value by 6.7% in the Reference scenario, 10.6% in the High VRE scenario, and 22.2% in the High VRE High AS scenario. The relative decrease in value from a corresponding reduction in AS market participation from 10% to 0% is comparable but generally slightly smaller.

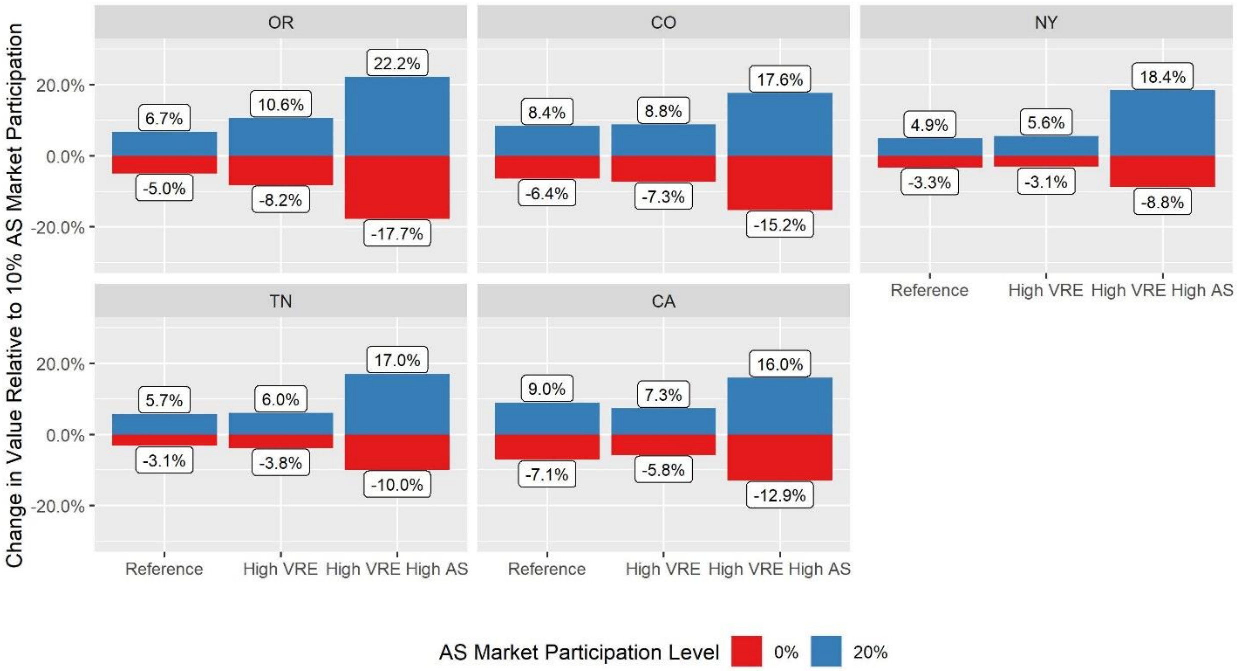

Figure 3-12 The change in value from increased (20%) or decreased (0%) AS market participation, relative to the Reference plant assumption in which up to 10% of capacity can be allocated to providing AS in each hour.

Finding 12 Daily energy price spreads explain variations in PSH value better than annual price distributions.

In order to create value from providing energy, PSH plants must take advantage of arbitrage opportunities, or differences between prices that occur in relatively close proximity to one another. We therefore consider that the size of the spread between the daily maximum and minimum energy price may explain value better than the prices themselves, and we analyzed the relationship between different percentiles of this daily spread and total energy value. This analysis includes only the Reference plant configuration, 10 hours of storage, and 10% AS market participation, as changes in those parameters strongly influence value largely independent of the price spread.

As depicted in Figure 3-13, we find the 75th percentile of the daily price spread to be the most explanatory of variations in energy value, with an R^2 value of 85%. In contrast, the highest R^2 value obtained from a regression directly on price percentiles—as well as for the 75th percentile of the energy price alone—is only 59%.

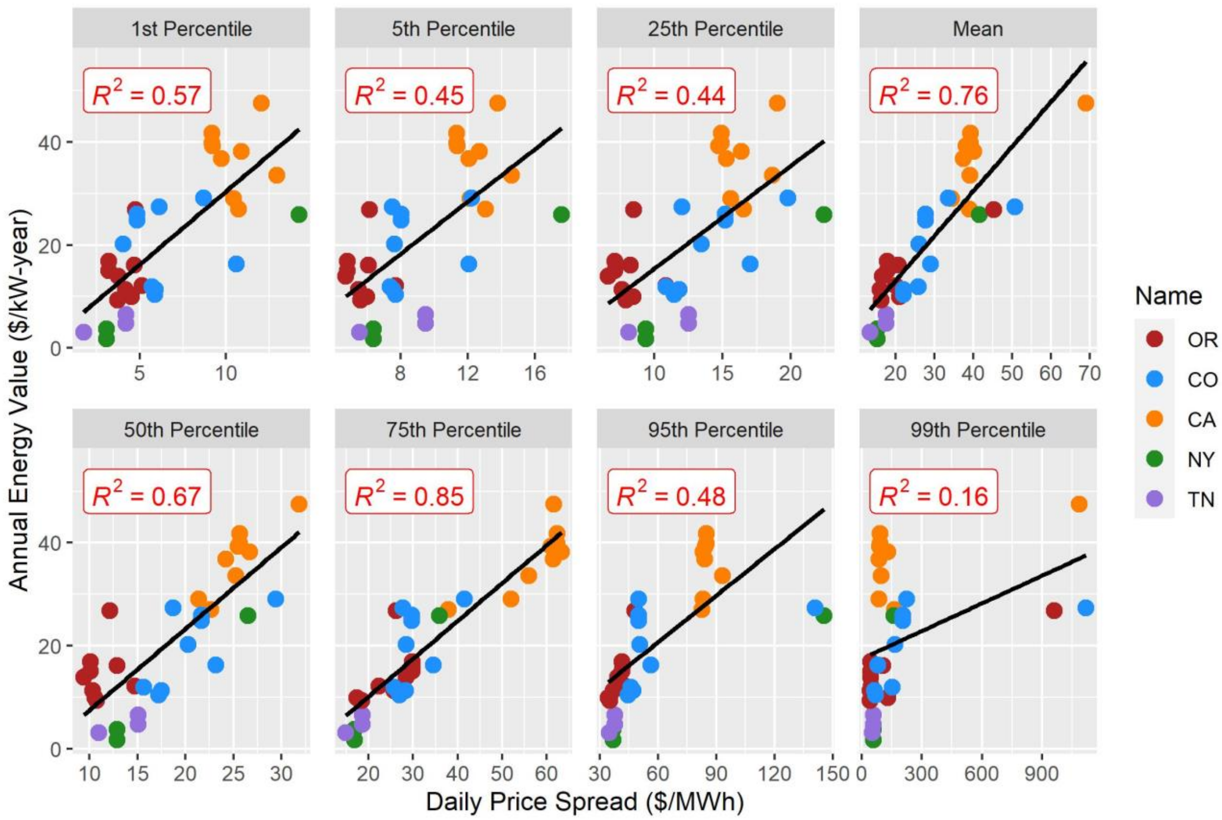

Figure 3-13 The correlation among mean daily price spread, seven different daily price spread percentiles, and the total PSH value derived from energy.

Finding 13 Capacity price, daily energy price spread, and AS market participation levels explain 92% of the variation in PSH value.

Table 3-2 shows the results of a multivariate regression analysis of PSH value, similar to the one performed for conventional hydropower plants in Table 3-1. Capacity price alone is found to explain 70.1% of the variation in PSH value. Recall that two different methods are used to determine capacity prices for the regions in the WI and the EI. The capacity prices that are calculated for New York and Tennessee are generally lower than those calculated for Oregon, California, and Tennessee and do not follow the same positive correlation between capacity price and total value observed across the whole sample.

Adding the 75th percentile of daily price spread and the AS market participation level increases the explanatory value to 92.4%. Storage capacity and the mean regulation up price are both statistically significant predictors of total value ($p<0.01$) but do not add much additional explanatory value to the broader multivariate regression model.

Table 3-2 The impact of adding successive explanatory variables to a multivariate regression model of PSH value.

PSH Value					
	Dependent variable:				
	Annual Value				
	(1)	(2)	(3)	(4)	(5)
Capacity Price	0.919***	1.050***	1.050***	1.050***	1.061***
	(0.035)	(0.023)	(0.018)	(0.018)	(0.016)
75th Percentile of Daily Price Spread		0.774***	0.774***	0.774***	0.763***
		(0.037)	(0.029)	(0.028)	(0.025)
AS Limit (% of Capacity)			0.699***	0.699***	0.699***
			(0.054)	(0.053)	(0.047)
Storage Capacity (Hours)				0.285***	0.285***
				(0.069)	(0.062)
Mean Reg Up Price				1.360***	(0.157)
Constant	33.519***	-1.102	-8.092***	-11.418***	-22.955***
	(2.260)	(2.171)	(1.817)	(1.943)	(2.189)
Observations	297	297	297	297	297
R^2	0.702	0.882	0.925	0.929	0.944
Adjusted R2	0.701	0.881	0.924	0.928	0.943
Residual Std. Error	15.080 (df = 295)	9.513 (df = 294)	7.602 (df = 293)	7.401 (df = 292)	6.612 (df = 291)
F Statistic	696.589*** (df = 1; 295)	1,098.800*** (df = 2; 294)	1,202.997*** (df = 3; 293)	956.239*** (df = 4; 292)	973.408*** (df = 5; 291)

Note: *p<0.1; **p<0.05; ***p<0.01

3.2.2 Value Concentration

Finding 14 PSH value is less concentrated with high VRE penetration and more concentrated with high electrification.

In contrast to the case with conventional hydropower plants, the fraction of PSH value derived during the 100 most valuable hours of the year decreases as VRE penetration increases. Higher VRE penetration results in periods of low prices, but this creates value opportunities for PSH by enabling them to pump when prices are low or negative. The result is that there are more opportunities to provide value throughout the year, so value becomes less concentrated in a small number of periods.

The High Electrification case, however, leads to a small number of short periods with energy scarcity and very high energy prices. This also creates high-value opportunities for PSH during these hours and thereby concentrates more value over this relatively small number of periods. This effect was also observed for conventional hydropower plants, but on a smaller scale.

The storage capacity AS market participation level of the PSH plant does not have a strong impact on the concentration of value, and therefore these sensitivities are not shown in Figure 3-14.

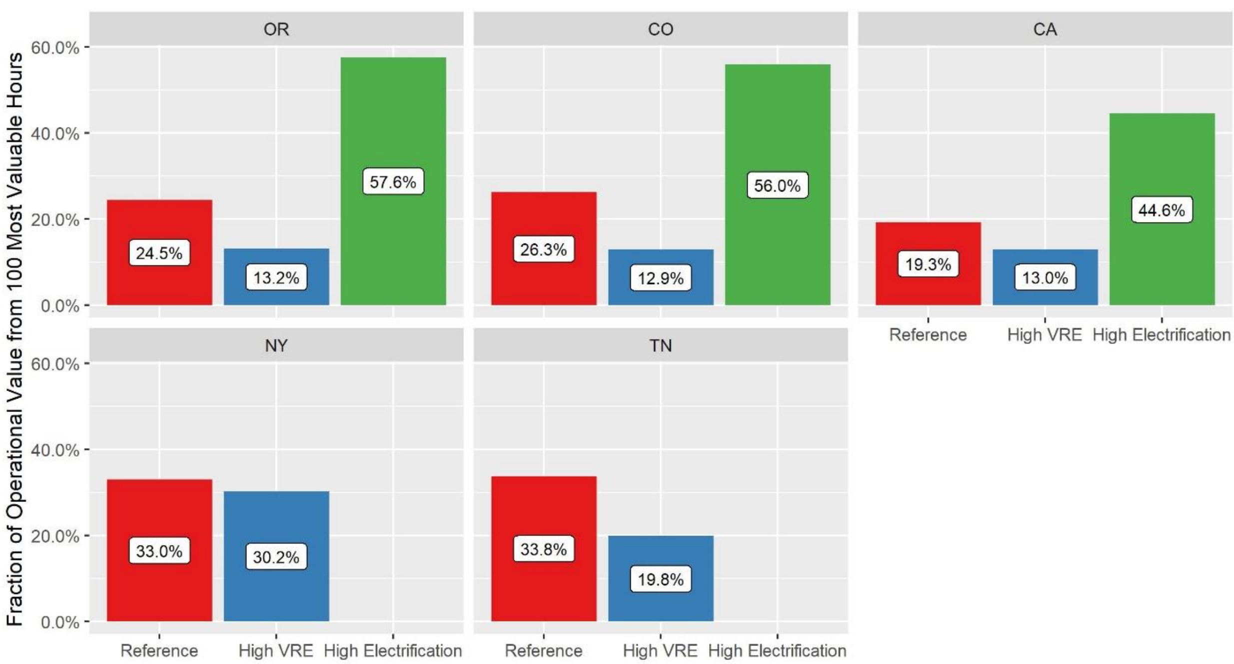

Figure 3-14 The fraction of operational value generated during the 100 most valuable hours.

Finding 15 High PSH value periods are less temporally clustered with high VRE and more temporally clustered with high electrification.

As was the case for conventional hydropower plants, PSH value becomes less temporally clustered as VRE penetration increases. Figure 3-15 shows these results for Colorado and Tennessee, the two regions with the largest changes in VRE penetration across scenarios. In the Colorado Reference scenario, high-value periods largely occur during summer evenings, but when VRE penetration increases, high value hours occur much more frequently in the early mornings. These are periods where energy prices are frequently negative and plants can generate value simply by pumping.

The High Electrification scenario even further concentrates high value periods around high electricity demand and therefore scarcity conditions and extreme price events. The occurrence of extremely high prices is a bigger driver of value in this case than the occurrence of low prices because of the sheer magnitude of these high prices.

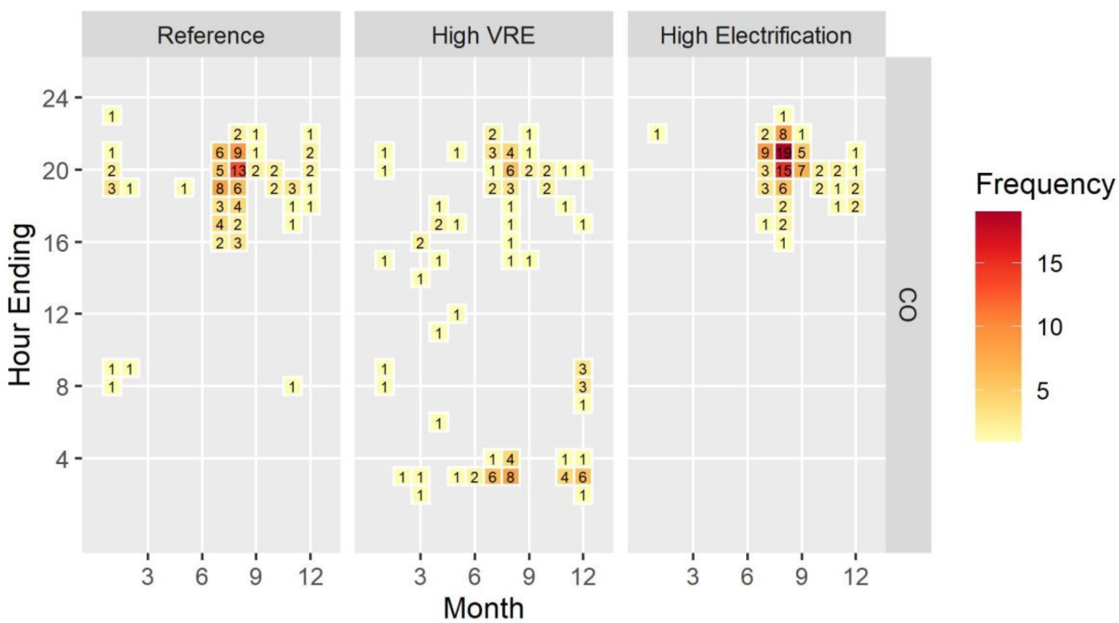

Figure 3-15 A heat map indicating the temporal distribution of the 100 most valuable hours for PSH in Colorado throughout the year. Each data point depicts the occurrence frequency of a high value period during the specified month and hour.

3.2.3 Technology

Finding 16 The marginal value of additional PSH storage capacity above 12 hours is much greater when negative prices are frequent.

In addition to the core storage capacity sensitivity cases with 5, 10, and 20 hours of storage capacity, we also performed a set of higher resolution sensitivity analyses for four key scenarios to examine the relationship between storage capacity and PSH value in more detail. Figure 3-16 shows how value increases with increasing storage capacity in systems with various levels of VRE penetration. In each case, value increases with storage penetration, but the increase is much more pronounced in higher VRE systems.

For example, in the Colorado Reference scenario, the marginal additional value created by adding another hour of storage capacity to a standardized plant diminishes rapidly after about 6 hours of capacity. This suggests that 6 hours of storage is roughly sufficient to capture the energy arbitrage opportunities presented during a typical daily operating cycle. However, this dynamic changes as VRE penetration increases, both in Colorado and California. Interestingly, the High VRE scenario results in less PSH value than the Moderate VRE scenario for low levels of storage capacity, but this dynamic reverses at around 13 hours of capacity. This is because in the Colorado High VRE scenario, prices are relatively flat and frequently close to zero or even negative, so there are fewer opportunities for arbitrage on daily timescales. However, with greater storage capacity, the plant can produce value by pumping more water during these periods of negative prices, and then produce additional value by generating energy when prices are positive again, even if they are still relatively low. A lower storage capacity limits the ability of the plant to capitalize on these negative price periods

In fact, for higher storage capacities, the frequency of negative price periods is a stronger indicator of PSH value than VRE penetration alone. For example, the California Reference scenario has a higher VRE penetration (45%) than the Colorado Moderate VRE scenario (24%), yet its standardized PSH plant provides less value because negative prices occur less often.

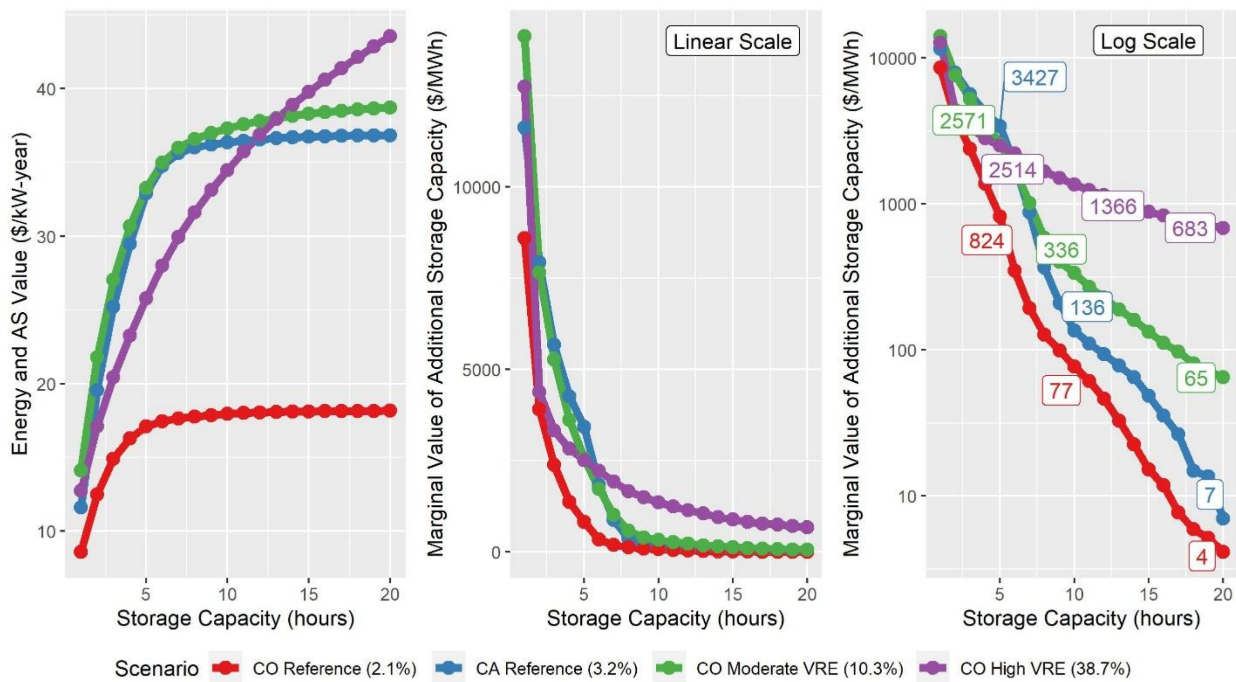

Figure 3-16 PSH value created by providing energy and AS increases with increasing storage capacity. The middle and right plots show the same data with a linear (middle) and log (right) y-axis scale.

3.2.4 Implications for Industry

- PSH plants should evaluate AS market participation strategies to ensure that they are maximizing value, particularly if VRE penetration and AS prices increase in the region.
- PSH energy value is more strongly correlated with daily price spreads than annual price distributions.
- PSH value is strongly correlated with the prevailing capacity price. This can make PSH valuation difficult, as capacity prices are volatile and more difficult to model than energy prices.
- In the high-VRE future, PSH plants may become less reliant on a relatively small number of periods to generate all of their value.
- Much of the value from daily arbitrage opportunities can be captured by short-duration storage technologies with less than 8 hours of storage capacity. Medium- to long-duration storage can provide value in systems with frequent occurrences of negative prices, as these resources can store large quantities of energy when prices are negative and generate energy when prices are positive again.

3.3 System Conditions

The findings discussed in Sections 3.1 and 3.2 indicate that energy price dynamics are, unsurprisingly, a primary driver of hydropower value in future system conditions. We therefore further directly analyzed the production cost modeling results generated by GridView for the WI to better understand how changes in system factors can drive changes in energy prices across temporal and geographic dimensions as well as changes in hydropower generation across the interconnection.

Finding 17 System composition impacts energy prices and therefore drives resource value.

The difference in generation output between scenarios has an impact on energy prices. The extent of this effect is illustrated in Table 3-3, which compares the mean annual energy prices generated by GridView for three selected balancing areas: CIPV (California), WACM (Colorado) and BPA (Oregon). As expected, the High Gas Price and High Electrification scenarios lead to higher energy prices in all three areas, since natural gas (NG) units (usually *peaking* natural gas units) frequently provide the marginal unit of electricity and therefore set the price. These higher prices are especially noticeable in California, which relies heavily on natural gas resources to supply peak demand.

Table 3-3 Average electricity prices for selected scenarios in the WI. See Table C-1 for more detail.

Scenario	CIPV (California)	WACM (Colorado)	BPA (Oregon)
Reference	$54.92	$22.39	$23.01
High Electrification	$56.42	$24.37	$24.96
High Gas Price	$66.53	$30.71	$32.95
High VRE	$51.78	$5.00	$18.20
High VRE with LDES	$51.16	$4.47	$17.68

On the other hand, lower energy prices are consistently observed in the two High VRE scenarios, as the system depends less on thermal generation resources. That is particularly noticeable in the WACM area, which experiences very low energy prices due to the high penetration levels of solar and wind resources that displaced coal facilities. Note that the WACM area had the greatest portion of retired coal resources in the WI (Figure 3-8), and therefore the observed impacts are relatively larger. In the High VRE with LDES scenario, where 10-hour storage replaces 4-hour, mean energy prices decrease by a small amount since the longer-duration storage offers enhanced arbitrage opportunities. However, the overall impact in the systems analyzed here is relatively minor. More detailed analysis would be needed to generalize these findings or identify grid conditions where increasing the duration of storage resources has a more substantial impact on aggregate prices. The general finding that increasing VRE penetration tends to decrease average wholesale electricity prices is supported by the broader literature (see Appendix B), as summarized in Wiser et al. (2017) and Mills et al. (2021).

Finding 18 Increasing the duration of all new storage resources from 4 hours to 10 hours modestly decreases wind and solar curtailment.

Total annual wind and solar curtailment across the entire WI for each scenario is shown in Figure 3-17. Among all scenarios, the highest wind and solar curtailment is observed in the High VRE scenario, which reaches a combined 32.7 TWh when 4-hour storage units are used. This curtailment is reduced by 13%, to 28.5 TWh, when 10-hour storage units are used instead. However, total curtailment is still more than 12 times higher than it is in the Reference scenario in absolute terms and nearly 8 times higher as a fraction of total wind and solar generation. This suggests that increasing storage capacity can help to mitigate wind and solar curtailments in systems with very high VRE penetration, but may not completely eliminate it. It also further supports Finding 16, which determined that increasing storage capacity beyond 12 hours provided small marginal value in systems with low or moderate VRE penetration.

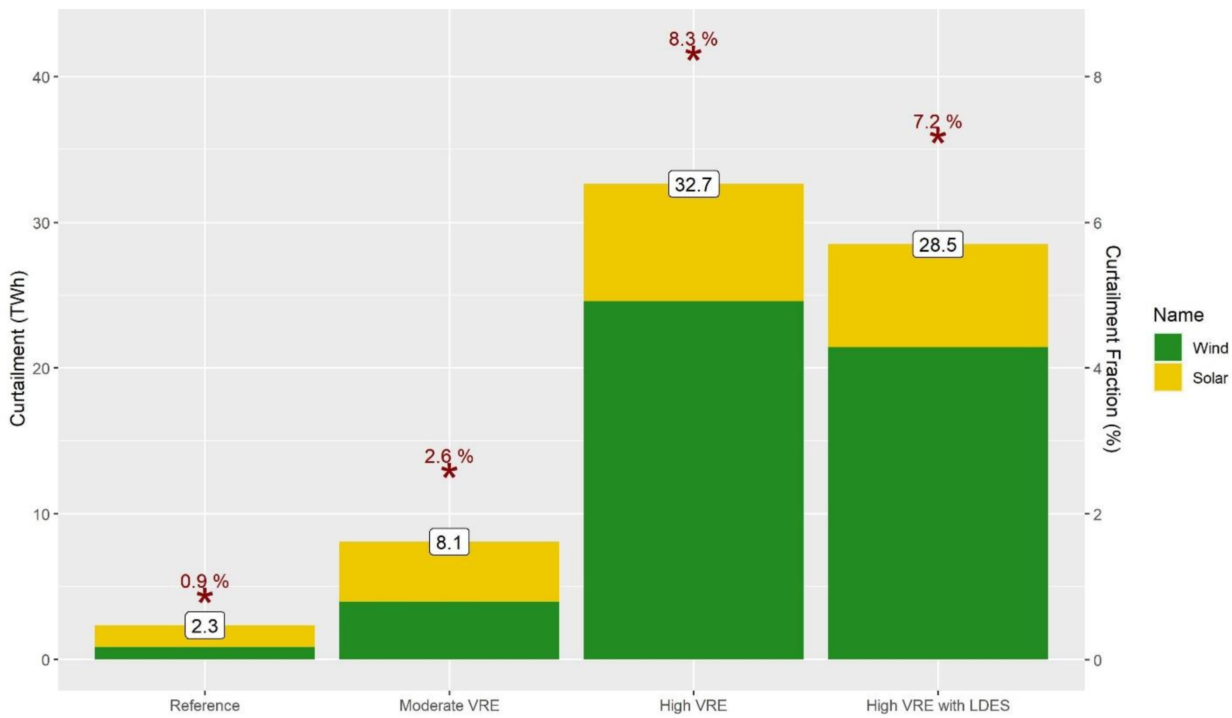

Figure 3-17 Total annual wind and solar curtailment across the entire Western Interconnection for each scenario (TWh). The red data points indicate the fraction of total potential wind and solar generation that is curtailed.

Finding 19 Natural gas is the primary substitute for hydropower generation when water availability is low.

Figure 3-18 shows the total WI generation output in 2030 for each technology type and each scenario. We modeled a number of variants of the Reference scenario to understand the impacts of increasing VRE penetration, varying levels of water availability, higher natural gas prices, and higher penetration of electric vehicles.

In the Wet Hydro scenario, additional hydro generation displaces NG generation, while in the Dry Hydro scenario the reduction in hydro generation is accompanied by a corresponding increase in NG generation.

In the High NG Fuel Price scenario, NG resources are by definition more costly, which lowers their utilization, while less expensive coal resources increase their output to cover the reduced NG-based generation.

In the High Electrification scenario, NG generation is increased to supply the increased electrification demand. In the 30% coal replacement scenario, zero-marginal-cost wind and solar resources replace NG generation. An even greater NG generation reduction is observed in the 100% coal replacement scenarios, where solar and wind resources are preferred to supply the system demand.

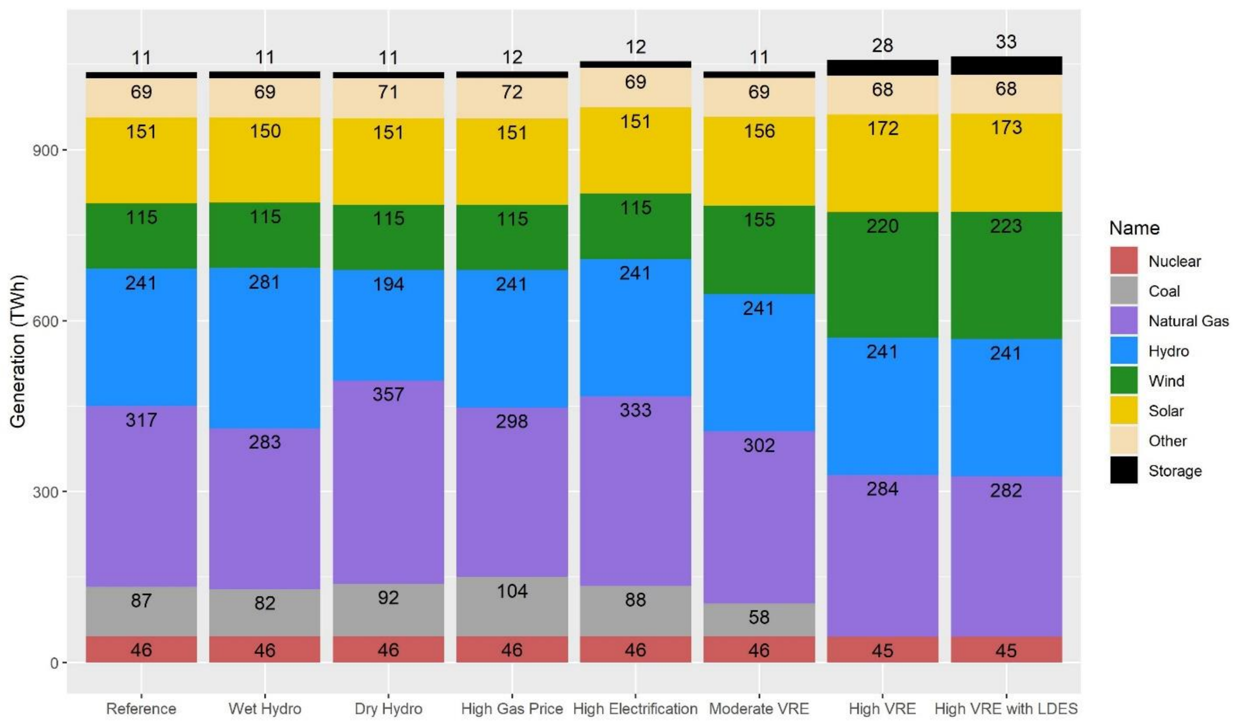

Figure 3-18 Total generation across the WI for each scenario.

Finding 20 Power flow patterns change substantially at higher VRE penetration.

The introduction of ZFC renewable generation resources to replace conventional thermal generators leads to substantial changes in regional power transfers. Figure 3-19 shows the net regional transfers for the 2030 High VRE scenario, the 2030 Reference scenario, and the 2020 Reference scenario in western regions of the U.S. and Canada. These changes in transfers, especially noticeable in the Basin and Rocky Mountain regions, can be attributed to different dispatch patterns caused by the changes in economics of power production at the regional and local levels.

The biggest change in regional power flows is observed between the Northwest and Basin regions. The Basin region was a net importer of energy from the Northwest in 2020, while it is projected to be a net exporter of energy to the Northwest in 2030 in all the scenarios. It should be noted that the Basin and Rocky Mountain regions see the most dramatic change in resource mix, especially in the High VRE case, in which all coal generation capacity is replaced by wind and solar.

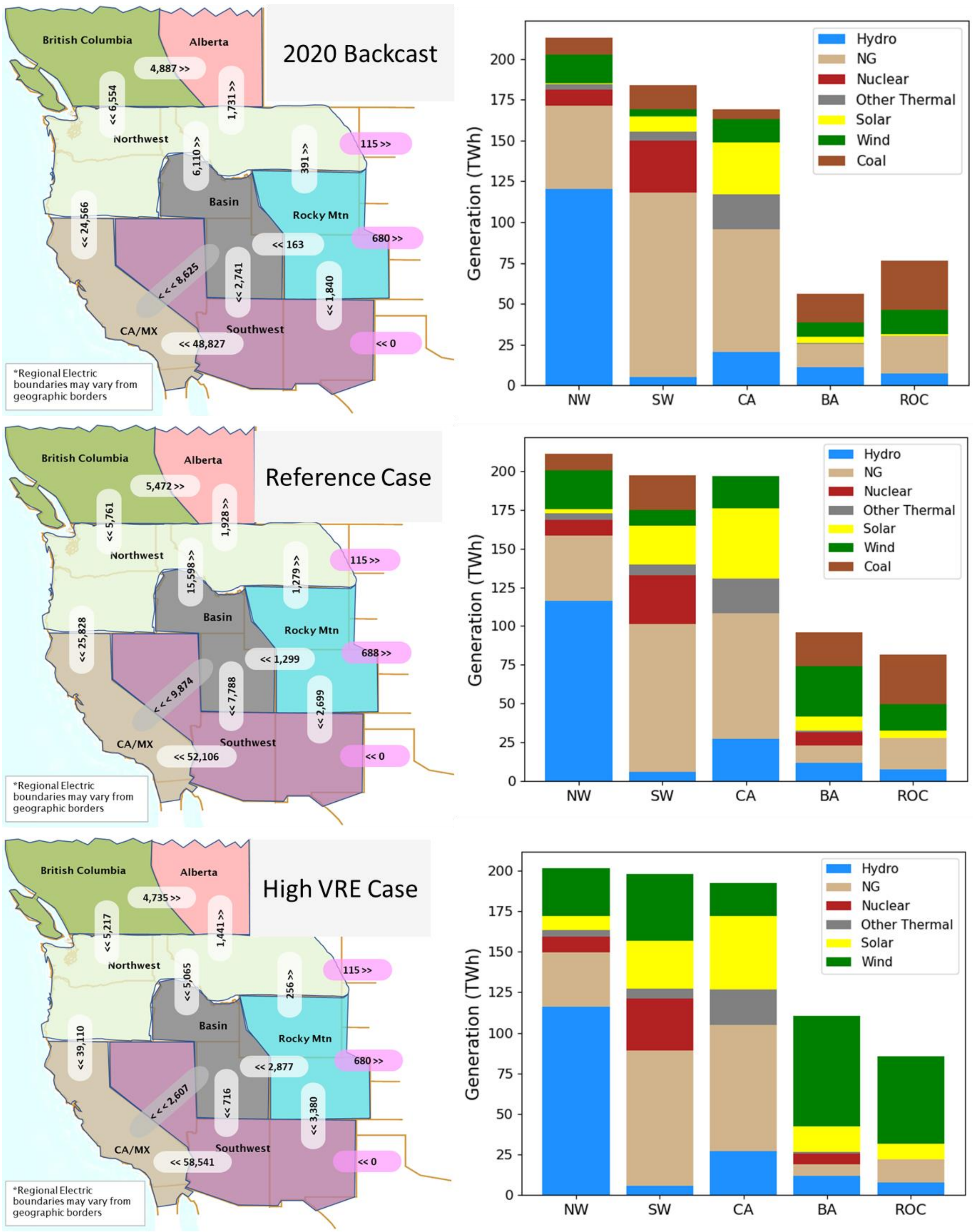

Figure 3-19 Net regional transfers for the 2030 High VRE scenario, the 2030 Reference scenario, and the 2020 Reference scenario.

3.4 Markets and Modeling

Finding 21 Energy storage representation must be enhanced to ensure that models accurately capture system value streams.

It is crucial to accurately represent the cost and performance characteristics of different technologies when modeling complex power system interactions and price formation throughout an entire interconnection. While certain assumptions and relaxations may always be necessary to ensure that models are tractable, methods for representing traditional thermal resources with sufficient accuracy have been fairly well established and refined over several decades of model development and application. However, emerging technologies, such as energy storage resources, have a number of unique characteristics that have not traditionally been captured in production cost or capacity expansion models, and methods for incorporating such resources into models are still being researched and developed. The representation of these characteristics is important for assessing the value of energy storage resources themselves and has implications for the value of other technologies as well. Three of the most important fundamental model enhancements are suggested for future development:

Capturing opportunity costs. In a future with high penetration of VRE resources, energy storage may frequently provide the marginal unit of electricity during periods when wind and solar availability are low. As a result, the marginal generation costs of storage resources may also frequently set energy prices, which are a major driver of value for all resources in a system. For this reason, it is important to accurately capture and represent the opportunity costs that storage resources exhibit through their offers in competitive markets in order to ensure that this behavior is accurately reflected in modeled price outcomes.

Increased temporal fidelity. Capturing the operational dynamics of storage resources requires greater temporal fidelity than has traditionally been represented in models. This includes the implementation of intertemporal constraints, sub-hourly temporal granularity, full chronological timeseries representation, longer look-ahead periods (particularly for LDES), determination and representation of opportunity costs for storage dispatch, and improved logic for state-of-charge management.

Improved uncertainty representation. Finally, traditional deterministic production cost modeling underestimates system uncertainty, and therefore underestimates the value that energy storage can provide to mitigate this uncertainty. Improved stochastic optimization methods are needed to capture both short- and long-term uncertainties in production cost and capacity expansion models and, in particular, their impact on value streams for energy storage. New computation methods may be needed to ensure that these methodologies can be implemented with sufficient geographic and temporal granularity to inform real-world decision making.

Finding *22* Energy prices produced by production cost models are not predictions of the future but can be valuable for comparative analysis.

PCMs are commonly used to generate “energy prices” that are intended to be representative of the locational marginal prices that result from real-world market clearing processes. However, such modeled prices are often found to differ from historical price distributions for a number of reasons.

First, many PCMs reduce temporal and geographic granularity in order to maintain computational tractability. Full nodal resolution with proper DC power flow representation is needed to capture the price impacts of transmission congestion. This is important in practical terms for capturing the tails of price distributions and the price differences between different locations in the same system.

Second, most PCMs determine the marginal generation costs of different system resources based on their presumed fuel cost, heat rate, and variable operations and maintenance (O&M) costs. While excellent data are available to inform these assumptions, it is still difficult to capture all differences in resources of a similar type. Furthermore, fuel prices vary through time and can be volatile, and resources may use complex bidding structures to reflect their risk tolerance or other operational constraints or strategies. All this contributes to creating real-world price dynamics that are difficult to fully capture in models.

Third, while the first two issues apply generally to both day-ahead and real-time prices, PCMs generally face even greater challenges in capturing real-time price dynamics, as most do not fully capture power system uncertainty, specifically the two-stage day-ahead to real-time market clearing process. By underestimating uncertainty, PCMs may also underestimate real-time price volatility and the prevalence of periods with moderate to high prices.

Since it is extremely challenging—often impractical or impossible—to overcome these challenges, informational deficiencies, and the resulting deviations in modeled outcomes, we suggest that modeling can be most effectively implemented to carry out comparative analyses between different scenarios, as was the focus of our analysis, rather than attempting to forecast precise future values for any one specific plant in any one specific grid scenario.

Finding 23 Current power system models have limited ability to capture AS price dynamics.

As resources with near-zero marginal generation costs continue to proliferate, AS may provide an increasingly important value stream for hydropower and other technologies. Many traditional power system models do not capture unit-level AS allocations for specific products. Rather, they may seek to ensure that sufficient reserve capacity is available through aggregate operating reserve capacity requirements or long-term constraints, such as a planning reserve margin. Recently, there has been an increasing focus on both identifying how AS requirements might change as system conditions evolve and understanding the associated cost and revenue implications for different supply- and demand-side resources. However, capturing these dynamics in power system models presents a number of challenges, as AS value streams depend on several factors that differ from those that drive energy value streams. Several of these challenges are explored below.

Offer price assumptions. Perhaps most important, determining the costs that units incur or internalize while providing different AS is not straightforward. Such costs may be largely attributed to opportunity costs, which themselves can be subjective and depend on perceptions of future prices and owner risk tolerance. In addition, even if the true AS costs incurred by a unit when providing AS are known, offers into competitive markets may not be perfectly reflective of these costs.

Marginal energy costs, on the other hand, can generally be calculated with reasonable accuracy based on three relatively well-established parameters—variable O&M cost, heat rate, and fuel cost—and are therefore more tightly regulated by market power monitors. Many models assume that resources face no physical costs when providing AS and offer their full capacity into each market at zero price. This approach tends to generate market clearing prices that are consistently lower than real-world outcomes.

Offer quantity assumptions. Similarly, determining how much of its capacity a particular unit is able to allocate to providing a given ancillary service, or alternatively how much it may choose to allocate, is also not straightforward. One analysis has found that assuming all units allocate their full technical capacity to the PJM frequency regulation market leads to an underestimation of market clearing prices, suggesting that many units do not offer their full technical capacity into the market (Levin, 2018). This finding is supported by another analysis of historical AS offer behavior in the Electric Reliability Council of Texas (ERCOT).

System requirements. Just as energy prices are generally higher during periods of high electricity demand, prices for AS are strongly influenced by service requirements. As generation portfolios continue to evolve, these requirements may also change in terms of both aggregate and increasing intra-day variations. Those capacity expansion models that do consider hourly AS requirements typically rely on exogenous determinations for each service requirement, e.g., a tool such as GRAF-Plan. As changes in these requirements may influence investment decisions, ideally they should be endogenously incorporated into the model logic that is used to determine optimal capacity expansion plans.

Finding 24 The value of capacity depends on other value streams.

Six of the seven competitive wholesale electricity markets in the U.S. currently have some form of capacity remuneration mechanisms, with (ERCOT being the one exception). These mechanisms have been implemented to support and address the so-called "missing money problem," which is a consequence of offer caps in energy spot markets (Hogan, 2005).

Demand curves for capacity in the competitive capacity markets are typically defined in relation to the net cost of new entry (CONE) of a representative generation unit, traditionally a gas combustion turbine. Net CONE is determined by subtracting the revenues that the unit is expected to obtain through participation in energy and AS markets from its CONE. The amount that a system operator is willing to pay for capacity, and therefore the value of capacity in that system, directly depends on the size of other value streams.

This makes it difficult, if not impossible, to determine and generalize an intrinsic value of capacity across different systems and market constructs. There are mathematical approaches that can be used, such as those detailed in Section 1.3, but these may not perfectly reflect real-world conditions.

3.5 References for Section 3

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4.0 Conclusions and Path Forward

Power systems are currently in a state of rapid evolution due to increasing reliance on zero-carbon generation technologies, increasing end-use electrification, and evolving policy, regulatory, and market landscapes. This transition is leading to a corresponding increase in the need for energy storage technologies and resources with operational flexibility to help balance net load variations. As a zero-carbon, flexible resource with storage capabilities, hydropower is poised to play a leading role in this transition. It is therefore crucial to understand how hydropower value streams will evolve and then quantify the factors that will drive these changes in value.

In this report we presented a value drivers framework for hydropower and apply it to a number of case studies. To this end, we first defined and executed a set of 164 value analyses for conventional hydropower and 297 value analyses for PSH across a range of system scenarios and plant sensitivities. The results of these analyses were then compared to quantify the relative impact of the different hydropower value drivers.

We found that conventional hydropower resources generate the majority of their value from providing energy in most system conditions. This share may decrease as VRE penetration increases due to both decreases in energy prices and potential displacement of energy generation from these new resources. However, energy will still likely provide the largest share of value for most plants unless or until system conditions or market designs change significantly. As average energy prices are expected to decrease with increasing VRE penetration, this will likely also decrease total hydropower value unless markets or value paradigms change as well. We further find that higher VRE penetration and faster ramping capabilities tend to concentrate conventional hydropower value into fewer time periods, while also allocating these high value periods more consistently throughout the year.

Findings for PSH are often directly the opposite of those for conventional hydropower. For example, for PSH, energy provision accounts for the minority of value in most conditions, while capacity generally provides the largest share of total value. However, it is important to note that capacity value is highly dependent on the prevailing market or planning paradigm in a given region.

Contrasting the PSH case with conventional hydropower, we find that 1) total value is expected to increase with increasing VRE penetration, 2) daily price spreads explain variation in value across scenarios better than average price statistics, and 3) PSH value becomes less concentrated with increasing VRE penetration, and arbitrage opportunities arise more frequently. We further find that a plant's AS market participation level is a key driver of value. As participation level can vary across plants, sometimes significantly, it will be important to understand how plants choose to allocate capacity between energy and AS markets as well as any associated operational constraints that limit participation. Finally, we find that the marginal value of storage capacity beyond 12 hours is small in the grid conditions that were analyzed, unless negative price periods occur with some frequency.

The collective analyses and findings summarized in this report may also motivate a number of important future research directions.

Assess the Value Impacts of Increasing VRE Penetration in Greater Detail

We identify system VRE penetration as a key driver of hydropower value and specifically find that the total system value of conventional hydropower decreases as VRE penetration increases. This finding is aligned with a wealth of literature in which energy price impacts have been analyzed more generally (see Appendix B). However, much more work is still needed to understand in greater detail how changing VRE penetration impacts hydropower value dynamics.

First, it is important to quantify these value impacts across a range of different conditions and understand other concurrent system- and plant-level factors that may mitigate or exacerbate these effects. Second, it will be important to understand how any observed trends may change as a system nears 100% VRE penetration. For example, are the value impacts consistently linear with increasing VRE penetration, or is there a tipping point where impacts either increase or diminish? Finally, increasing VRE penetration affects almost all generation units to some extent by influencing electricity prices, so it is important to understand how the value impacts experienced by hydropower compare to those experienced by other resources. Such universal value impacts may motivate fundamental changes in market design (or value determination in a vertically integrated planning paradigm) in order to ensure revenue sufficiency for all of the resources needed to maintain system reliability. These questions could be elucidated by applying the value drivers framework to a set of scenarios that span a wider range of VRE penetration, combined with different complementary non-VRE portfolios, in a number of different regions.

Analyze the value impacts of new and proposed policies

Our analysis does not reflect the Inflation Reduction Act that became law in 2022. This new law provides a number of incentives that will impact the evolution of the U.S. generation portfolio over the next decade. Some of these incentives, notably the production tax credit, will also decrease the marginal generation cost of eligible resources and therefore tend to decrease market clearing prices. At the same time, the production tax credit may increase the prevalence of negative price periods, which can impact the value of PSH, particularly those resources with higher storage capacity (Finding 16). On the other hand, carbon emissions pricing increases the marginal cost of emitting resources and therefore tends to increase average energy prices (Levin et al., 2019). These changes in price outcomes have implications for all generation resources in a system, not just those that are eligible for the credits.

Conduct more targeted case study analyses

We applied the VDF to case study analyses of standardized units to help isolate the relative impact of individual value drivers. However, this framework could also be applied to analyze the value drivers for specific real-world resources if sufficient data and operational details are available. For more targeted analyses, PCMs could be executed with a smaller geographic footprint and higher geographic resolution to improve the fidelity of modeled price dynamics relevant to the specific location.

Consider the ability of a targeted resource to influence prices

The analysis presented in this report optimizes the operational strategies of standardized hydropower plants based on the prices generated by system-wide PCMs. Implicit in this framework is the assumption that changes in the operational strategies of the standardized plants will not impact market clearing prices. This is generally a reasonable assumption when a modeled plant represents a relatively small fraction of the total generation capacity in a region or there is limited transition congestion in the area. However. it may be a less suitable assumption in other cases. The price-influencing potential of a specific hydropower plant could be evaluated by directly integrating a hydropower optimization tool such as CHEERS into a PCM framework. This process is currently being implemented as part of the Pumped Storage Valuation Tool (Argonne, n.d.)

Analyze hydropower value in zero-carbon systems

The findings presented in this report are based on a set of case study analyses using prices generated by PCMs designed to analyze tradition power systems dominated by large thermal generation resources. More work is needed to understand how well these models are able to capture price and value dynamics in systems with very high (e.g., more than 80%) penetration of zero-carbon resources (Zhou et al., 2022). Such analysis may identify corresponding needs for model enhancements that could improve the fidelity of PCMs when applied to highly decarbonized power systems. These enhancements could then be implemented and the updated PCMs used to generate prices.

Assess value impacts of new and proposed competitive wholesale market designs

In regions with competitive wholesale electricity markets, the specifics of market design can play an important role in determining the value of different services. This is particularly the case for capacity markets and other resource adequacy mechanisms, as noted in the previous section. Electricity markets are constantly evolving alongside our evolving power systems (Sun et al., 2021), and they may need to change dramatically to accommodate highly decarbonized generation portfolios (Zhou et al., 2022). New methodologies, models and tools may be required to capture the intricacies of future market designs. As it is also difficult to predict exactly how markets will evolve over the coming years and decades, such enhanced models and tools could be integrated into the VDF to analyze how various potential changes to market designs themselves drive changes in hydropower value streams.

Consider evolving climate conditions and extreme weather events as potential value drivers

While our production cost modeling considered possible changes across a range of system conditions, such as generation portfolios and electricity demand, our representation of the climate and weather is largely based on historical data, as is the case with most traditional applications of PCM and capacity expansion models. However, it is now well established that climate conditions are changing, and it is therefore important to consider how future climate and weather conditions will impact the optimality of investment decisions made today. Changes in climate will differ regionally but will have the potential to impact solar activity, wind speeds, and water availability, all factors that influence electric grid operations and planning.

Furthermore, the ability of extreme weather events to dramatically impact electricity systems has been highlighted by a range of incidents over the past decade, including Winter Storm Uri in Texas (2021), Hurricane Maria in Puerto Rico (2017), Hurricane Sandy in New York (2014), and the North American polar vortex (2014) among many others (Levin et al., 2022). While it is difficult to attribute any one extreme event to changes in climate conditions, extreme weather events are projected to occur with increasing frequency as the world warms. The increasing prevalence of such events will also impact the value streams of different technologies, particularly those with storage capacity that can be reliably called upon to help mitigate impacts from generation and transmission outages or disruptions in fuel supply. More work is needed to incorporate future climate conditions into capacity expansion models and probabilistically assess how the changing climate will impact the magnitude of current value streams and possibly even create new sources of system value.

4.1 References for Section 4

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Appendix A: Methods and Data

A.1 Overview

These sections outline the specific tools we used for this application, but the general VDF can follow this process with other models and tools.

A.2 Production Cost Modeling

A.2.1 NREL Standard Scenarios (ReEDS + PLEXOS)

We used the NREL Standard Scenarios to model electricity prices in the EI.

The NREL Standard Scenarios (NREL, 2020a) are a set of scenarios created annually to simulate the future development and operation of the U.S. power system through capacity expansion modeling and production cost modeling. These scenarios represent different assumptions that lead to different simulated investment and operational decisions throughout he power system.

While the Standard Scenarios and the modeling processes used to simulate them cover the entire U.S., the cases studies analyzed in this report focus on two specific regions: upstate New York (zone p127) and Tennessee (zone p92). We used the scenario definitions and associated simulated data from the 2020 Standard Scenarios (NREL, 2020a; Cole et al., 2020). Our analysis uses two of the 45 scenarios developed for the 2020 Standard Scenarios: the Mid case, which represents a "business as usual" scenario, and the Low Renewable Energy Cost case, representing a scenario with relatively higher contributions from wind and solar generation. We refer to these as the Reference scenario and High VRE scenario, respectively, throughout this report.

Hourly electricity price estimates are determined through a multi-stage process. First, the NREL ReEDS model performs a co-optimization of generation and transmission capacity expansion. Then the resulting generation portfolios are translated into a zonal production cost model (134 zones to represent the Eastern, Western, and Texas Interconnections), and an hourly unit commitment and economic dispatch analysis is performed. The PLEXOS energy simulation model was used to perform the production cost analysis using assumptions consistent with the Standard Scenarios. Electricity prices are calculated for each hour and each zone through standard marginal-cost based pricing. Prices for several ancillary services are calculated by PLEXOS through a similar process; however, the ancillary prices utilized in our case studies are based on historical data from the NYISO market in 2020.

The Mid case represents "business-as-usual" conditions for assumptions regarding demand growth, fuel prices, generation technology costs, retirements, and current laws and policies. The Annual Technology Baseline (ATB) for 2020 (NREL, 2020b) is used to provide a consistent set of assumptions regarding electricity generation technologies. The Mid case uses "moderate" technology cost projections provided by the ATB, and the Low Cost Renewable Energy case uses the "advanced" cost projection.

The subsequent buildouts are then independently simulated in the zonal production cost model. The capital expenditures for several different technologies in each of these scenarios are shown in Figure A-1. The resulting generation portfolios for each scenario and reliability assessment zone are shown in Figure A-2. The High VRE High AS scenario analyzed in this report uses all the data from the same Low Renewable Energy Cost case, but AS prices are doubled.

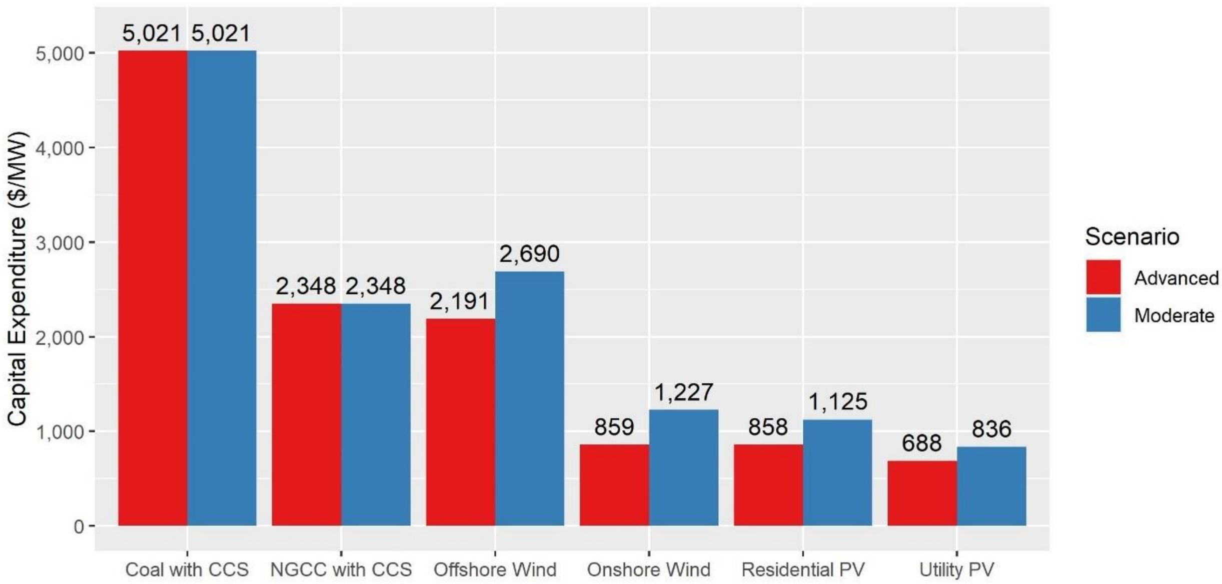


Figure A-1 Moderate and advanced capital expenditure projections for 2030 from the 2020 ATB.

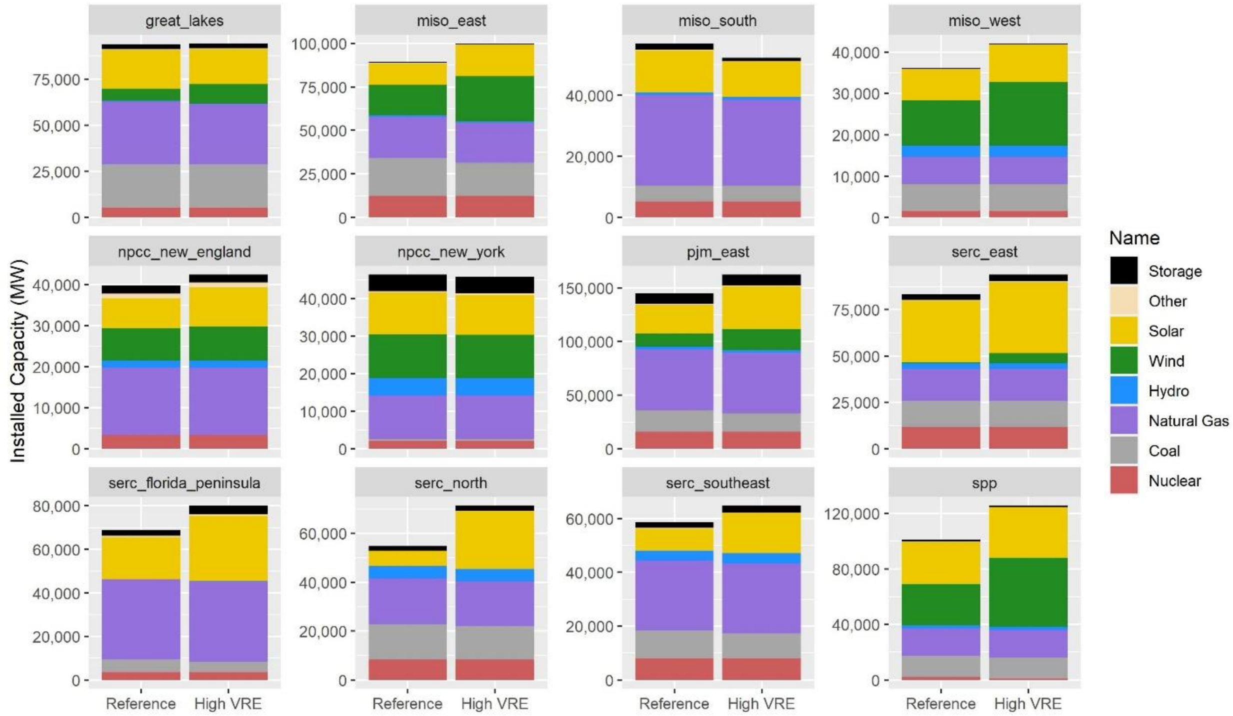


Figure A-2 Installed capacity by fuel type for each reliability assessment zone in the EI, generated by the 2020 NREL Standard Scenarios.

A.2.2 WECC 2030 ADS (GridView)

For this report, we used the GridView PCM tool (Yang et al., 2003) to simulate power grid operations in the WI with high spatial resolution, including more than 22,000 nodes. GridView is a chronological security-constrained unit commitment and security-constrained economic dispatch model that minimizes the system operating costs of meeting electricity demand and reserve requirements while simultaneously satisfying a wide variety of operating constraints. These constraints consist of unit-specific constraints (e.g., maximum/maximum capacity limits, minimum up and down times, ramping limits) and system-wide constraints (e.g., transmission line capacity limits, interface capacity limits, operating reserves, emission constraints, hurdle rates). Operating costs largely consist of fuel costs, variable operating and maintenance costs, and start-up/shut-down costs. Hourly power flows and transmission congestion are captured through a DC optimal power flow representation of the nodal transmission network. In this work, GridView is used to simulate the market-clearing prices (also referred to as locational marginal prices) of electricity used to serve customer load in the WI. As is the case with PLEXOS, market-clearing prices are determined by calculating the shadow price of the electricity demand constraint for each balancing authority and timestep. As a production cost model, GridView does not simulate or optimize infrastructure investment and retirement decisions.

The GridView system representation and input data (resources, demand, and grid topology) used for this analysis are based on the WECC 2030 Anchor Data Set (ADS) Version 2.3 (WECC, 2015). This is a common industry developed and vetted case study that is intended to represent anticipated WI infrastructure and operations in 2030. The transmission network topology for the

WECC 2030 ADS was carried over from the 2030HS1 (heavy summer) power flow, which was compiled by the WECC Reliability Assessment Committee using General Electric positive sequence load flow software. That transmission topology was imported into the WECC 2030 ADS case as a foundation for the transmission network topology and represents the best available projection of new generation, generation retirements, transmission assets, and load growth in the WECC grid planning community 10-year planning horizon.

In the WECC 2030 ADS case, wind and solar resource availability is defined hourly for each wind and solar generator. The hourly wind resource profiles are based on 2009 NREL wind speed and weather data, while the hourly solar resource profiles are based on 2009 NREL irradiance and weather data (WECC, 2021). Hydro resources are modeled using monthly average generation values from EIA Forms 906 and 920 for the year 2009, which is considered to be an average hydrologic year. Hourly electricity demand profiles are projected for each WI load area, which in most cases are analogous to the balancing authority boundaries. These demand profiles are adjusted to account for anticipated behind the meter generation so that they reflect only the native load of what is visible to the transmission system. The adjusted hourly load-area profiles are then disaggregated to the nodes of each load area using predefined nodal participation factors with a 2009 historical load shape.

The nine WI grid scenarios presented in Table 2-1 are further elaborated here. The Reference scenario corresponds to the WECC 2030 ADS. All other scenarios are designed based on the Reference scenario after modifying their modeling inputs. The Reference scenario and the first five sensitivity scenarios all use the same generation portfolio across the WI. The final three scenarios include adjustments to the system generation portfolio as detailed below.

- In the Wet Hydro and Dry Hydro scenarios, the monthly energy targets and monthly minimum and maximum operating capacity of each hydropower resource in the model are adjusted to reflect 1997 and 2005 hydrologic conditions, respectively. These changes result in a net +4.0%/-4.6% increase/decrease in hydro generation compared to the Reference scenario.

- In the High Electrification scenario, the total WECC load is increased by +2.7% over the reference year to represent potential accelerated electrification of the transportation sector. This projection is based on a study that modeled the aggregate hourly electricity demand requirements of 30 million light- and heavy-duty electric vehicles.[15] This projection is then added to the hourly electricity demand profile of the Reference scenario. This load increase is applied to four load areas in California: Northern California, the PG&E Bay area, the San Diego Gas & Electric area, and the Los Angeles Department of Water and Power area.

- The High Natural Gas Price scenario assumes that natural gas prices for the power sector are 50% higher ($4.20/MMBtu) than in the Reference scenario ($2.80/MMBtu).

The final three scenarios include adjustments to the system generation portfolio. In each case, some coal units present in the Reference scenario are replaced with a combination of wind, solar, and energy storage resources.

- In the Moderate VRE scenario, 30% of the total coal capacity in the WI (4,490 MW) is replaced with 14,395 MW of wind and 3,565 MW of solar, with no changes in energy storage capacity.

- In the High VRE scenario, 100% of the total WI coal capacity (14,975 MW) is replaced with 46,500 MW of wind, 13,400 MW of solar, and 20,300 MW of 4-hour energy storage.

- Finally, in the High VRE with LDES scenario, 100% of the total WI coal capacity (14,975 MW) is replaced with 46,500 MW of wind, 13,400 MW of solar, and 20,300 MW of 10-hour energy storage.

To create these generation portfolios, we first assumed that all coal retirements are replaced by four times as much combined wind and solar capacity. The breakdown between wind and solar capacity that replaces each retired coal plant is then determined based on the corresponding projected ratio between wind and solar in the North American Electric Reliability Corporation (NERC) sub-region where the plant is located. More specifically, these ratios are determined based on EIA-860M datasets that project wind and solar deployment through 2035 (EIA, 2022). The replacement ratios for each sub-region in are shown in Figure A-3.

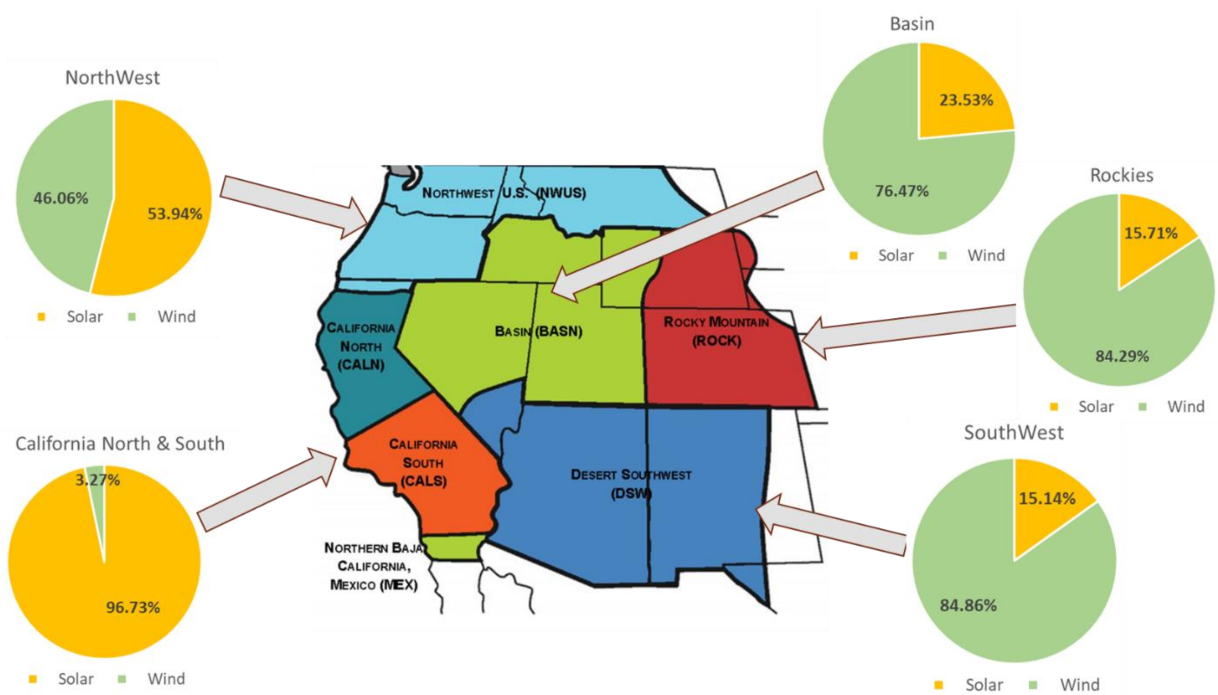


Figure A-3 Replacement ratios for the six NERC subregions.

The amount of energy storage capacity added to each High VRE scenario is determined based on currently deployed hybrid generation and storage projects across the U.S. (Berkeley Lab, 2021). We used these datasets to compute the current average ratio of wind and solar to storage. These ratios are then multiplied by the installed capacity of solar and wind resources to determine the energy storage capacity. The wind to storage ratio was found to be approximately 25% (for every

1 MW of wind, 0.25 MW of energy storage is installed) while the solar to storage ratio is around 68% (for every 1 MW of solar, 0.68 MW of energy storage is installed). Applying these ratios to the 46,500 MW of wind and 13,400 MW of solar that are added to the WI in the High VRE scenario results in 20,300 MW of additional storage capacity. The first High VRE scenario assumes that this capacity consists entirely of 4-hour lithium-ion batteries, while the High VRE with LDES scenario assumes that the capacity consists entirely of 10-hour lithium ion batteries.

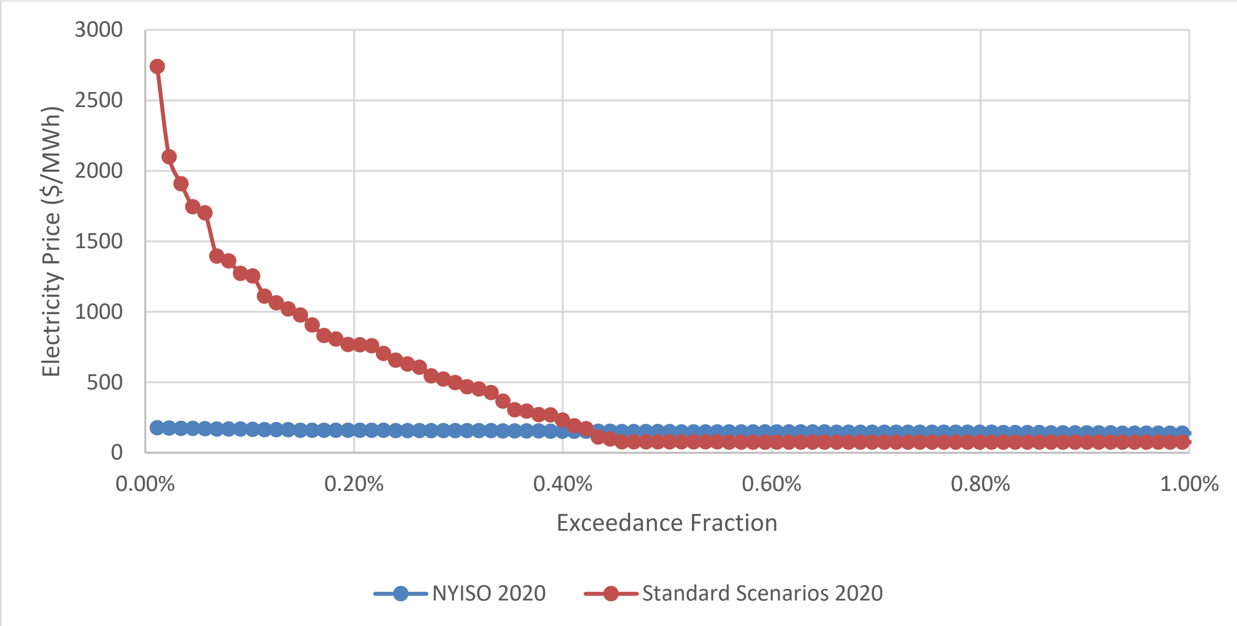
A.3 Statistical Price Calibration

A.3.1 Limitations of PCMs

PCMs generate electricity prices by calculating the shadow price of the demand constraint in a particular region at a particular timestep. This shadow price is the additional cost that would be incurred if electricity demand were increased by one unit, or alternatively the marginal generation cost of the resource that would serve this additional unit of demand. This is generally the same process used to form prices in wholesale electricity markets.

PCMs are valuable tools for simulating power system outcomes and analyzing trends. However, they are generally not able to replicate the full complexity of real-world power systems due to data and computational limitations, and therefore the results they produce must be interpreted in the proper context. There are several factors that may cause simulated prices to systematically deviate from real-world outcomes. First, they may not fully capture system input details, such as electricity demand, wind or solar availability, or generator outages. Second, they may not fully capture transmission congestion, due to zonal aggregation or by electing not to model physics-based power flows. Third, the costs, performance characteristics, and market behavior of individual resources may be simplified in PCMs.

Price exceedance curves for the historical day-ahead electricity prices from the NYISO market in 2020 and the prices generated by the NREL Standard Scenarios Mid case for upstate New York in the year 2020 are shown in Figure A-4 to illustrate the differences in their distributions (NERL, 2020). In this specific case, the prices generated by the Standard Scenarios are generally higher than the historical market prices from NYISO, with mean values of $36.43/MWh and $21.49/MWh respectively. This is particularly apparent at both tails. At the upper tail of the distribution, the Standard Scenarios prices reach $2,739/MWh compared to a maximum price from the NYISO market of $177/MWh. At the lower end of the distribution, negative prices are observed in nearly 5% of historical time periods, while the PCM price never falls below $22/MWh. These findings are specific to this individual case and cannot necessarily be generalized more broadly to other regions or other models. However, this specific example, particularly the large divergence in distributions at the tails, does serve to point out the need for both further investigation and the development and implementation of the calibration methodology presented in the following section.



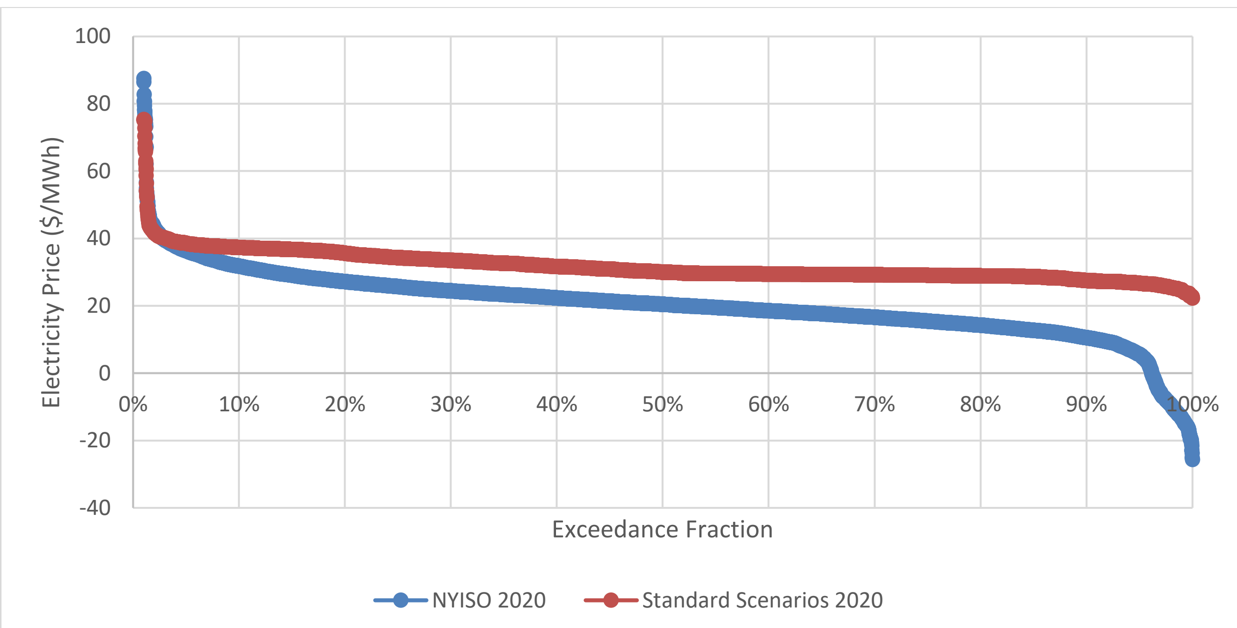


Figure A-4 Price exceedance curves for the first 1% of the distribution (top) and the remaining 99% of the distribution (bottom).

A.3.2 Methodology

In order to improve the fidelity of the electricity prices used in this application of our VDF, we implemented a statistical price calibration methodology to adjust the PCM-generated price distributions. To this end, we developed a four-step process to first establish a preferred statistical approach and then apply it to calibrate the PCM price profiles:

1. Data pre-processing

2. Residual distribution modeling
3. Data calibration
4. Model validation

A.3.2.1 Data Pre-processing

We first establish the historical price residuals, which represent the differences between historical prices and the corresponding PCM prices. The residuals are defined by Equation 1.

$$R_t = P\_historical_t - P_{PCM_t} \tag{1}$$

Here $P\_historical_t$ is the price from a real-world market at time *t*, and P_PCM_t is the outcome of a PCM at time *t*. For a given time period, e.g., one year, if the mean of R_t is zero, and the variance is constant, we consider the model to have no bias. If the mean is non-zero, the PCM prices require some level of calibration to ensure that they are aligned with the price distribution from the corresponding real-world market that the PCM simulates. Several additional variables from the PCM can serve as inputs for this calibration process, including electricity demand, renewable generation, and renewable curtailment. Assuming price calibration is desired, we apply a series of pre-processing steps to clean up, normalize, and synchronize the data as needed.

A.3.2.2 Residual Distribution Modeling

The purpose of residual distribution modeling is to model the distribution of the residuals (e.g., the difference between prices generated by the PCM and those that result from the real-world wholesale electricity market). We assume that the residuals are correlated both temporally and with other data that are either inputs to or outputs from the PCM. Variables such as total load, conventional generation, renewable generation, and renewable curtailment are referred to as PCM input features. The distribution of price residuals in each modeled timestep is assumed to be normal (Gaussian), and it remains to estimate the parameters of this normal distribution that define the residuals based on input features.

Once the parameters of the normal distribution function are estimated, the distribution can be used to generate random sample residuals. These are then added back to PCM electricity prices, ensuring that resultant distribution of calibrated PCM prices is more closely aligned with the historical price distribution.

Given the limited availability of input data, the stochastic nature of the underlying physical system, and the need to retain inherent uncertainty in the calibrated prices, Bayesian inference is applied to infer the properties of the residual distribution, e.g., the parameters of the distribution function. Bayesian inference is a statistical inference method to estimate the probability of a hypothesis in which a prior knowledge of the distribution is used as a starting point. Bayes' theorem is then applied to update the estimation as more data become available (Efron, 2013). Specifically, in our application, both a Bayesian linear regression and a dual-headed Bayesian neural network (DBNN) are developed to estimate the parameters of residual distributions.

A neural network is currently considered to be the most powerful type of learning model because of its ability to approximate any function with an arbitrary degree of accuracy (universal function approximation). For our application we implement a DBNN that utilizes Bayes' theorem to train its parameters.

A.3.2.3 Data Calibration

The data calibration architecture consists of the main body, which processes the inputs, and two heads, each producing a single value as output (e.g., the mean and variance of an assumed distribution). Like conventional neural networks, the DBNN is also parameterized by weights and biases and may be trained using supervised learning algorithms. During model training, the model parameters are optimized to improve the fidelity of the outputs that the model produces. However, unlike conventional neural networks, the DBNN parameters do not converge to a point estimate. Instead, each DBNN parameter is sampled from a distribution. The trainable parameters in our DBNN model are the mean and standard deviation of the desired residual distribution. We do this to account for the inherent uncertainty in the model parameters due to the limited availability of training data. The DBNN therefore produces two values, representing mean and standard deviation, which collectively parameterize the normal distribution that represents the residuals. This enables us to account for uncertainty due to the stochastic nature of the process.

Once the distribution of the price residuals has been established in the previous step, residual samples can be generated and added back to the price data from the PCM. This process is implemented through Monte Carlo sampling methods. The performance of the calibration is validated on multiple simulation paths to ensure the efficiency of the proposed model. The temporal dependence of the price time-series data is also conserved in the sampling process.

A.3.2.4 Model Validation

Finally, we define two types of metrics to quantify the level of similarity between the calibrated PCM price profile and the historical price profile: point-wise metrics and distribution level metrics.

Point-wise metrics: Two error metrics quantify the point-to-point error of the calibrated PCM price profiles: the symmetric mean absolute percentage error and the median absolute deviation. These are calculated, as shown in Equations 2 and 3, to compare the performance of calibrated samples with real, observed samples.

$$sMAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{|\hat{y}_i - y_i|}{(|y_i| + |\hat{y}_i|)/2} \times 100\% \qquad (2)$$

$$MAD = median(|\hat{y}_i - y_i|) \qquad (3)$$

where $\hat{y}_i$and y_i are the i^{th} data points from compared price profiles, respectively, and n is the number of data points.

Distribution level metrics: Often it is either unnecessary or impossible to accurately estimate the point-to-point error, especially in a long-term forecasting application. In this case, the overall similarity of the two distributions can be quantified in terms of the differences between two or more statistics across the two distributions, i.e., the statistical distance, as shown in Equation 4.

$$SD = \sqrt{\frac{\sum_{i=1}^{S} w_i(\hat{s}_i - s_i)^2}{S}} \tag{4}$$

where $\hat{s}_i$ and s_i are the i^{th} statistics that have been selected from the two price distributions, w_i is the weight of i^{th} statistic, and S is the number of statistics selected to quantify the statistical distance. Possible statistics to consider include minimum, maximum, median, mean, and standard deviation.

A.3.3 Case Studies

A.3.3.1 Validation

The following shows this calibration process using data generated by NREL's Standard Scenarios for zone p127 and real-world historical data from zone E of the NYISO electricity market. In this demonstration, hourly prices from the 2018 calendar year are used for training, while those from the 2020 calendar year are used for calibration testing. Figure A-5 illustrates the training and testing process with 2018 and 2020 data sets.

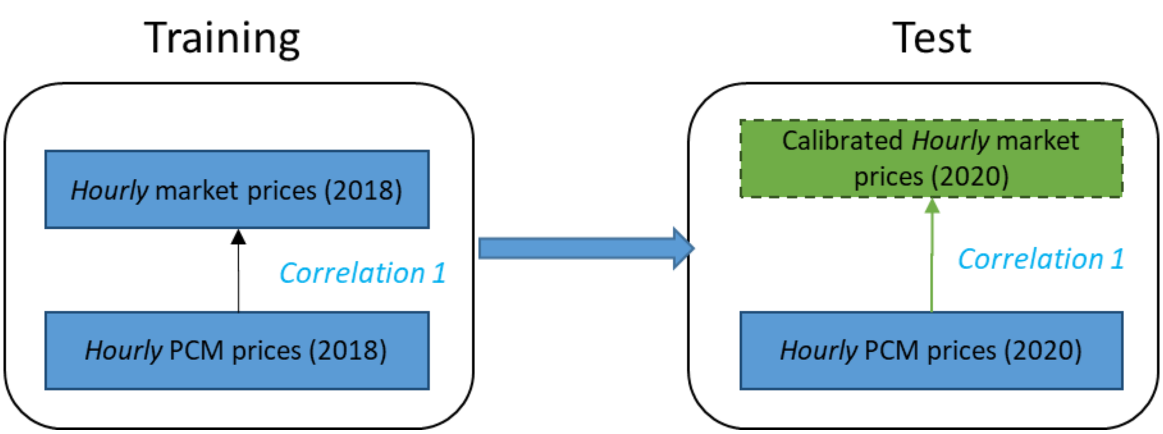


Figure A-5 Diagram of calibration process in the case study.

Figure A-6 compares the distributions for historical prices from NYISO in 2020, the uncalibrated PCM prices, and the calibrated PCM prices. Additional detail is provided in Table A-1. It is clear that this calibration process is able to shift the distribution of the original PCM prices to align it more closely with historical market data. This overall improved alignment between price distributions enables us to conduct the hydropower value analysis outlined in the following sections with greater confidence and reliability.

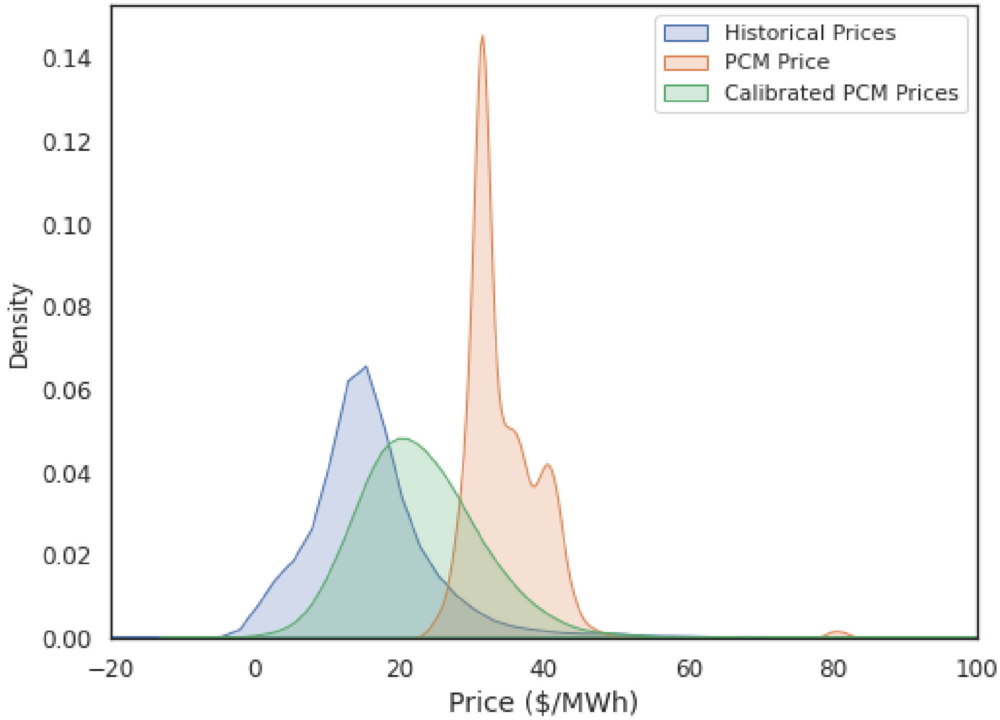


Figure A-6 Probability density comparison of price profiles from historical market data, the original PCM data and the calibrated PCM data.

Table A-1 Comparison of price statistics from historical market data, the original PCM data and the calibrated PCM data

Statistic	Historical Prices ($)	PCM Prices ($)	Calibrated PCM Prices ($)
Maximum	350.06	82.97	173.82
Minimum	-136.47	23.53	-91.39
Median	15.07	32.36	14.50
Mean	16.50	34.45	16.07
Standard Deviation	11.92	6.01	11.90

A.3.3.2 Forward Application

The primary application of this process is calibrating PCM prices that are generated in future system conditions that may differ somewhat substantially from current system conditions. To this end, we make the following assumptions: 1) the distribution of residuals between PCM outputs and the real-world system is consistent over time, and 2) the PCM is able to capture the high-level impacts of changes in system conditions, e.g., generation mix, load, etc. The residual distribution is then trained with historical data and applied to calibrate the outputs from the PCM for a target future year, e.g., 2030. As illustrated in Figure A-7 , the residual distribution is trained on electricity prices from the PCM and the day-ahead real-world market, both in 2020. These are then applied to calibrate the PCM prices generated in 2030 in future system conditions. The output is a calibrated time series of hourly prices that is expected to closely follow the distribution of day-ahead prices that would result in the real-world market in the modeled system conditions.

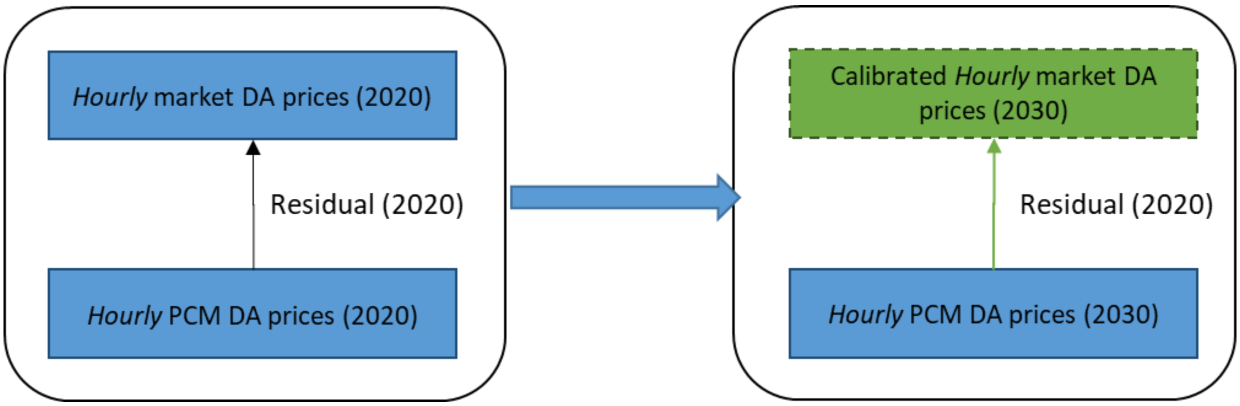


Figure A-7 Diagram of applying trained residual distribution to calibrate PCM-generated prices for a target future year.

A.4 Reservoir Hydropower Optimization

A.4.1 Weekly Water Allocation

Reservoir water management plans and actual water releases are typically based on operating rules and guidelines that consider known factors such as the current state of reservoir(s) and environmental operating criteria. Managers also use projections of various uncertain futures such as reservoir water inflows, power market prices, and water delivery demands. In real time, reservoir operators make decisions and deploy water releases with the understanding that these actions will have long-term consequences. That is, the release of limited water resources today typically reduces the amount of water that will be available in the future. Therefore, release decisions made today will impact scheduling and planning decisions made over a longer period, for as long as a one-year period or more for reservoirs with a large water storage capacity.

As time passes, reservoir states often differ from what was previously envisaged because actual inflows did not exactly match what was initially projected. Water managers, therefore, react to reservoir elevation deviations from the schedule by updating projected futures based on the newly unfolded reality and by adjusting current water release amounts.

In order to simulate the real-world operations of a reservoir hydropower resource, it is therefore important to have a modeling framework that mimics this process, in which decisions are made based on anticipated future conditions (inflows and market prices), and then plans and actions are updated based on current/actual water and power grid states. For example, a model that simultaneously optimizes an entire year of hydropower resource based on predefined inflow and price profiles would have more foreknowledge than is available in practice and would not capture the impacts of uncertainty. Alternatively, a model that myopically optimizes a single day or week of operations at a time, without consideration of potential future conditions, may sacrifice future value opportunities in pursuit of less lucrative opportunities in the current period.

The water allocation tool (WAT) developed by Argonne simulates this process of water management decision making, actions, and reactions in order to generate periodic (e.g., daily, weekly, etc.) water release targets. These are then used to constrain a more detailed hourly hydropower dispatch optimization tool, the CHEERS model (Section A.4.2). It combines a simulation of water scheduling decisions with an optimization tool to mimic reservoir and hydropower operator actions in a simulated "reality" framework. WAT first schedules water releases at the beginning of a simulated week as well as planned water releases for the next 51 weeks. These weekly water releases are optimized to maximize the expected value of energy based on the reservoir elevation at the beginning of the current week and a deterministic future of projected weekly inflows and grid energy prices (e.g., most probable projection).

The model then releases the scheduled amount over the current week. Then "actual" inflows are realized during the week, based on a historical or stochastic sequence of events that were unknown to the model's decision-making process. For this analysis, we selected historical water release patterns that represented various plausible future hydrological conditions ranging from dry to wet. The model then computes the reservoir elevation at the end of the current simulated week. Typically, this simulated elevation differs from what was anticipated at the beginning of the week. Next, WAT advances the date by one week and repeats the process; that is, it revises scheduled and planned releases over the next 52 weeks, makes "actual" releases during the current week, simulates inflows, and computes the end-of-week reservoir elevation. For the applications outlined in this report, the process is repeated for each week of a simulated year.

As shown in Figure A-8, water storage reserves at the top of the reservoir accommodate simulated "actual" water inflows that are higher than forecasted to reduce the risk of non-power water releases via bypass and spillway routes. Similarly, capacity reserves at the low end of the reservoir storage range accommodate lower than projected inflows to help maintain, but not guarantee, a pool elevation above the minimum required for power production.

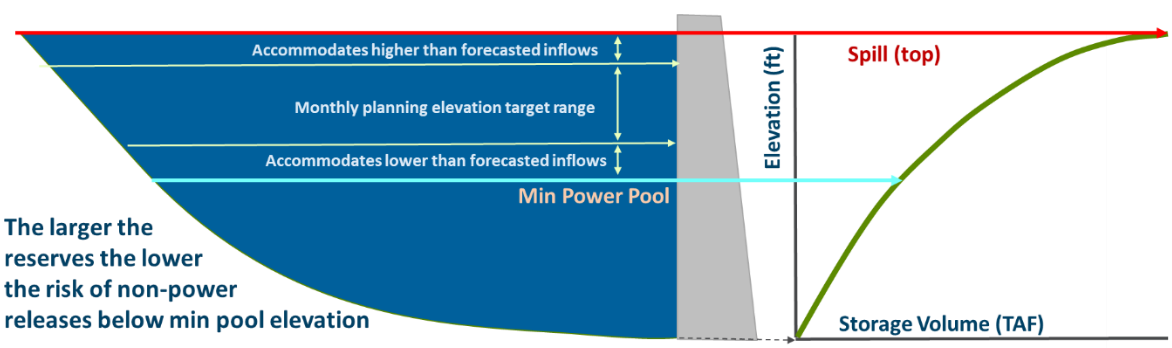


Figure A-8 Illustration of the WAT risk-based operating and planning concept.

The size of the WAT water storage reserves at the top and bottom of the reservoir are based on user-defined risk tolerance levels associated with a probability distribution of inflow forecast errors. This risk calculation is based on short-term (current week) and long-term (rest of the year) probability distributions of inflow forecast error. Reservoir reserve requirements vary with the time of the year, because some seasons have lower forecast errors than others. The higher the reserves, the lower the risk. However, as the target reservoir operating range narrows, both hydropower plant operating flexibility and economic/financial value diminish.

Projected market prices are the primary driver that shapes the release of a limited annual water volume from a reservoir during a one-year period. In general, water resource/reservoir managers and hydropower plant schedulers can project approximate long-term and diurnal price trends with some level of accuracy. However, any attempts to predict exact prices for a specific points in time are subject to a wide range of forecast error. For example, it is possible to anticipate that average prices in July and August will typically be relatively high and will display a single daily up/down cycle pattern, and it can be expected that prices during May and October will be lower. However, projecting the price for any one specific hour many months in the future with a reasonable level of accuracy is not practical. Therefore, operational decisions that have implications for future revenue streams must be made under uncertainty.

The modeling framework mimics this decision making process under uncertainty by first computing an average weekly price trend and then superimposing “typical” hourly price profiles onto this long-term trend. More specifically, average weekly energy prices are computed with a PCM, and then a polynomial equation is used to fit a trend line to the 52 chronologically ordered weekly averages. Next, average diurnal energy price profiles are constructed by computing average prices; that is, an average energy price is computed for all hours ending at 01:00 during the week. Likewise averages are computed for each hour of the day, i.e., the hours ending 02:00, 03:00, and up to 24:00. A shaping index is then computed as the ratio of the weekly average price (all hours) to the average price for a specific time (e.g., the hour ending 01:00). Prices that are higher than the weekly value have an index above 1, while prices below the average have a value less than 1. The daily shaped indexes are then used to superimpose the hourly price pattern for each day onto the weekly smooth price trend line and thereby generate a weekly average price curve.

Next, a value-of-water curve is constructed for each week of the year by ranking hourly prices during a week from highest to lowest and then multiplying the project price by both a water-to-power conversion factor and the maximum turbine flow at the plant. Cumulative values are then computed to construct a concave curve. The result of this procedure is shown in Figure A-9 (blue line) for the first simulation week. However, when water is first allocated to generating power in hours with the highest energy prices, there are decreasing marginal returns (green line). WAT uses an approximation of this value-of-water curve by selecting specific points on the curve (red points) to compute a piecewise linear curve (PWLC) of water release volume versus economic value.

The WAT model then uses 52 separate PWLCs (one for each week of the year) along with projected inflows and reservoir elevation and volume limits to determine the weekly allocation of water releases throughout a year that yields the highest possible expected total annual value.

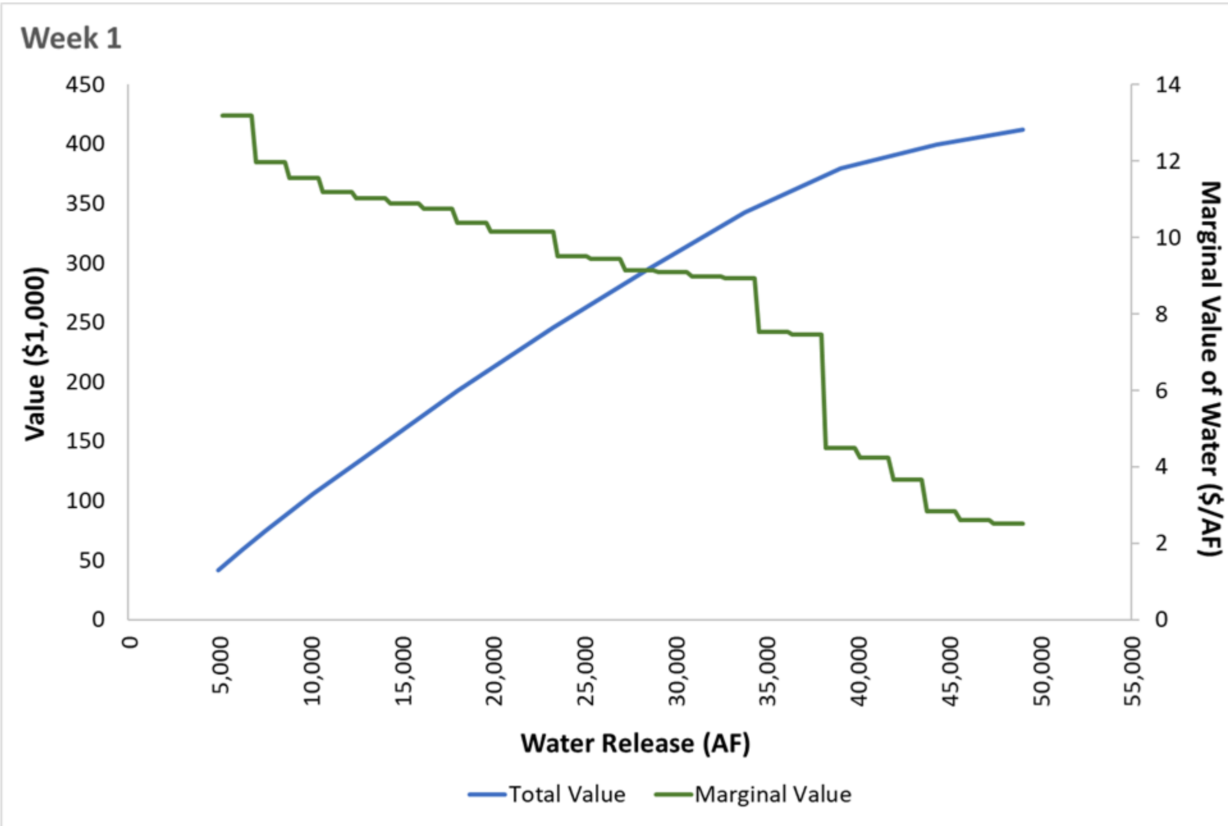


Figure A-9 Sample value of water curve for the first week of the year.

A sample result of a water management plan generated by WAT in the first week of a year is shown in Figure A-10. In this simulation, the projected water reservoir elevation (dark blue line) is a function of projected inflows (dark green dashed line) and optimal water releases (red line). The objective of the mixed-integer linear optimization problem solved by WAT is to maximize the value of water releases for hydropower production based on anticipated future locational marginal price patterns.

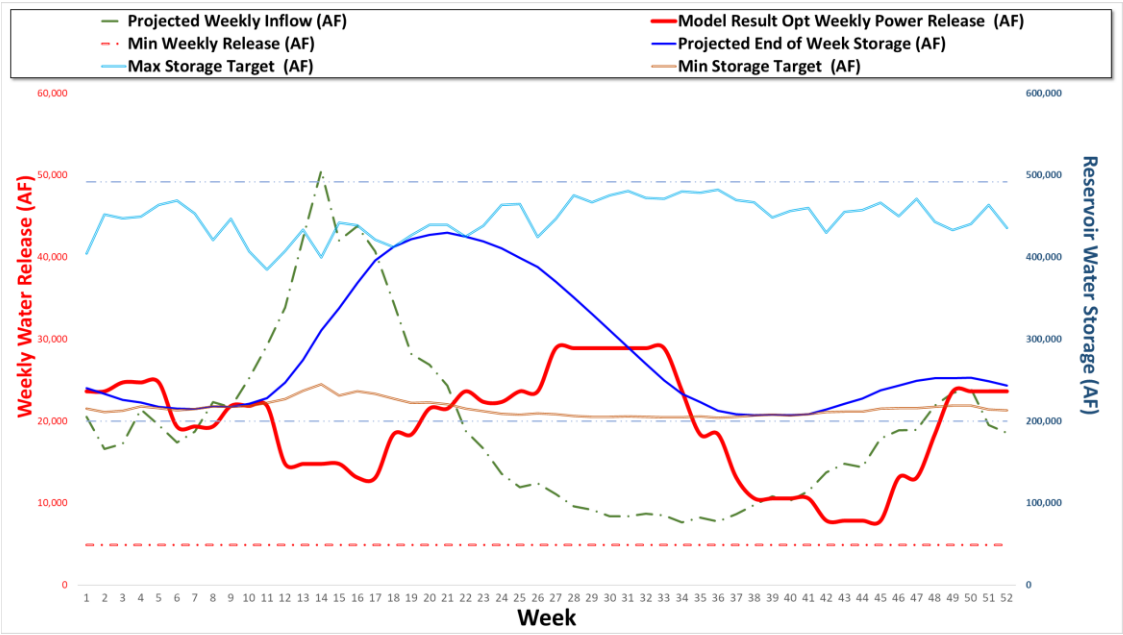


Figure A-10 A simulated water planning schedule produced at the beginning of a year.

Note that the reservoir elevation does not exceed the maximum storage target (light blue line) or drop below the minimum storage target (light brown line). As described above, reservoir water reserves are based on a user-defined risk-tolerance ruleset that attempts to avoid negative outcomes due to forecast error, such as non-power water releases, unmet water deliveries, and reservoir elevations dipping below the minimum power pool.

As WAT progresses through the year, simulated water decisions and scheduling are adjusted each week because the reservoir state at the end of the week differs from the previous plan (see Figure A-11). Depending on simulated "actual" inflow levels and energy market prices, the final model results differ from initial projections due to inflow forecast error and the actions taken by water managers as simulated time unfolds.

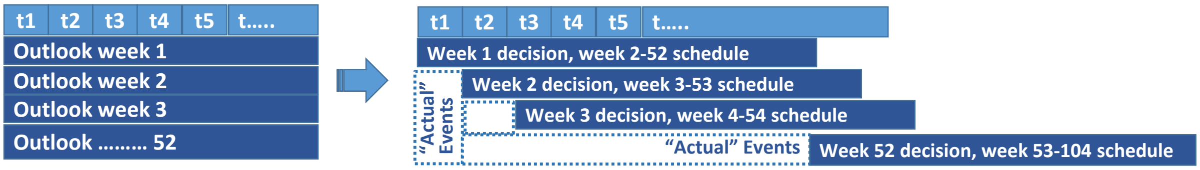


Figure A-11 Simulated water release decision-making process.

In contrast to Figure A-10, where the reservoir elevation remains within the targeted band, shows the simulated scheduling and operating decisions that were made over a one-year period (52 decision points), each of which was based on a forward outlook of one year. Note that because of forecast error, water storage levels at times exceeded the maximum target level and at other times were below the minimum.

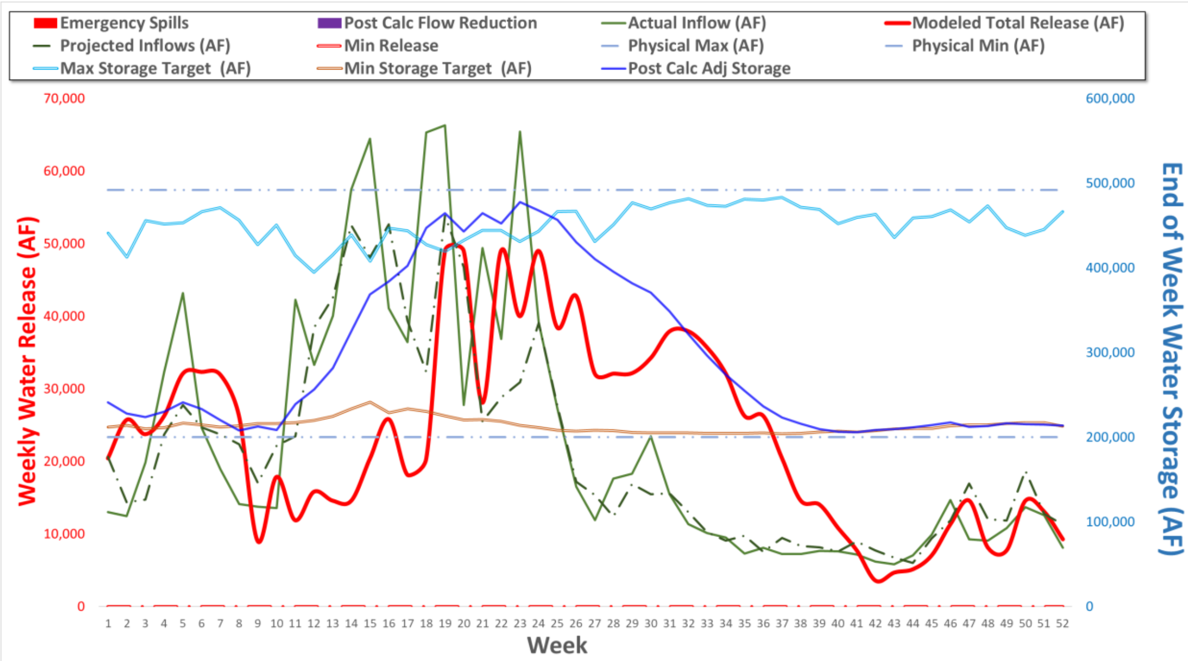


Figure A-12 A simulated water planning schedule that is updated throughout the year.

However, the reservoir water volume reserves avoid non-power water releases, and the elevation always remains above the minimum power pool despite the fact that projected inflows (dashed green line) and actual inflows (continuous green line) differ significantly at some points in time and in some instances for extended periods (i.e., several weeks). Note that the projection of inflows (dashed green line) in Figure A-10 and Figure A-12 differs because as simulated time unfolds, inflows during the following week can be more accurately projected than projections over the entire year.

The end result of this process is a set of periodic water allocation targets—in our case, 52 weekly allocations—for the hydropower resource being modeled. These then serve as inputs to CHEERS and constrain the optimization of AS provision and hourly water releases for electricity generation over 52 successive one-week periods. Without these targets, the CHEERS model would maximize value in each week myopically, having no incentive to save water to provide value in future periods.

A.4.2 Hourly Dispatch and Water Management

As discussed in the body of this report, the analysis presented here is based on a set of a "standardized" plants that provide representations of realistic, but hypothetical, generic plants rather any particular real-world plant. We use this approach because a standardized plant provides a neutral platform that can better isolate and evaluate the value-driving factors being varied across modeling runs. Actual plants each have a number of specific or even unique features and characteristics that ultimately lend a site-specific color to the modeling results. For example, a given real-world plant's generators may have rough zones that must be avoided, have certain location-specific physical ramp or flow rate restrictions, operate as a coordinated component of a larger resource portfolio, or be subject to time-based output limitations due to local transmission contracts.

In addition, modeling of an actual plant typically requires the cooperation and effort of the plant's operational staff in order to gain the level of knowledge necessary to accurately represent the plant as well as to obtain the data required to model all of the plant's functional relationships—data that are often incomplete or problematic in other ways that require manual inspection and clean-up. Overall, in the context of this analysis's objectives, attempting to model actual plants would introduce complexity and require significant effort that would not be justified by any potential insights that could not be reached by modeling standardized plants.

In order to optimize the operations of conventional hydropower resources with reservoirs, we used Argonne National Laboratory's CHEERS model, a network-based optimization model that permits a user to build an arbitrary representation of the plant and system being analyzed. Nodes can be used to represent physical structures such as hydro reservoirs, entire hydropower plants or individual generating units, water inflow and outflow locations, and economic structures such as energy load centers, energy contracts, and spot markets. Links represent connections between nodes such as rivers or other flow channels, transmission lines, or contractual power flows connecting various resources and demands.

After building the network, the user provides technical specifications for individual components and the constraints describing how the system components can interact with one another, and defines the priorities and goals to be ultimately achieved via the system optimization. Finally, the user defines the temporal structure of the period to be optimized, provides relevant temporal input data (such as expected water inflows and projected energy market prices), and invokes the optimization, which is solved in the form of a mixed integer linear program. Following the optimization, the user is informed of when, where, and how to best apply available resources in order to meet the stated system goals. A detailed technical description of the CHEERS model along with sample applications can be found in Gasper et al. (2013).

The physical structure of the model defined for this analysis is shown in Figure A-13. The system starts with a *system inflow* point at which incoming water originates. The incoming water flows to an *upper reservoir* node where it can be released immediately and/or stored for later release. Water released from the *upper reservoir* can either flow to the *plant* or bypass the *plant* and flow directly to the *lower reservoir*. Any water released to the *plant* is converted into energy and/or AS that are sold to the *market*, with the water in turn flowing down to be stored in the *lower reservoir*. The *feasibility water* node is connected to each reservoir and acts as a water source or sink of last resort; it would only be activated in order to satisfy system constraints if there is no other possible way to do so according to the relevant input data provided, and any such activation serves as a signal to the modelers that the constraints and/or data must be reviewed and adjusted accordingly.

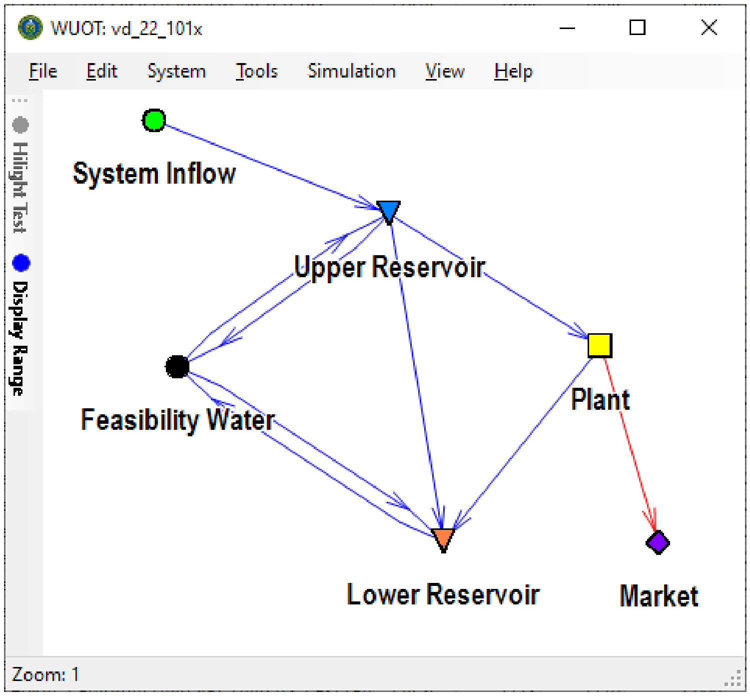


Figure A-13 Physical structure of the model as displayed in the CHEERS software.

In CHEERS, a single scenario is evaluated across a set of 52 one-week runs, covering a calendar year, with each run consisting of 168 one-hour timesteps. Although each one-week run is optimized independently of the others, system continuity is maintained from week to week via the model inputs provided by WAT: the initial reservoir volume at the beginning of the week and the total weekly reservoir release target for the week.

The objective function of the model is simply to maximize market revenue from the production and sale of energy and AS that can be produced by the *plant* from the available water. Hourly prices for energy and each of four ancillary services (regulation up, regulation down, spinning reserve, and non-spinning reserve) are provided as inputs to the *market* node.

The most important system technical specifications and constraints are provided on a weekly basis by the weekly scheduling tool:

- The *upper reservoir* begins the week with an initial specified volume of stored water. During each hour, a certain volume of water enters the *upper reservoir* from the *system inflow*, at a flow rate that remains constant throughout the week.

- During each hour the *upper reservoir* volume must remain within certain minimum and maximum levels. Each hour a certain minimum flow rate must be released from the *upper reservoir*.

- Throughout the week a certain volume of water must flow into the *lower reservoir*, either by passing through the *plant* or by spilling directly from the *upper reservoir*.

- The water-to-power conversion rate of the *plant* is defined based on the reservoir volume and is updated each week.

- Likewise a maximum power output is specified for each week that also naturally serves to limit the total quantities of energy and AS that can be produced in any given hour.

Several other operational constraints are applied to the system uniformly across all scenarios. The plant is allowed to shut down in any given hour and halt all production of energy and AS. When the plant is running, a minimum output of 10% installed capacity must be maintained. A $10/MW cost is applied in the objective function for each startup or shutdown event. Any hourly regulation service must be symmetrical; that is, whenever the plant is providing regulation service, the same level must be provided in both directions, up and down. In our Reference case, a ramp limit constrains the hourly change in generation output to 25% of the plant's maximum output—it takes four hours for the plant to transition from zero to maximum generation. With slow ramp plant sensitivity this limit is 12.5% (8 hours), and with fast ramp plant sensitivity there is no limit on ramping (1 hour).

After the optimization has been completed according to the specifications and constraints described above, the hourly provision of energy for each ancillary service is multiplied by the market prices provided for each service to obtain the total market value generated over the course of the year.

A.5 Pumped Storage Hydropower Optimization

We use the Pumped Storage Hydropower Market Analysis Tool (PMAT) to assess the value of PSH across a range of plant characteristics and future system conditions. PMAT is part of the Argonne Low-carbon Electricity Analysis Framework (A-LEAF), an optimization model that determines the optimal market participation strategy and scheduling of a closed-loop PSH plant based on potential revenue streams from various grid services.

The grid services in this application include energy, regulation up, regulation down, spinning reserve, and non-spinning reserve. PMAT performs a time-coupled co-optimization of energy and AS provision to determine the optimal market participation strategy and scheduling of a PSH plant to maximize net plant revenue. PMAT is a price-taker model; therefore, the model provides an upper bound of the possible profit of a PSH plant for a fixed set of market prices, assuming perfect price foresight over the optimization period. PMAT includes a detailed representation of the physical and operational constraints of a closed-loop PSH plant, as shown in Figure A-14.

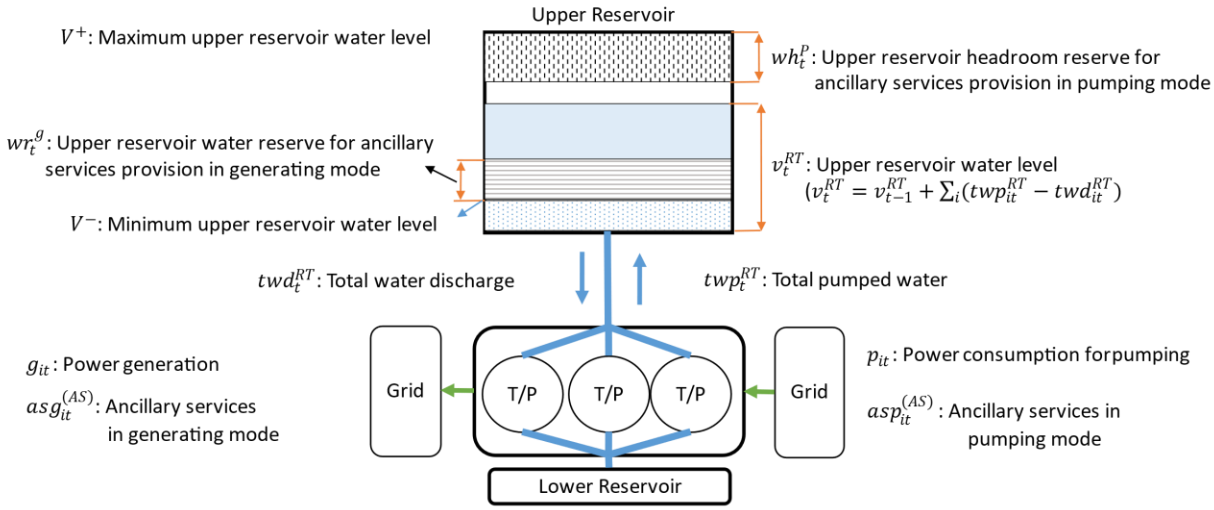


Figure A-14 Modeling of PSH in PMAT.

In this project, we apply PMAT to a standardized closed-loop PSH plant. Table A-2 summarizes the Reference model parameters used in the case study. Note that these technical specifications are based on realistic assumptions, but do not represent any one specific real-world PSH plant currently in operation.

Table A-2 Reference PSH plant parameters

Category	Technical Specification	Value
Plant	Number of units	1
	Round-trip efficiency (%)	84
	Fixed O&M cost ($/kW-yr)	$21.00
	Variable O&M cost ($/MWh)	$4.00
	Storage capacity (MWh [hours])	400 [4]
Generator	Maximum capacity (MW)	100
	Minimum capacity (MW)	20
	Energy conversion rate (MW/AF-min)	42.7
	Ramp rate (MW/min)	10
Pump	Maximum capacity (MW)	100
	Minimum capacity (MW)	60
	Energy conversion rate (MW/AF-min)	81.5
	Ramp rate (MW/min)	10
Market Participation	Maximum AS participation (MW)	10

We also considered eight additional sensitivity scenarios with varying PSH storage durations and AS provision limits, as summarized in Table A-3. We adjusted the upper reservoir maximum water level according to the PSH storage duration in each scenario. The AS provision limits are modeled to prevent the unrealistic provision of AS from PSH and reflect the fact that AS markets are relatively small compared to energy markets. Therefore a single PSH plant may only be able to provide individual ancillary services with a portion of its capacity before satisfying the entire requirement or impacting prices. The AS provision limit constraints in PMAT dictate that the total provision of AS in each hour is less than the predefined percentage of the nameplate capacity.

Table A-3 PSH storage duration and AS provision limit scenarios

Sensitivity Name	PSH Storage Duration (Hours)	Maximum AS participation (%)
Low Storage + Low AS	5	0
Low Storage + Mid AS	5	10
Low Storage + High AS	5	20
Mid Storage + Low AS	10	0
Reference	10	10
Mid Storage + High AS	10	20
High Storage + Low AS	20	0
High Storage + Mid AS	20	10
High Storage + High AS	20	20

A.6 References for Appendix A: Methods and Data

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Appendix B: Findings from Literature

Appendix B presents findings from a review of 67 studies related to quantifying how power system value streams may evolve in different future conditions. Many of these studies were not specific to hydropower, and some are only tangentially related to understanding value, but they still provide results that can be used to draw relevant conclusions. Figure B-15 provides a simplified high level summary of our findings from this review. Green cells with plus signs represent a positive correlation, while red cells with minus signs represent a negative correlation. Grey cells represent unavailable or inconclusive findings. Table B-1 provides more details on the specific findings extracted from 39 of the studies reviewed. We also present 17 key conclusions from this review that represent a synthesis of all the individual findings.

Most of the findings reported in the individual papers are presented in a technology-neutral manner in terms of the implications for the value of different grid services, though some of them are specific to hydropower. Therefore some original interpretation is used in drawing these conclusions and relating them more specifically to hydropower.

	Energy Price	Energy Generation	Ancillary Service Value	System Value
Carbon Price	+			
Water Availability	+			
Electricity Demand	+		-	
Flow Restrictions		-		
Operational Flexibility		+	+	
Fossil Fuel Prices	+	+		
System Storage Capacity	-			+
System Resource Adequacy	+			
Transmission Capacity				+
Natural Gas Capacity			-	
VRE Penetration	-	-	+	

Figure B-15 Summary of findings from literature review

Table B-1 Summary of specific key findings extracted from literature

Finding	Value Driver	Value Stream	Value Impact	Description	References
1	Increased VRE generation	Energy	Decreases	Lower energy prices from the merit order effect	Wiser et al. (2017), Mills et al. (2021), (Swinand and O'Mahoney (2015), Dillig et al. (2016), Brancucci Martinez-Anido et al. (2016), Zarnikau et al. (2020), Doering et al. (2021), Ranzani et al. (2018), Kern et al. (2014), Seel et al. (2018), Bushnell and Novan (2018), Csereklyei et al. (2019), Ketterer (2014), Woo et al. (2013), Pereira and Saraiva (2014), Benhmad and Percebois (2018), Kaufmann and Vaid (2016), Quint and Dahlke (2019), Sensfuß et al. (2008)
2	Increased VRE generation	Ancillary services	Increases	Higher demand for ancillary services	Levin (2018), Kern et al. (2014), Seel et al. (2018), Badesa et al. (2021)
3	Increased VRE generation	Total	Decreases	Reduced generation from substitution effect	Schäffer et al. (2019)
4	Increased VRE generation	Energy	Increases	Greater frequency and magnitude of energy price spikes caused by VRE resource shortfalls	Doering et al. (2021), Seel et al. (2018)
5	Increased VRE generation	Flexibility	Increases	Higher short-term system ramping requirements	Schäffer et al. (2019)
6	Increased carbon prices	Energy	Increases	Higher energy prices and competitive advantage for zero-carbon generation	(Levin et al. (2019), Ranzani et al. (2018), Sensfuß et al. (2008)
7	Decreased water availability	Energy	Decreases	Reduces energy generation	Lucena et al. (2018), Zhou et al. (2018), Markoff and Cullen (2008), Arango-Aramburo et al. (2019), Boehlert et al. (2016), Lehner et al. (2005)
8	Decreased electricity demand	Energy	Decreases	Decreased energy demand decreases prices	Ghiani et al. (2020)
9	Decreased electricity demand	Ancillary services	Increases	Decreased energy demand reduces available generation and increases AS value	Badesa et al. (2021), Ghiani et al. (2020)
10	Increased flow restrictions	Energy	Decreases	Reduced operational flexibility	Schillinger et al. (2020)

Finding	Value Driver	Value Stream	Value Impact	Description	References
11	Increased operational flexibility	Total	Increases	Allows resources to provide reserves or pump between reservoirs	Gonzalez-Salazar and Poganietz (2021), Ak et al. (2019), Helseth et al. (2017)
12	Increased fossil fuel prices	Energy	Increases	Increases marginal generation costs	Levin et al. (2019), Zarnikau et al. (2020), Ranzani et al. (2018), Helseth et al. (2017), Denholm et al. (2013), Zou and Chau (2020)
13	Increased system storage capacity	Energy	Decreases	Reduced arbitrage opportunities for hydropower	Levin (2018)
14	Increased system storage capacity	System	Increases	Reduced wind and solar curtailments	Denholm and Mai (2019)
15	Decreased system resource adequacy	Energy	Increases	High energy prices and more frequent scarcity conditions	Frew et al. (2019)
16	Increased transmission capacity	System	Increases	Greater intraregional access to hydropower	Dimanchev et al. (2021)
17	Increased natural gas capacity, replacing coal and nuclear	Regulation	Decreases	Greater regulation supply	Levin (2018)

Table B-2 Summary of findings from 39 studies relevant to hydropower value drivers

Finding Supported	Study	Value Stream	Location	Value Driver	System Change	Value Impact
1	Swinand and O'Mahoney (2015)	Energy	Ireland	VRE penetration	Wind generation increases by 1%	System energy price decreases by 0.06%.
1	Dillig and Karl (2016)	Energy	Germany	VRE penetration	68.6 GW of VRE removed	Energy price increases to $52.90/MWh.
1	Martinez-Anido et al. (2016)	Energy	ISO-NE	VRE penetration	Wind penetration increases from 0% to 21.21%	Average energy price decreases by 25% with no forecasting and by 2% with perfect forecasting.
1	Wiser et al. (2017)	Energy	U.S.	VRE penetration	VRE penetration increases by 1%	Average energy price decreases by $0.10/MWh to $0.80/MWh.
1	Zarnikau et al. (2020)	Energy	MISO	VRE penetration	Wind generation increases by 1MWh	DAM energy price decreases from $0.0006/MWh to $0.0021/MWh.
1	Doering et al. (2021)	Energy	ERCOT	VRE penetration	Wind penetration increases	Average energy spot price decreases.
1	Ranzani et al. (2018)	Total value	Switzerland	VRE penetration	VRE generation increases by 20%	Revenues decrease by 5%.
1	Kern et al. (2014)	Total value	Southeastern U.S.	VRE penetration	Wind penetration increases to 5%	Profit decreases by 4%.
1	Seel et al. (2018)	Energy	U.S.	VRE penetration	VRE penetration increases by 1%	Energy price decreases by $0.20 to $0.90/MWh.
1	Seel et al. (2018)	Energy	CAISO	VRE penetration	VRE penetration increases from 22% to 41%	Load-weighted average energy price decreases from $58/MWh to $42-44/MWh.
1	Seel et al. (2018)	Energy	NYISO	VRE penetration	VRE penetration increases from 4% to 40%	Load-weighted average energy price decreases from $43/MWh to $26/MWh.
1	Seel et al. (2018)	Energy	ERCOT	VRE penetration	VRE penetration increases from 17% to 38%	Load-weighted average energy price decreases from $35/MWh to $30/MWh.
1	Seel et al. (2018)	Energy	SPP	VRE penetration	VRE penetration increases from 18% to 44%	Load-weighted average energy price decreases from $33/MWh to $24/MWh.
1	Bushnell and Novan (2018)	Energy	CAISO	VRE penetration	Daily solar generation increases by 1 GWh	RTM energy price decreases by $0.10/MWh.
1	Csereklyei (2019)	Energy	Australia	VRE penetration	Wind capacity increases by 1 GW	Instantaneous energy price decreases by $11 AUD/MWh.

Table B-2 Summary of findings from 39 studies relevant to hydropower value drivers (Cont.).

Finding Supported	Study	Value Stream	Location	Value Driver	System Change	Value Impact
1	Csereklyei (2019)	Energy	Australia	VRE penetration	Solar capacity increases by 1 GW	Instantaneous energy price decreases by $14 AUD/MWh.
1	Swinand and O'Mahoney (2015)	Energy	Ireland	VRE penetration	Wind generation increases by 1%	Energy price decreases by 0.06%.
1	Ketterer (2014)	Energy	Germany	VRE penetration	Wind power generation increases	Energy price decreases, volatility increases.
1	Woo et al. (2013)	Energy	ERCOT	VRE penetration	Average wind generation increases by 100 MW	Energy price decreases by $0.565/MWh.
1	Mills et al. (2021)	Energy	U.S.	VRE penetration	VRE penetration increases by 1%	Energy price decreases by $0.14/MWh.
1	Pereira and Saraiva (2014)	Energy	Portugal	VRE penetration	Wind generation increases by 2.85 TWh	Energy price decreases by 1 €/MWh.
1	Benhmad and Percebois (2018)	Energy	Denmark	VRE penetration	Wind generation increases by 1% during peak hours	Average peak energy price decreases by 0.06% to 0.07%.
1	Kauffmann and Vaid (2016)	Energy	Massachusetts	VRE penetration	Rooftop solar generation increases by 1 MWh	Energy price decreases by $0.26 to $1.86/MWh.
1	Quint and Dahlke (2019)	Energy	MISO	VRE penetration	Wind generation increases by 100 MWh	Energy price decreases by $0.14 to $0.34/MW.
1	Seel et al. (2018)	Energy	CAISO	VRE penetration	VRE penetration exceeds 40%	Early morning energy price decreases by $25/MWh in spring and $10/MWh in fall and winter.
1	Seel et al. (2018)	Energy	NYISO	VRE penetration	VRE penetration exceeds 40%	Early morning energy price decreases by $20/MWh in spring and $5/MWh in summer.
1	Seel et al. (2018)	Energy	NYISO	VRE penetration	VRE penetration exceeds 40%	Afternoon energy price decreases by $30/MWh in spring and summer and $15/MWh in the fall.
1	Sensfub et al. (2008)	Energy	Germany	VRE penetration	VRE generation increases by 40%	Merit-order effect increases by 31%.
2	Levin (2018)	Regulation	PJM	VRE penetration	Wind penetration increases from 2% to 30%	Regulation price increases by 32%.

Table B-2 Summary of findings from 39 studies relevant to hydropower value drivers (Cont.).

Finding Supported	Study	Value Stream	Location	Value Driver	System Change	Value Impact
2	Levin (2018)	Regulation	PJM	VRE penetration	Wind penetration increases from 2% to 30% and regulation requirement doubles	Regulation price increases by 84%.
2	Kern et al. (2014)	Total value	Southeastern U.S.	VRE penetration	Wind penetration reaches 25%	Profit increases by 16% due to increased reserve value.
2	Kern et al. (2014)	Reserves	Southeastern U.S.	VRE penetration	Wind penetration reaches 25%	Reserve provision increases to 1:1 (energy:reserves) vs. 8:5.
2	Seel et al. (2018)	Ancillary services	U.S.	VRE penetration	VRE penetration exceeds 40%	Regulation and spinning reserve price decreases by a factor of 2 to 8 depending on region.
2	Seel et al. (2018)	Non-spinning Reserve	U.S.	VRE penetration	VRE penetration exceeds 40%	Non-spinning reserve price increases modestly.
2	Badesa et al. (2021)	Ancillary services	Great Britain	VRE penetration	Net-zero emissions by 2050	Share of system costs attributable to ancillary services increases from 2% to 35%.
3	Schaffer et al. (2019)	Energy	Europe	VRE penetration	VRE penetration increases from 27% to 54%	Hydropower generation decreases by 0% to 5%.
3	Schaffer et al. (2019)	Total value	Europe	VRE penetration	VRE penetration increases from 27% to 54%	Hydropower income decreases by 4% to 6%.
4	Doering et al. (2021)	Energy	ERCOT	VRE penetration	Wind penetration increases	Frequency of price spikes (>$1,000/MWh) increases.
4	Seel et al. (2018)	Regulation	U.S.	VRE penetration	VRE penetration exceeds 40%	The frequency of high-priced hours (>$25/MWh) for regulation down increases from almost zero to 5%-40% depending on region.
5	Schaffer et al. (2019)	Flexibility	Europe	VRE penetration	VRE penetration increases from 27% to 54%	Added value of flexibility increases by 5-18% for gas and hydropower plants.
6	Ranzani et al. (2018)	Energy	Switzerland	Carbon price	35 euro/ton carbon price	Revenue increases by 15%.
6	Ranzani et al. (2018)	Energy	Switzerland	Carbon price	50 euro/ton carbon price	Revenue increases by 26%.
6	Sensfub et al. (2008)	Energy	Germany	Carbon price	40 euro/ton carbon price	Merit-order effect reduces by 16%.

Table B-2 Summary of findings from 39 studies relevant to hydropower value drivers (Cont.)

Finding Supported	Study	Value Stream	Location	Value Driver	System Change	Value Impact
6	Levin et al. (2019)	Energy	ERCOT	Carbon price	$60/ton carbon price	Energy price increases by 36%.
7	Lucena et al. (2018)	Energy	Brazil	Water availability	Low impact climate scenario	Hydropower generation decreases by 1.4% to 2.4%.
7	Zhou et al. (2018)	Energy	Global	Water availability	RCP 8.5 climate scenario in 2100	Hydropower generation changes globally, decreasing 71% in Middle East and increasing 14% in former Soviet Union.
7	Markoff and Cullen (2007)	Energy	Pacific Northwest	Water availability	Various climate projections	Expected hydropower generation decreases by 1 GW average output from 2010 to 2039, compared to 1961 to 1990.
7	Markoff and Cullen (2007)	Total value	Pacific Northwest	Water availability	Various climate projections	Revenue impact varies from -15% to -2% from 2010 to 2039 and -30% to 2% from 2040 to 2069, both compared to 1961 to 1990.
7	Arango-Aramburo et al. (2019)	Energy	Colombia	Water availability	Dry climate scenario (CRNM)	Hydropower generation decreases by approximately 10% by 2050.
7	Boehlert et al. (2016)	Energy	Pacific Northwest	Water availability	Climate scenario for 2100	Summer hydropower generation decreases by 9%-14%.
7	Lehner et al. (2005)	Energy	Europe	Water availability	Moderate climate change scenario in 2070	Hydropower potential decreases by 6%.
8	Ghiani et al. (2020)	Energy	Italy	Electricity demand	Electricity demand decreases by up to 37%	Energy price decreases by approximately 30%.
9	Ghiani et al. (2020)	Ancillary services	Italy	Electricity demand	Electricity demand decreases by up to 37%	Ancillary service costs increase by about 70%.
9	Badesa et al. (2021)	Ancillary services	Great Britain	Electricity demand	Electricity demand decreases by 28%	Ancillary service cost increases from £101 million to £302 million.
10	Schilinger et al. (2020)	Energy	Switzerland	Flow restrictions	Restriction to 10% (20%) monthly deviation from the natural river flow	Annual revenue decreases by up to 7% (6%).
10	Schilinger et al. (2020)	Energy	Switzerland	Flow restrictions	Restriction to 10% (20%) monthly deviation from the natural river flow	Annual revenue decreases by up to 24% (22%).

Table B-2 Summary of findings from 39 studies relevant to hydropower value drivers (Cont.).

Finding Supported	Study	Value Stream	Location	Value Driver	System Change	Value Impact
11	Gonzalez-Salazar (2021)	Energy	Latin America	Water availability	Droughts caused by ENSO (El Nino Southern Oscillation)	Hydropower generation decreases by 13.1% in Northern Hemisphere and 3.5% in Southern hemisphere.
11	Ak et al. (2019)	Energy	Turkey	Operational flexibility	Pumped storage capabilities are added to an existing hydropower resource	Revenue increases by 2.9% to 10.4% with an average of 6%.
11	Helseth et al. (2017)	Reserves	Norway	Operational flexibility	Plant provides 35.8% of capacity for reserves (vs. 0%)	Expected profit increases by 7.33%.
12	Helseth et al. (2017)	Reserves	Norway	Operational flexibility	Plant provides 43.3% of capacity for reserves (vs. 0%)	Expected profit increases by 10.78%.
12	Ranzani et al. (2018)	Energy	Switzerland	Fossil fuel prices	Fossil fuel prices increase by 50%	Revenue increases by 13% compared to 2015.
12	Ranzani et al. (2018)	Energy	Switzerland	Fossil fuel prices	Fossil fuel prices increase by 100%	Revenue increases by 29% compared to 2015.
12	Levin et al. (2019)	Energy	ERCOT	Fossil fuel prices	Natural gas price increases from \$4.64/MMbtu to \$7.12/MMbtu	Energy price increases by 16%.
12	Levin et al. (2019)	Regulation	ERCOT	Fossil fuel prices	Natural gas price increases from \$4.64/MMbtu to \$7.12/MMbtu	Regulation price increases by 10%.
12	Levin et al. (2019)	Spinning reserve	ERCOT	Fossil fuel prices	Natural gas price increases from \$4.64/MMbtu to \$7.12/MMbtu	Spinning reserve price decreases by 32%.
12	Levin et al. (2019)	Non-spinning Reserve	ERCOT	Fossil fuel prices	Natural gas price increases from \$4.64/MMbtu to \$7.12/MMbtu	Non-spinning reserve price is unchanged.
12	Denholm et al. (2013)	Spinning reserve	PSCO and WACM	Fossil fuel prices	Natural gas price increases from \$4.10/MMbtu to \$8.20/MMbtu	The value of spinning reserves provided by storage increases from \$65/kW-year to \$148/kW-year.
12	Denholm et al. (2013)	Regulation	PSCO and WACM	Fossil fuel prices	Natural gas price increases from \$4.10/MMbtu to \$8.20/MMbtu	The value of regulation reserves provided by storage increases from \$110/kW to \$205/kW.

Table B-2 Summary of findings from 39 studies relevant to hydropower value drivers (Cont.).

Finding Supported	Study	Value Stream	Location	Value Driver	System Change	Value Impact
12	Zarnikau et al. (2020)	Energy	MISO	Fossil fuel prices	Natural gas price increases by $1/Mmbtu	Regional DAM energy price increases by $4.17/MWh to $7.48/MWh.
12	Zou and Chau (2020)	Energy	China	Fossil fuel prices	Crude oil price increases	Hydropower use in China increases with price elasticity of 0.242 (long-term).
13	Levin (2018)	Regulation	PJM	System storage capacity	Battery storage capacity increases from 350 MW to 1750 MW	Regulation price to decreases by 28%.
14	Denholm and Mai (2019)	System value	ERCOT	System storage capacity	8.5 GW of 4-hour battery storage capacity is added to a 55% VRE system	Wind curtailment decreases from 11%–16% to 8%–10%.
14	Denholm and Mai (2019)	System value	ERCOT	System storage capacity	8.5 GW of 8-hour battery storage capacity is added to a 55% VRE system	Wind curtailment decreases from 11%–16% to 6.5%–9%.
14	Denholm and Mai (2019)	System value	ERCOT	System storage capacity	8.5 GW of 12-hour battery storage capacity is added to a 55% VRE system	Wind curtailment decreases from 11%–16% to 6%–8.5%
15	Frew et al. (2019)	Energy	32% VRE Test System	System resource adequacy	Resource adequacy decreases from .00037 hr/year to 2.7 hr/year (LOLE)	Average energy price increases by 2%, standard deviation increases by 16%.
15	Frew et al. (2019)	Energy	68% VRE Test System	System resource adequacy	Resource adequacy decreases from .00012 hr/year to 2.4 hr/year (LOLE)	Average energy price increases by 32%, standard deviation increases by 97%.
16	Dimanchev et al. (2021)	System costs	New England and Quebec	Transmission capacity	4 GW of new transmission capacity in a 99% decarbonization scenario	System costs decrease by $3/MWh ($913 million per year, 13% of total).
16	Dimanchev et al. (2021)	System costs	New England and Quebec	Transmission capacity	4 GW of new transmission capacity in a 100% decarbonization scenario	System costs decreases by $7/MWh ($2,387 million per year, 24% of total).
17	Levin (2018)	Regulation	PJM	Natural gas capacity	All coal capacity is replaced with natural gas	Regulation price decreases by 42%.
17	Levin (2018)	Regulation	PJM	Natural gas capacity	All nuclear capacity is replaced with natural gas	Regulation price decreases by 11%.

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Appendix C: Data Tables

Table C-1 Summary price statistics

		Mean Price ($/MWh or $/MW-h)							
Location	**Scenario**	**Energy**	**Reg-up**	**Reg-down**	**Spin**	**Non-spin**	**Capacity Price ($/kW-yr.)**	**VRE %**	**ZFC %**
NY	Reference	$21.49	$5.82	$0.00	$3.61	$3.09	$30.48	42.4%	63.5%
NY	High VRE	$15.00	$5.82	$0.00	$3.61	$3.09	$35.51	43.1%	64.7%
NY	High VRE High AS	$15.00	$11.64	$0.00	$7.23	$6.18	$35.51	43.1%	64.7%
TN	Reference	$17.27	$5.82	$0.00	$3.61	$3.09	$33.59	10.4%	18.8%
TN	High VRE	$14.49	$5.82	$0.00	$3.61	$3.09	$36.67	18.2%	27.3%
TN	High VRE High AS	$14.49	$11.64	$0.00	$7.23	$6.18	$36.67	18.2%	27.3%
OR	Reference	$23.01	$7.55	$6.58	$3.75	$1.61	$97.94	13.2%	75.5%
OR	Wet Hydro	$18.50	$7.55	$6.58	$3.75	$1.61	$121.19	12.0%	80.5%
OR	Dry Hydro	$29.11	$7.55	$6.58	$3.75	$1.61	$84.99	14.5%	69.7%
OR	High Electrification	$24.96	$7.55	$6.58	$3.75	$1.61	$89.46	13.2%	75.3%
OR	High Gas Price	$32.95	$7.55	$6.58	$3.75	$1.61	$76.75	13.3%	75.8%
OR	Moderate VRE	$19.94	$7.55	$6.58	$3.75	$1.61	$134.25	13.4%	76.6%
OR	High VRE	$18.20	$7.55	$6.58	$3.75	$1.61	$47.11	13.7%	78.3%
OR	High VRE with LDES	$17.68	$7.55	$6.58	$3.75	$1.61	$50.63	13.7%	78.6%
OR	High VRE High AS	$18.20	$15.09	$13.16	$7.50	$3.21	$47.11	13.7%	78.3%
CO	Reference	$22.39	$7.55	$6.58	$3.75	$1.61	$74.47	10.3%	34.3%
CO	Wet Hydro	$20.54	$7.55	$6.58	$3.75	$1.61	$76.85	10.5%	36.0%
CO	Dry Hydro	$23.86	$7.55	$6.58	$3.75	$1.61	$70.59	10.5%	29.3%
CO	High Electrification	$24.37	$7.55	$6.58	$3.75	$1.61	$60.44	10.3%	34.1%
CO	High Gas Price	$30.71	$7.55	$6.58	$3.75	$1.61	$68.50	9.8%	32.5%
CO	Moderate VRE	$15.47	$7.55	$6.58	$3.75	$1.61	$86.23	24.4%	48.2%
CO	High VRE	$5.00	$7.55	$6.58	$3.75	$1.61	$61.60	78.2%	97.8%
CO	High VRE with LDES	$4.47	$7.55	$6.58	$3.75	$1.61	$62.24	78.8%	97.9%

Table C-1 Summary price statistics (Cont.)

		Mean Price ($/MWh or $/MW-h)							
Location	Scenario	Energy	Reg-up	Reg-down	Spin	Non-spin	Capacity Price ($/kW-yr.)	VRE %	ZFC %
CO	High VRE High AS	$5.00	$15.09	$13.16	$7.50	$3.21	$61.60	78.2%	97.8%
CA	Reference	$54.92	$7.55	$6.58	$3.75	$1.61	$44.87	45.5%	70.8%
CA	Wet Hydro	$51.48	$7.55	$6.58	$3.75	$1.61	$45.77	42.5%	75.4%
CA	Dry Hydro	$58.35	$7.55	$6.58	$3.75	$1.61	$40.57	46.6%	67.5%
CA	High Electrification	$56.42	$7.55	$6.58	$3.75	$1.61	$26.49	45.1%	70.2%
CA	High Gas Price	$66.53	$7.55	$6.58	$3.75	$1.61	$45.95	45.8%	71.3%
CA	Moderate VRE	$51.93	$7.55	$6.58	$3.75	$1.61	$46.43	45.7%	71.2%
CA	High VRE	$51.78	$7.55	$6.58	$3.75	$1.61	$47.59	46.0%	72.0%
CA	High VRE with LDES	$51.16	$7.55	$6.58	$3.75	$1.61	$49.42	46.0%	72.0%
CA	High VRE High AS	$51.78	$15.09	$13.16	$7.50	$3.21	$47.59	46.0%	72.0%

This report was prepared for the U.S. Department of Energy (DOE). As such, this document was prepared in compliance with Section 515 of the Treasury and General Government Appropriations Act for fiscal year 2001 (public law 106-554) and information quality guidelines issued by DOE. Although this report does not constitute "influential" information, as that term is defined in DOE's information quality guidelines or the Office of Management and Budget's Information Quality Bulletin for Peer Review, the study was reviewed both internally and externally prior to publication.

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