The moonshot 100% clean electricity study

Assessing the tradeoffs among clean portfolios with a PNM case study

Technical Appendix 1:
Load forecasting and Practitioner Toolkit

GridLAB

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Table of Contents

Load Forecasting

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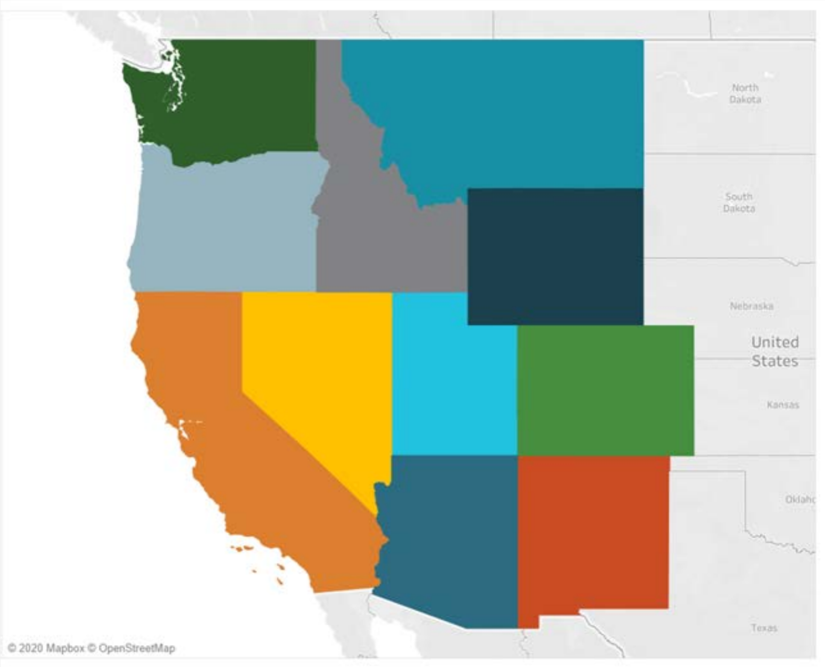
Load forecasting objectives

- Develop Load shapes and end use profiles for all states in the West
  - 8 weather years and a TMY weather year
- Use the economy-wide demand side model EnergyPATHWAYS so that the forecasted loads incorporate decarbonization impacts, especially in terms of electrification
  - Includes a bottom-up representation of technology stocks that consume electricity
- Forecast load shapes through 2050 based on scenario assumptions
  - (Note although the study was focused on a 2035 target year, EnergyPATHWAYS develops forecasts through to 2050.)
  - How do these stocks evolve over time based on assumptions about customer sales?
  - How do energy service demands change over time?
  - How do population and productivity change over time?

Understand the impacts of different demand side futures for New Mexico

Overview of load forecast modeling approach in EnergyPATHWAYS



- EIA Annual Energy Outlook datasets downscaled from census division to state in order to characterize stock, service, and energy demand by subsector.
  - User defined s-curves for future technology adoption
- End-use shapes for buildings, industry, and transportation developed across multiple weather years
  - NREL Restock and Comstock models used for building HVAC
  - EVI-Pro Lite used to develop EV charging profiles
  - EPRI load shape library used for industrial customers
- Bottom up-load shapes are benchmarked against FERC form 714 historical load data to produce a set of hourly statistical reconciliations.
- A detailed description of methodology and data sources are include included in the supporting material of the 2022 Annual Decarbonization Perspective

Demand side modeling in EnergyPATHWAYS (1 of 2)

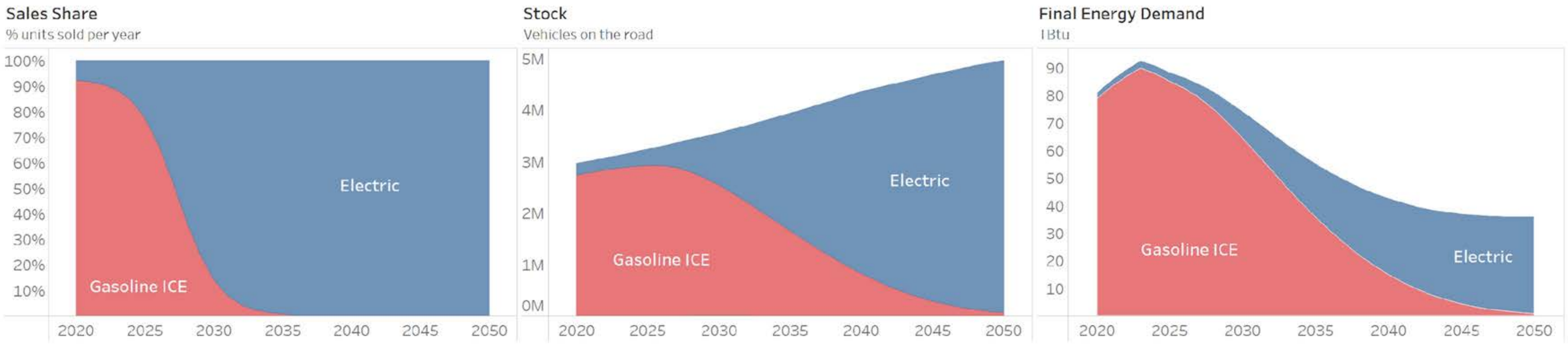
- Scenario-based, bottom-up energy model (not optimization-based)
- Characterizes rollover of stock over time at 1-year increments
- Simulates the change in total energy demand and load shape for every end use

Illustration of model inputs and outputs for light-duty vehicles

Input: Consumer Adoption
EV sales are 100% of consumer adoption by 2035 and thereafter

Output: Vehicle Stock
Stocks turn-over as vehicles age and retire

Output: Energy Demand
EV drive-train efficiency results in a drop in final-energy demand



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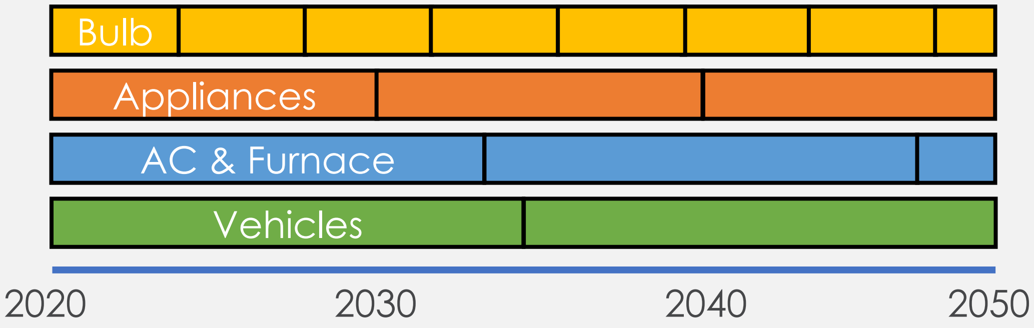
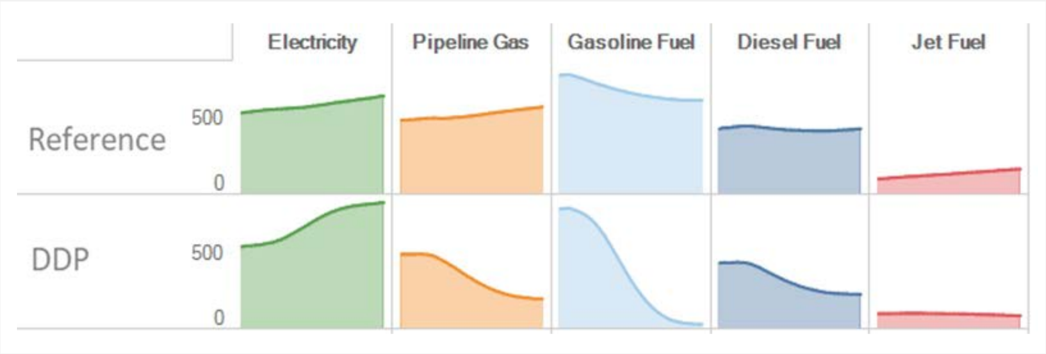
Demand side modeling in EnergyPATHWAYS (2 of 2)

Stock replacement assumptions before mid-century

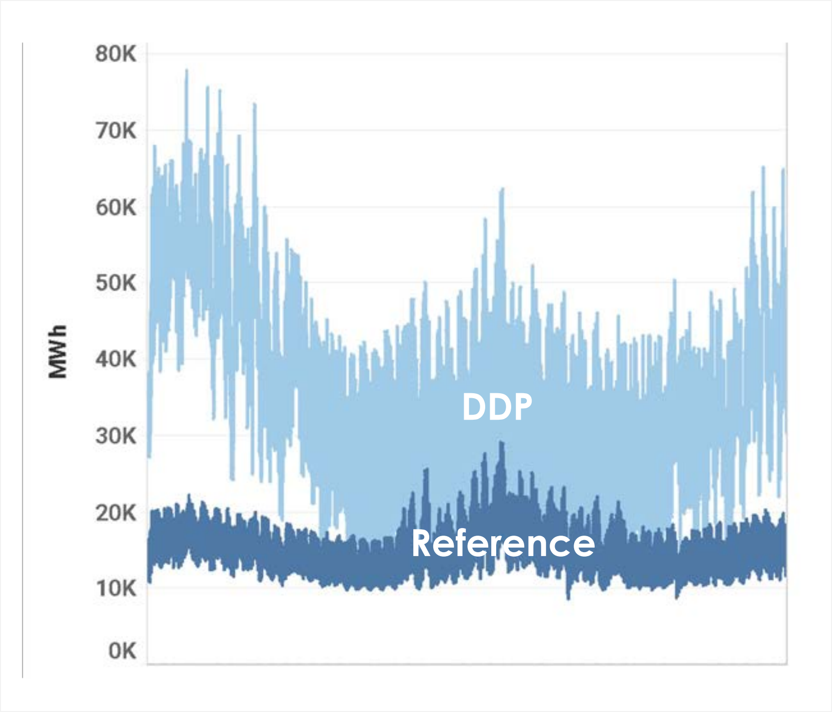


Resulting annual End-Use Energy Demand



This figure shows an illustrative example of how different energy types will change over time comparing a "Reference" case and a deep decarbonized case (DDP) due to electrification.

Hourly Aggregate and End Use Load Shapes



Example load shapes, not from this study.

GridLAB U.S. sectoral granularity based on EIA surveys

These are all the end uses that we represent in EnergyPATHWAYS that are based on EIA surveys.

Buildings

	Subsector		# Technologies
Commercial	commercial air conditioning	12 building types	22
	commercial cooking		4
	commercial lighting		26
	commercial other		N/A
	commercial refrigeration		18
	commercial space heating		18
	commercial unspecified		N/A
	commercial ventilation		4
	commercial water heating		7
	district services		N/A
	office equipment (non-p.c.)		N/A
	office equipment (p.c.)		N/A
Residential	residential air conditioning	3 building types	13
	residential clothes drying		3
	residential clothes washing		4
	residential computers and related		6
	residential cooking		3
	residential dishwashing		2
	residential freezing		4
	residential furnace fans		N/A
	residential lighting		39
	residential other uses		14
	residential refrigeration		6
	residential secondary heating		N/A
	residential space heating		18
	residential televisions and related		5
	residential water heating		6

Transportation

	Subsector	Sub-category	# Technologies
Transportation	aviation		N/A
	buses	3 duty cycles	5
	domestic shipping		N/A
	freight rail		N/A
	heavy duty trucks	2 duty cycles	6
	international shipping		N/A
	light duty autos		10
	light duty trucks	2 types	11
	lubricants		N/A
	medium duty trucks		6
	military use		N/A
	motorcycles		N/A
	passenger rail	3 types	N/A
	recreational boats		N/A

Industry

	Subsector	Sub-category
Industry	agriculture-crops	4 process types
	agriculture-other	4 process types
	aluminum industry	6 process types
	balance of manufacturing other	9 process types
	bulk chemicals	50 process types
	cement	8 process types
	coal mining	2 process types
	computer and electronic products	10 process types
	construction	3 process types
	electrical equip., appliances, and components	9 process types
	fabricated metal products	9 process types
	food and kindred products	9 process types
	glass and glass products	7 process types
	iron and steel	8 process types
	machinery	9 process types
	metal and other non-metallic mining	2 process types
	oil & gas mining	2 process types
	paper and allied products	7 process types
	petroleum refining	1 process type
	plastic and rubber products	9 process types
	transportation equipment	9 process types
	wood products	9 process types

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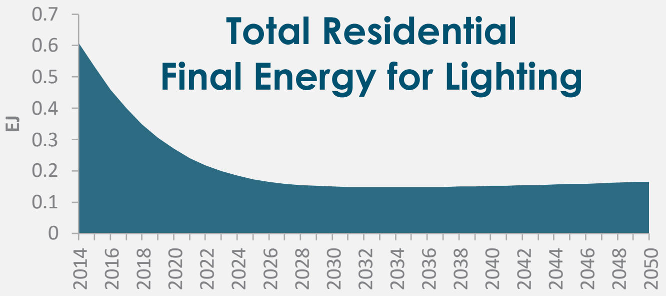
Load forecast scenarios developed for the Moonshot 100% clean electricity study

Input Assumption		Reference	High Electrification
Energy service demand		Annual Energy Outlook (AEO) 2022	
Efficiency	**Buildings**	AEO embedded efficiency	Sales of high efficiency appliances and improvement to building shell (2035 target)
	Transportation	Existing CAFÉ standards	1.5% per year aviation efficiency improvement
	Industry	AEO embedded efficiency	1% per year incremental efficiency improvements
Electrification	**Buildings**	Low electrification	100% electric technology sales by 2035
	Transportation	AEO adoption	100% ZEV sales by 2035
	Industry	None	Fuel switching for some process heat and other fuel use, DRI in iron and steel, carbon capture on cement

We developed two demand profile sets for this study to reflect approximate "book ends" of decarbonization possibilities. These input assumptions are consistent with several other decarbonization and power sector studies that Evolved Energy Research has conducted for US studies. Although these scenarios were developed before the IRA was formalized, the High Electrification scenario encompasses expected IRA impacts in terms of electrification impacts.

GridLAB Load shape development

The outputs of EnergyPATHWAYS, which include an hourly temporal resolution by end-use, for a representative weather year, for each state, are converted into hourly load profiles by applying end-use specific shapes derived from load research data.



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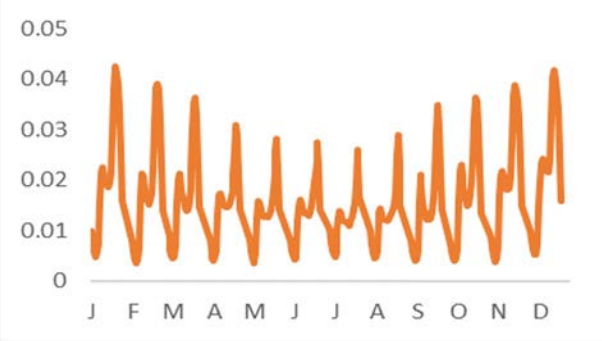


=

Projected lighting shape

+

Projected EV shape

+

Projected heating shape

+

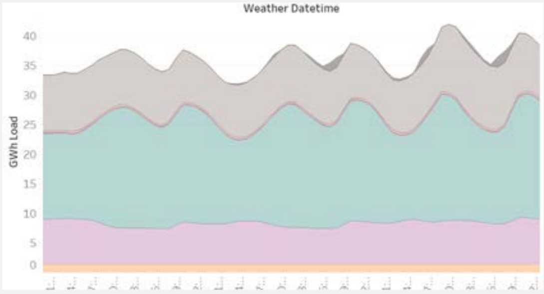
Projected dryer shape

+

Additional demand subsectors

=

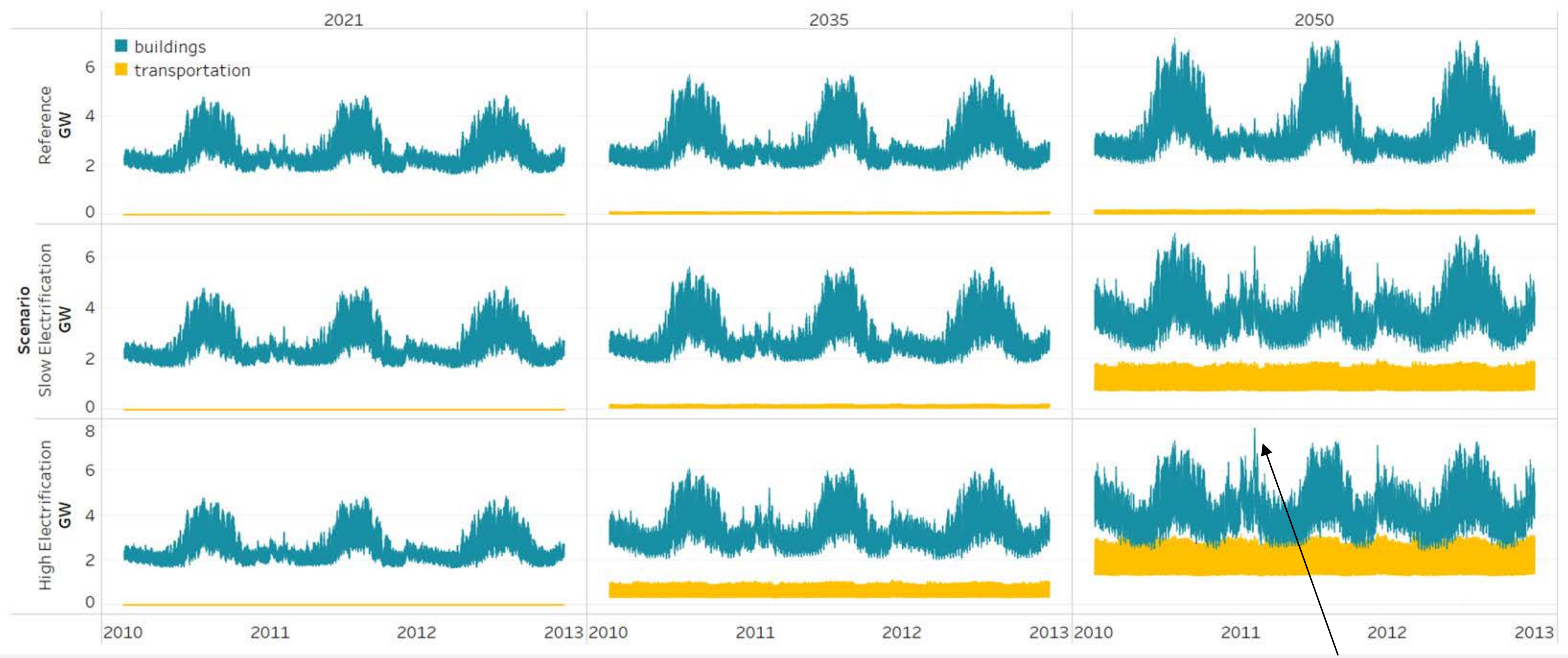
System Load



8 weather years of load shapes for all states in the West are used to construct the final load data. Instead of a single weather year or month-hour data, 70,080 hours of normalized end-use load data are multiplied by annual energy in this step.

Load Shape Results (NM 2010-2012 weather)

Economic Year

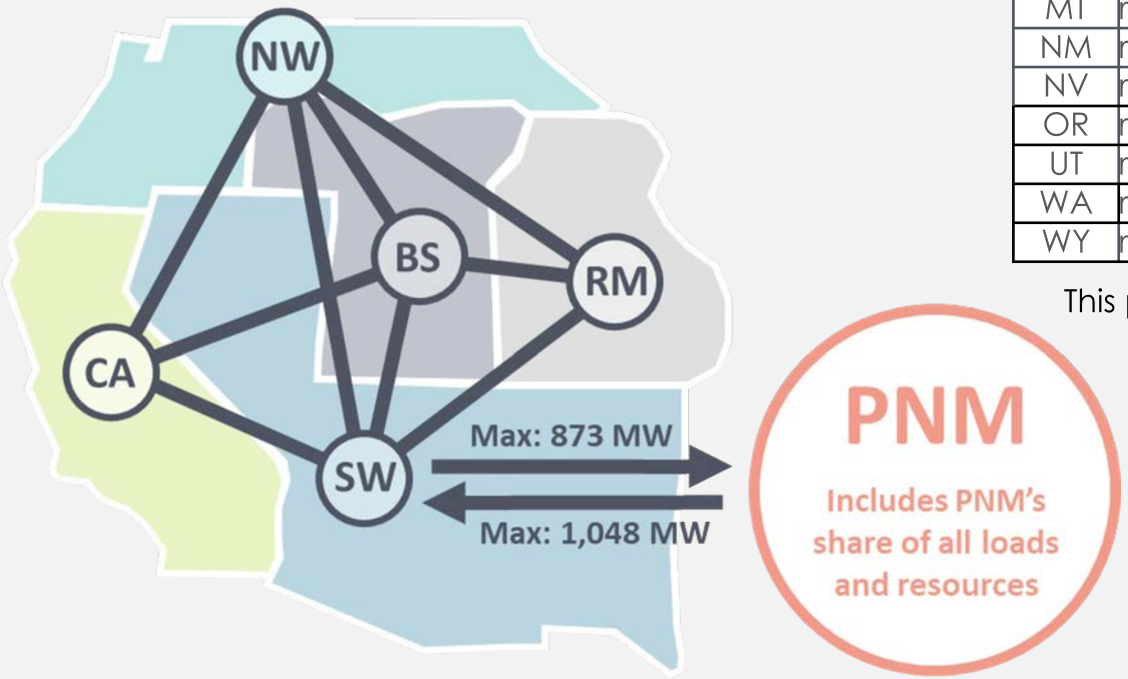


Weather Year

Multiple weather years are required to capture extreme heating load events

GridLAB State to PNM and BA conversion

The demand profiles generated by EnergyPATHWAYS were for each state in the West. The subsequent modeling steps required that this load be broken down to represent PNM's load, and the balancing areas (BAs) across the West.



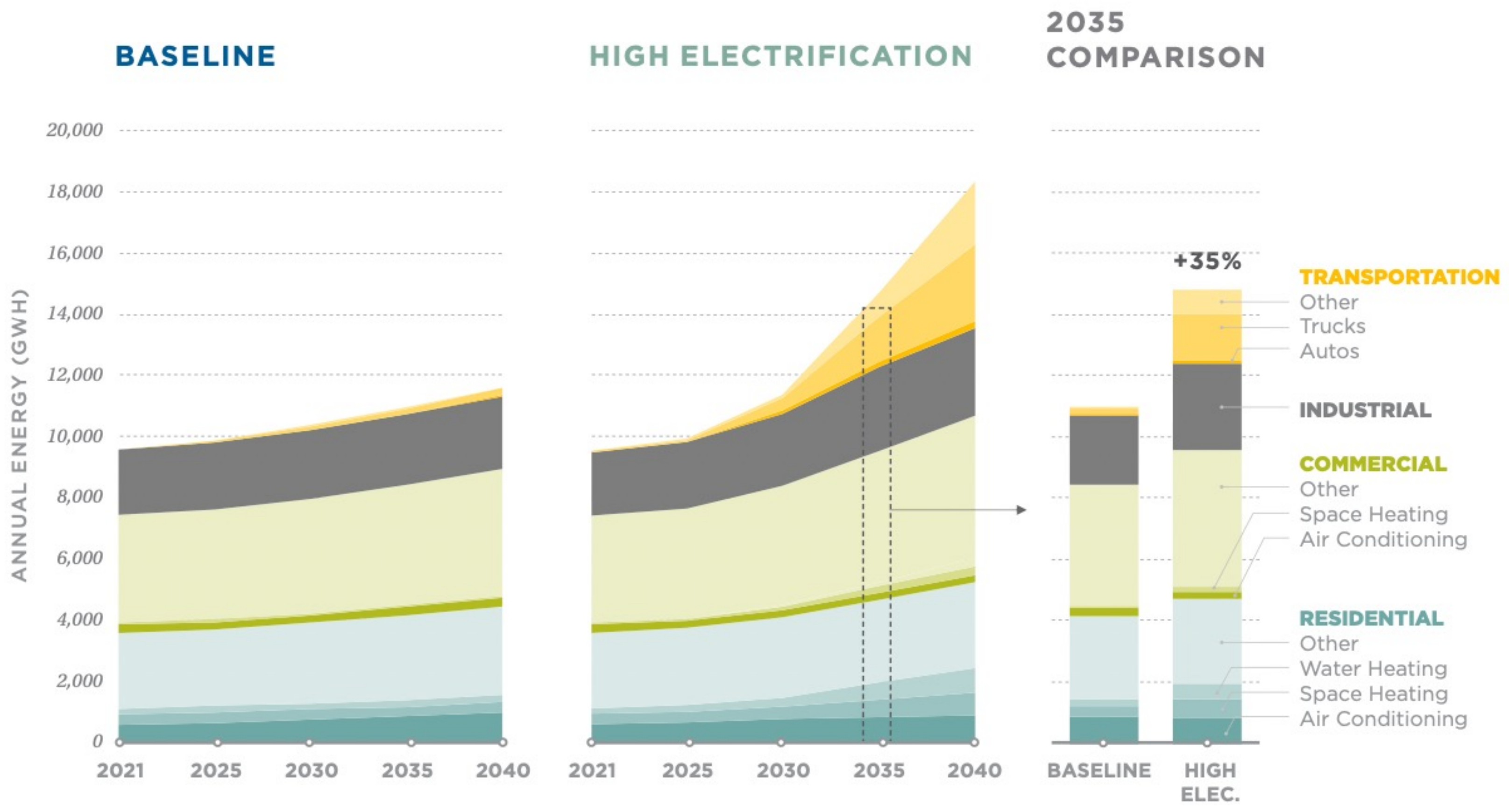
Example disaggregation State → Region

State	Sector	BS	CA	NW	RM	SW	PNM	TOTAL
AZ	residential	1%	0%	0%	0%	100%	0%	100%
CA	residential	0%	100%	0%	0%	0%	0%	100%
CO	residential	0%	0%	0%	100%	0%	0%	100%
ID	residential	85%	0%	15%	0%	0%	0%	100%
MT	residential	0%	0%	94%	0%	0%	0%	94%
NM	residential	1%	0%	0%	4%	25%	50%	80%
NV	residential	0%	0%	0%	0%	100%	0%	100%
OR	residential	1%	0%	99%	0%	0%	0%	100%
UT	residential	97%	0%	0%	3%	0%	0%	100%
WA	residential	0%	0%	100%	0%	0%	0%	100%
WY	residential	39%	0%	23%	38%	0%	0%	100%

This process was repeated for commercial, industrial, transportation sectors

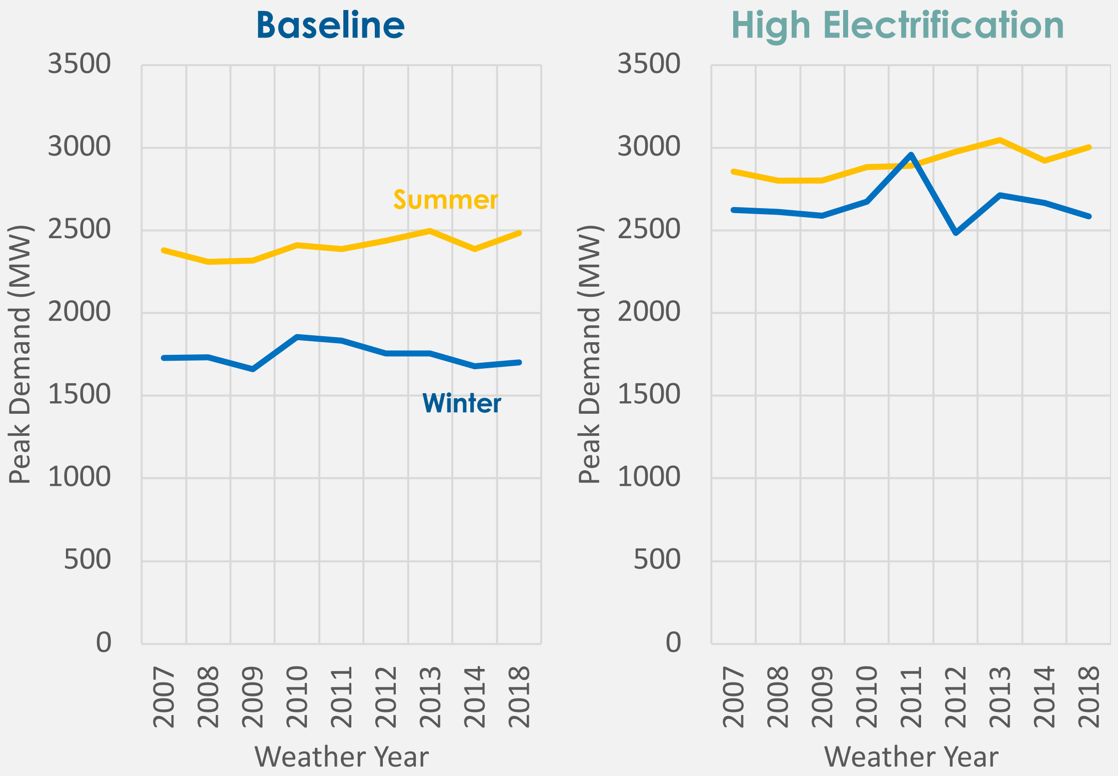
- Based on EIA Form 861
- Provides load by state, balancing authority, and by utility
- Scalars used to adjust first-year starting point to PNM current load

PNM Load Forecast by Electrification Scenario

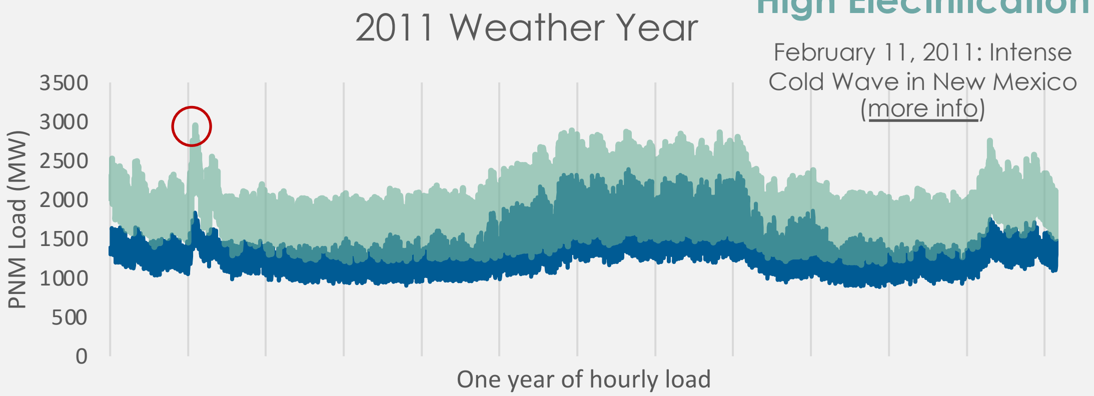


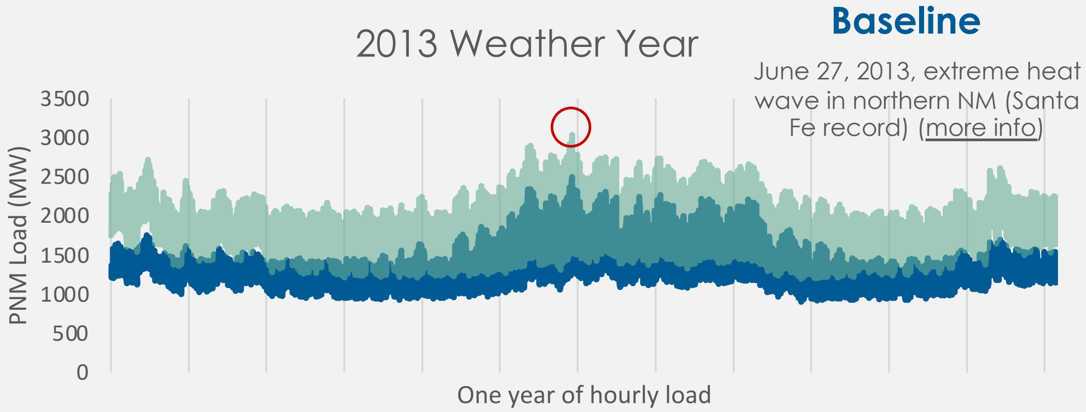
Seasonality in the High Electrification Load forecast

With high electrification assumptions, PNM becomes a dual-peaking system, with some weather years (2011) seeing a winter peak due to cold snaps



PNM effectively becomes dual peaking with increased electrification,
End-use load forecasts captures new seasonality patterns





2035 High Electrification Impacts by Layer (1)

This table shows the comparison of 2035 annual energy for PNM under both the Baseline and High Electrification assumptions.

Sector	Subsector	Baseline	High Elec.	Delta (GWh)	Delta (%)
Residential	Air Conditioning	890	830	-60	-7%
	Space Heating	310	590	280	90%
	Water Heating	220	550	330	150%
	Other	2,750	2,720	-30	-1%
Commercial	Air Conditioning	260	240	-20	-8%
	Space Heating	60	200	140	233%
	Water Heating	10	150	140	1400%
	Other	3,930	4,280	350	9%
Industrial		2,280	2,810	530	23%
Transport	Autos	10	140	130	1300%
	Trucks	200	1,490	1,290	645%
	Other	20	800	780	3900%
Total		**10,940**	**14,800**	**3,860**	**35%**

Heat pump adoption improves AC efficiency.

Electrification of space and water heating results in large load increases.

Energy efficiency improvements and population increases cancel to keep load flat.

Electrification of oil and gas extraction as well as other industrial end-uses results in increased load.

Large growth in transportation electrification from a very low baseline value

Values represent PNM sales and not include T&D losses. All values rounded to the nearest 10 GWh

2035 High Electrification Impacts by Layer (2)

PNM Annual Energy Forecast for 2035, Baseline vs. High Electrification, by End Use

Sector	Subsector	Baseline	High Elec.	Delta (GWh)	Delta (%)
Residential	Air Conditioning	890	830	-60	-7%
	Space Heating	310	590	280	90%
	Water Heating	220	550	330	150%
	Other	2,750	2,720	-30	-1%
Commercial	Air Conditioning	260	240	-20	-8%
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Total		**10,940**	**14,800**	**3,860**	**35%**

Values represent PNM sales and not include T&D losses. All values rounded to the nearest 10 GWh

Transportation, specifically medium, heavy-duty trucking, and fleet vehicles account for the largest increase in demand, followed by Industrial electrification and residential state and water heating.

On a percentage basis, transportation end uses account for the largest increase, followed by commercial electrification.

In total, high electrification assumptions increase the 2035 load growth 35% above baseline forecasts, requiring additional resources to meet reliability and clean energy objectives

Practitioner Toolkit:
Renewable
Generation Profiles

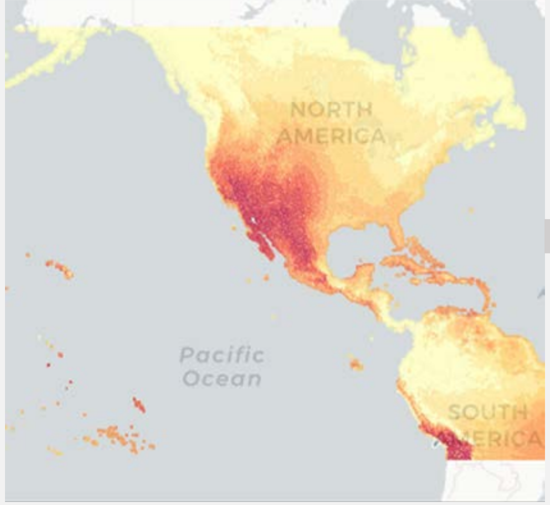
Methodology of developing system-wide, plant-level database of solar & wind power output profiles (1 of 2)

- Public sources of hourly solar and wind resource profiles for historical weather years served as the original source (NREL WindToolkit for wind and NREL NSRDB for solar)
- The public tools allow to develop specific outputs of solar or wind generators based on the weather conditions (using the NREL WindToolkit for wind and NREL System Advisor Tool for solar)
- Where there are existing solar and wind locations throughout the West, we developed representative profiles for multiple weather years for these specific plants
- To develop a 2035 profile, we assumed that the geographic distribution of wind and solar plants will remain consistent with historical installations (which is an approximation) for larger plants (see next slide for details)
- Because we had limited data for wind (i.e., 7 years), and 22 years for solar resources, a Monte Carlo approach was implemented to match wind data to additional historical weather years.
- There were 2 broad applications for these weather-based profiles:
    - In the capacity expansion modeling (EnCompass) we needed to include representative renewable profiles for PNM- we selected a typical weather year (2011) and developed 3 aggregate solar and wind profiles, each.
    - In the resource adequacy analysis, we needed to represent multiple weather year profiles across the West- we developed a representative balancing-area based aggregate renewable profile for solar and wind based on the project specific information developed in previous steps.
- Hydro resources were modeled with multiple years of monthly energy targets and were considered not to be weather-dependent on the same hourly timescales as wind, solar, and load.
- Because the analysis did not model thermal resources, weather dependent outages of thermal resources was not considered.

Methodology of developing system-wide, plant-level database of solar & wind ***power output*** profiles (2 of 2)

Solar: 22-year PNM & WECC-specific dataset developed using **NREL System Advisor Model** (1998 – 2019)

Wind: 8-year PNM & WECC-specific dataset developed using **NREL Wind Toolkit** (2007-2014), *focus on overlapping wind years to maintain correlation*



Source: NREL NSRDB

Meteorological Properties
- DNI
- DHI
- GHI
- Dew Point
- Temperature
- Pressure
- Relative Humidity
- Wind Direction
- Wind Speed
- Surface Albedo

PV Plant Properties
- System Size (DC)
- DC:AC Ratio
- Losses
- Module Type
- Array Type
- Inverter Efficiency
- Tilt
- Azimuth
- Ground Coverage Ratio

Power Production
- 30-min MW production by plant
- Capacity factors
- System level solar power availability

A similar process was developed for wind resources, and the same hourly, chronological weather years were considered for load

GridLAB Wind and Solar Profiles

Multi-year weather dataset, assumptions for new resources

Utility-scale PV

- NREL NSRDB + SAM, 22-years of data
- Single-axis tracking, ILR of 1.4
- Use existing solar sites >20 MW as proxy for future locations, aggregated by state
- Forecasted additions from IRPs

Rooftop PV

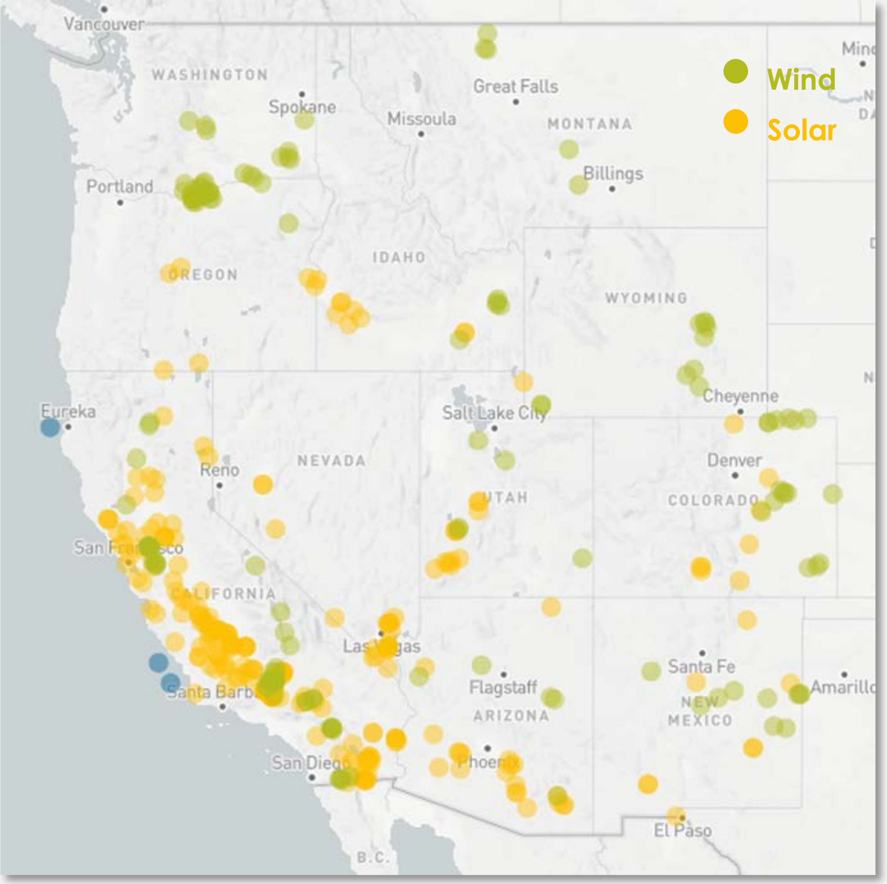
- NREL NSRDB + SAM, 22-years of data
- Roof mount, ILR of 1.1
- 1-profile per zip code aggregated by state, weighted using Project SunRoof
- Forecast based on historical trends

For California and Arizona, we use county-level data in place of zip codes

WIND

- NREL WIND ToolKit, 7-years of data
- 2.5 MW Turbine
- Use existing wind sites > 75 MW as proxy for future locations, aggregated by state
- Forecasted additions from IRPs

* *Existing wind and utility-scale solar plants used the same data source, but plant configuration was adjusted to align with historical energy production*



PNM Territory to included multiple candidates to capture benefits of geographic diversity

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West-wide Behind-the-meter-solar Forecast (1)

The demand profiles developed using EnergyPATHWAYS did not consider BTM solar. We developed the adoption rates of BTM solar as follows:

Data Source: EIA-861-M

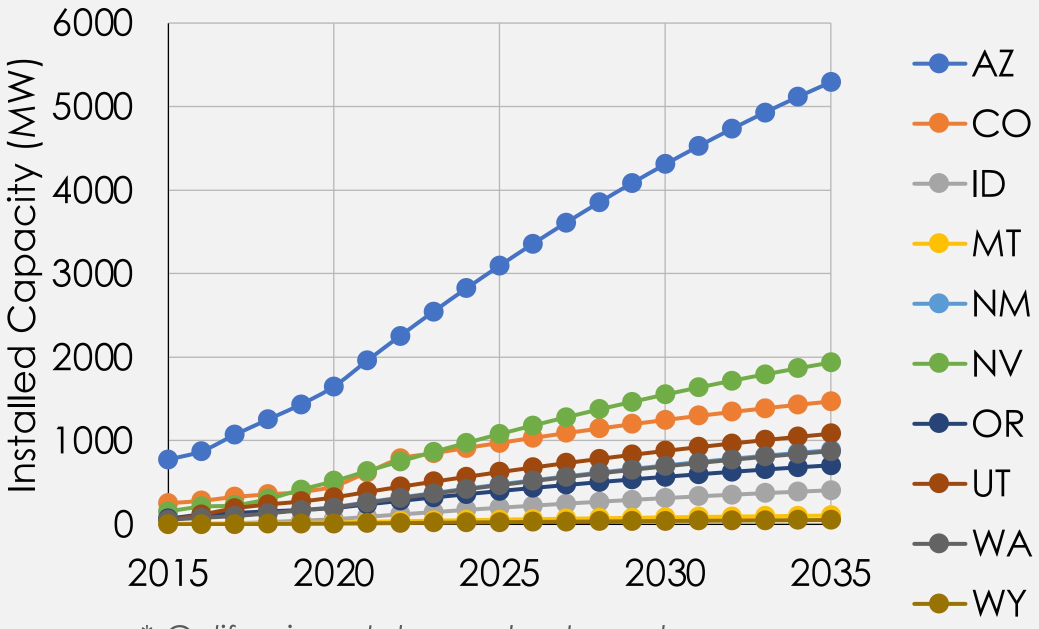
Estimated Small Scale Solar PV Capacity and Generation- Monthly Totals for States

https://www.eia.gov/electricity/data/eia861m/

State-level BTM-PV forecast

Assumes recent historical growth rates by state, tapering through the forecast period

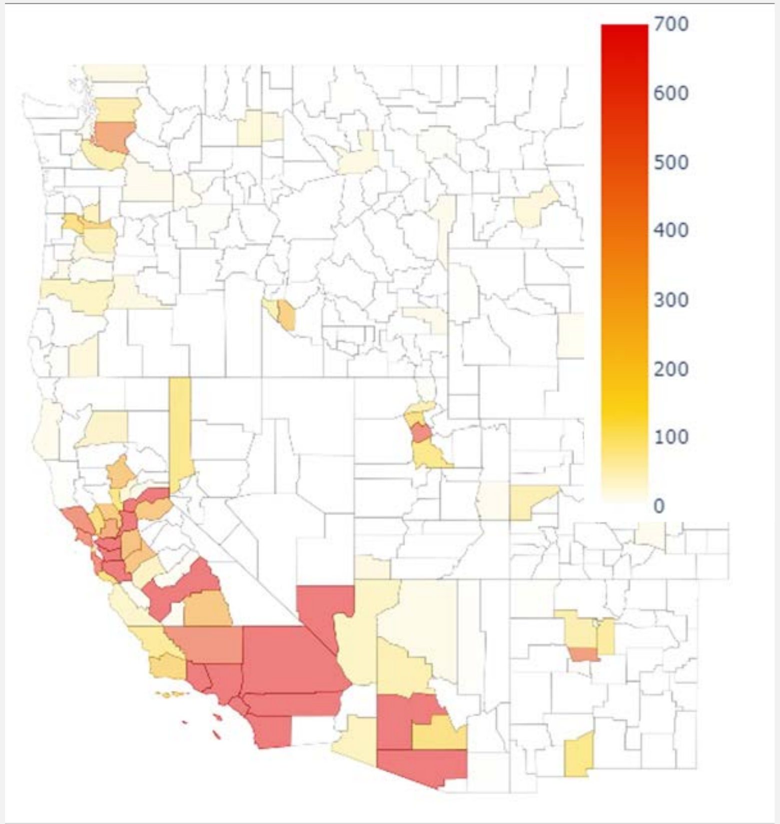
Project installed capacity of BTM solar for each state in the West (excl. CA)*



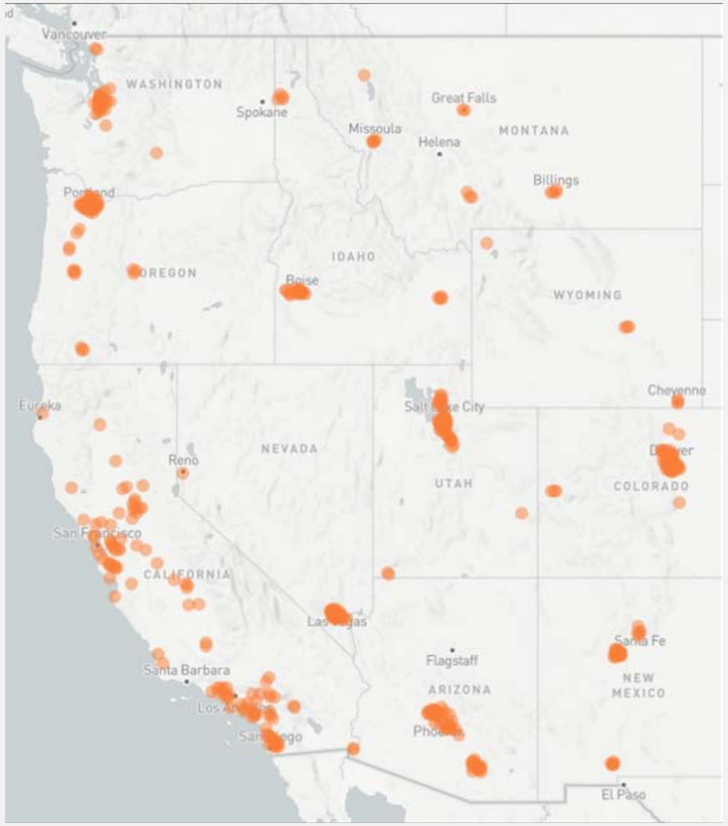
** California not shown due to scale.*
2025 = 18 GW, 2030 = 25 GW, 2035 = 30 GW

West-wide Behind-the-meter-solar Forecast (2)

Installed BTM-PV
By County, 2035



~500 PV Irradiance Locations
Weighted by total installed panel count*



* *based on existing panel counts, Google Project Sunroof*

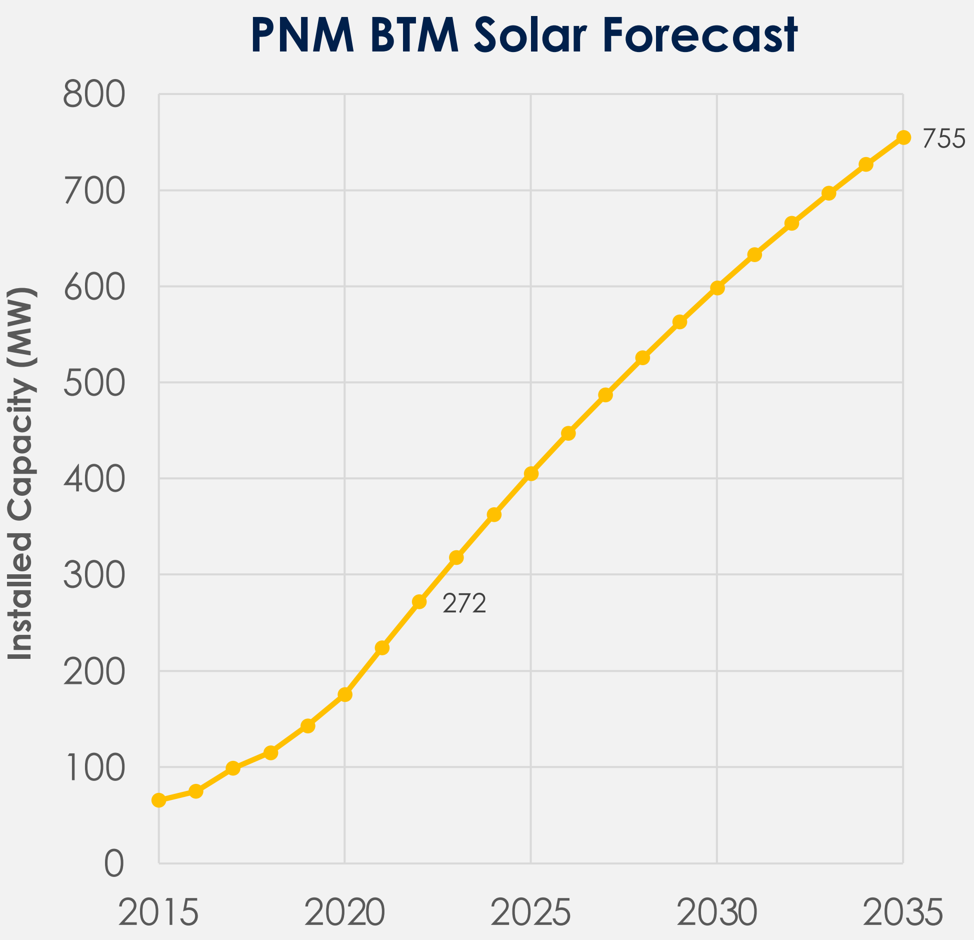
After developing a statewide forecast of rooftop PV capacity, the study developed chronological, hourly production profiles.

The first step was to develop a county-level disaggregation using satellite image estimates of rooftop panel counts (Google Project Sunroof)

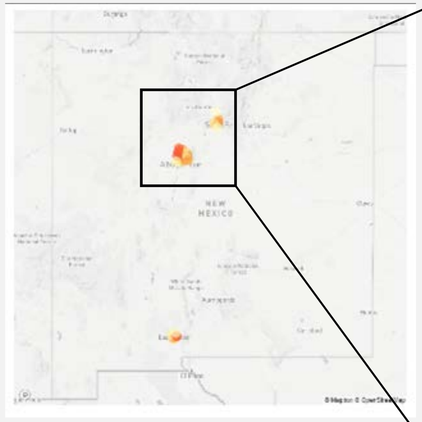
Each county then aggregated sites based on zip codes, with multiple sites for each county.

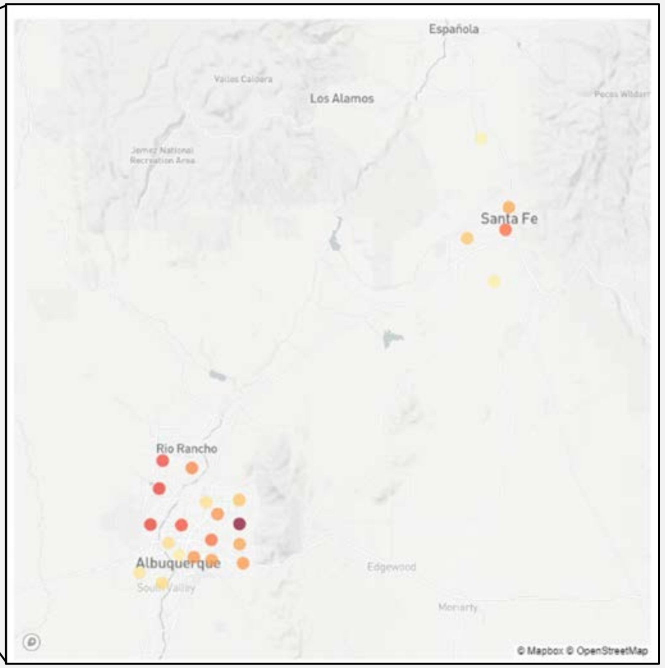
In total, 500 locations were selected for irradiance, and the output was weighted based on estimated capacity.

PNM Behind-the-meter-solar Forecast (3)



- PNM's BTM solar profile was based on ~28 PV Irradiance Locations
- One per zip code, weighted by total installed panel count*
- Used to develop a 22-weather year estimate of hourly, chronological VTM PV production
- Total generation was extrapolated to 2035 levels





* *based on existing panel counts, Google Project Sunroof*

Practitioner Toolkit: Capacity Expansion Modeling using EnCompass

Foundation of the capacity expansion modeling

The capacity expansion planning and analysis was conducted using EnCompass. This included two separate, but interconnected processes. First the model was used to compile multiple portfolios of resources, including new builds and retirements, to meet a 100% clean electricity target by 2035. In this step, the model compared the relative costs of different resources to meet demand in a least cost manner, considering variable operating costs, fixed operations and maintenance costs, and capital costs of new resources.

The resulting portfolios from this analysis was evaluated further in the resource adequacy analysis to determine if the portfolios were adequate. In each case, some firm capacity (hydrogen CTs) additions were further refined based on the RA analysis.

The second step of the modeling process was to conduct more detailed, chronological 8760-hour per year modeling of the resulting portfolios. This step included additional modeling constraints to better represent real-time operations. This step served two purposes. It ensured that the portfolios were operable, and it was used to develop the total cost and revenue requirements for each portfolio.

Portfolio Development: Capacity Expansion and Production Cost Modeling

- Portfolio development was done using a capacity expansion modeling approach, which includes the following two steps within the modeling software tool we used in the practitioner approach (EnCompass)
- **Step One:** Capacity Expansion (i.e., develop the portfolio based on a forecast of future loads over the planning horizon)
  - Optimize system costs given the costs of new and existing resources over the planning period of 2023-2035
  - Optimize to meet the planning reserve margin
  - Simplified unit commitment and dispatch
    - Problem size need to be manageable and one way to manage the problem size is to simulate two "typical" days per month
- **Step Two:** Production Cost (i.e., test the portfolio performance using hourly modeling in each year in the planning horizon)
  - Fix new resources from capacity expansion and dispatch along with existing resources
  - More granular time and full unit commitment
    - 8760 hour per year on a chronological basis for each year in the planning period
- **Note:** Not all capacity expansion modeling tools include the step of production cost modeling, however, one reason that it is conducted within the auspices of capacity expansion is because it provides a more accurate representation of operating costs within a year and can thus contribute more accurately towards the estimate of portfolio capacity and operating costs.

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EnCompass: Model Overview

- PNM's 2020 IRP model served as the starting point for EnCompass modeling
- EnCompass performs capacity expansion and production cost modeling
  - In the capacity expansion step, EnCompass optimizes to minimize system costs subject to the peak load plus a reserve margin (known as the Planning Reserve Margin)
    - Based on the Planning Reserve Margin input, the Effective Load Carrying Capacity (ELCC) values for renewables and storage, and Unforced Capacity (UCAP) values for other resources (ELCC and UCAP represent different approaches towards capacity value)
- Time sampling
  - One peak and off-peak day per month for capacity expansion
  - Full 8,760 hours for production cost modeling
- Topology
  - PNM's system with assumptions for imports/exports from an external market
  - Modeled flow constraints between 3 zones within PNM's LSE
- Time value of money
  - EnCompass modeling was conducted using nominal dollars (vs. real)

Existing and Planned Resources

The 2020 IRP was updated to reflect a more current set of existing and planned resources based on announced projects awarded by PNM and approved by the Commission (note that final capacities and/or retirement dates may be different than when the study was developed)

PNM Retirements

- **San Juan, Coal**
  -500 MW, 2022
- **Four Corners, Coal**
  -200 MW, 2025
  Partial ownership contract abandonment, plant remains online in WECC-wide analysis until 2031
- **Palo Verde, Nuclear**
  -114 MW, 2024
  contract expiration, plant remains online in WECC analysis
- **All existing thermal resources retired by 2035, requiring replacement in the capacity expansion model**

PNM Fixed Build

- **Arroyo Solar + Storage***
  300 MW PV, 150 MW (600 MWh) BESS
- **San Juan Solar + Storage***
  200 MW PV, 100 MW (120 MWh) BESS
- **Rockmont Solar + Storage***
  (100 MW PV, 30 MW (120 MWh) BESS
- **Jicarilla Solar + Storage***
  50 MW PV, 20 MW (80 MWh) BESS
- **Jicarilla 2 Solar** (50 MW PV)**
- **Atrisco Solar+Storage****
  300 MW solar, 300 MW (1200 MWh) BESS
- **Sandia Storage****
  100 MW, 200 MWh BESS (standalone0=)

BTM Solar

272 MW in 2022

755 MW in 2035 (+8.2%/yr.)

(details in earlier slides)

** Replacement resources for San Juan Coal Plant Retirement*

*** Replacement Resources for Palo Verde abandonment*

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Modeling Inputs: Planning Reserve Margin and ELCC

- 18% Planning Reserve Margin (PRM) is from the 2020 IRP
  - *PRM that meets a Loss of Load Expectation ("LOLE") standard of 0.2 days per year*
  - *Unforced capacity ("UCAP") and ELCC accounting for thermal and non-thermal resources*
- ELCCs for solar, wind, and battery storage are from PNM's 2020 IRP
- Multiday storage, geothermal, and hydrogen ELCC were assumed to be comparable to a UCAP rating of a thermal resource and based on engineering judgement.
- Green highlights on the table represent the ELCC values for PNM's existing and approved resources
- The ELCCs for solar, wind, and battery storage were modeled with a different value depending on the penetration of each resource technology (example shown in the table)
- We note that efforts are being made in the industry to implement multi-dimensional ELCC values that address the interdependent nature of ELCC values, and the evolution over time. However, these efforts are nascent and were not incorporated into our modeling.

Solar	**ELCC and UCAP values**
0 to 1000 MW	16.8%
1000 to 1200 MW	6.3%
1200 to 1500 MW	5.3%
1500 to 2000 MW	2.2%
Wind	
0 to 600 MW	28.8%
600 to 1000 MW	10.7%
1000 to 1500 MW	9.0%
> 1500 MW	2.2%
Battery Storage, 2-Hour	
0 to 100 MW	72.0%
Battery Storage, 4-Hour	
0 to 300 MW	95.7%
300 to 500 MW	92.5%
500 to 750 MW	84.5%
750 to 1000 MW	61.3%
1000 MW to 1500 MW	24.0%
Battery Storage, 10-Hour	
0 to 400 MW	95.6%
400 to 700 MW	85.0%
700 to 1200 MW	62.4%
Multiday Storage	95%
Geothermal	90%
Hydrogen CT	97%

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Modeling Inputs: Natural Gas and Hydrogen Fuel Prices

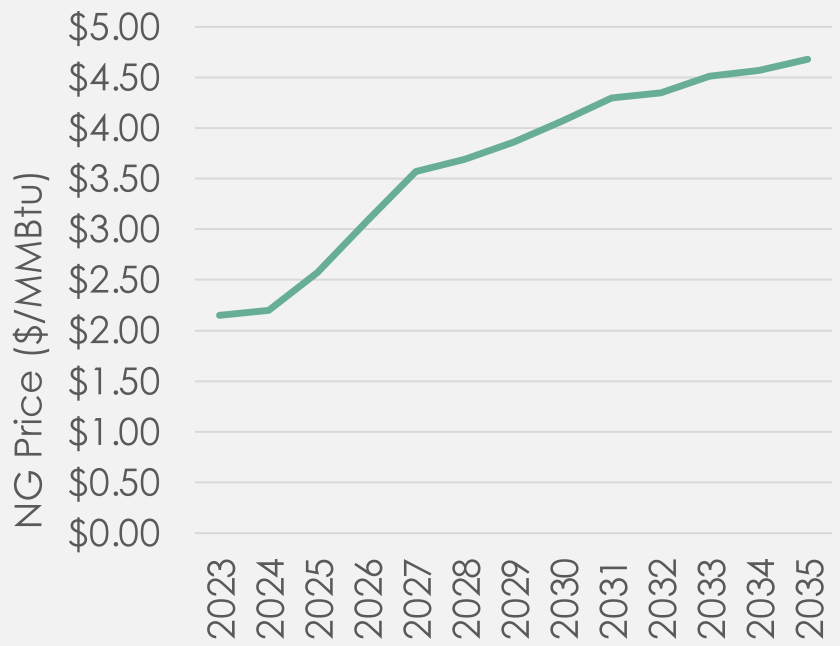
Natural Gas

- Fuel price forecasts were taken from PNM's 2020 IRP (Appendix G)
- We assumed that inflationary effects on natural gas prices are temporary, and as such, did not make adjustments to the PNM 2020 IRP assumptions;

Hydrogen

- Hydrogen fuel prices were taken from PNM's 2020 IRP modeling assumptions with corroboration to other industry sources
- Hydrogen prices start at $30/MMBtu in 2030
- Costs are inclusive of storage and transportation. The study did not endogenously model the electrolysis, storage, and delivery of H2, but did account for renewable energy needs required for electrolysis.
- Instead, the study assumed hydrogen was produced by a third-party and delivered to PNM with enough storage to be available when needed.

Natural gas price forecast used in EnCompass (nominal dollars)



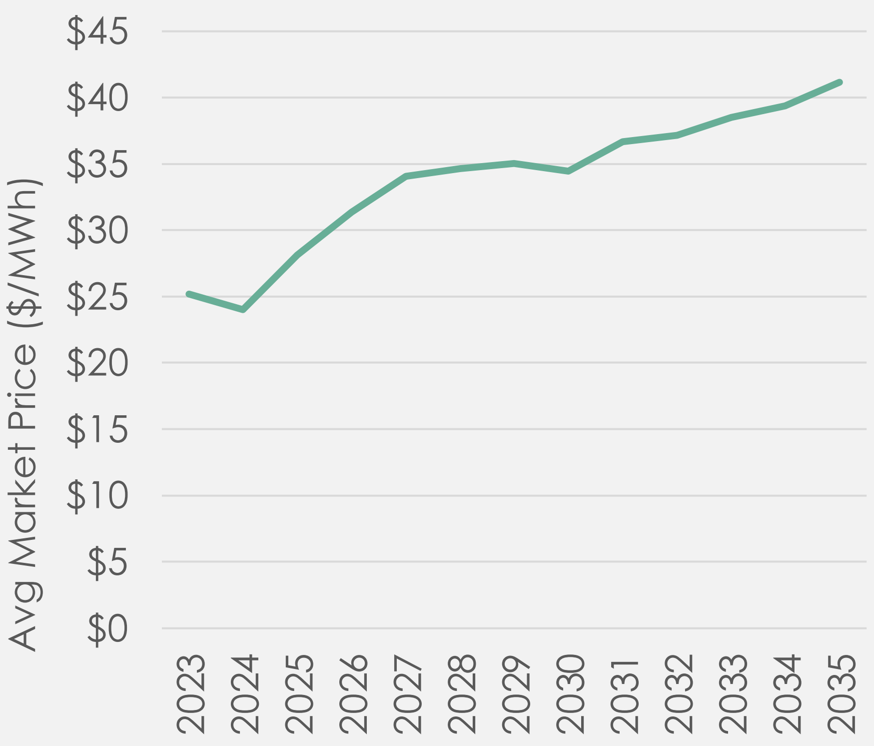
Modeling Inputs: Market Assumptions

Market prices were taken from PNM's 2020 IRP (Appendix G)

Import/Export assumptions

- Used in both the capacity expansion and production cost modeling steps.
- The EnCompass model assumed available import purchases up to 150 MW in any hour
- EnCompass did not allow sales of surplus energy to prevent the model from building additional resources above the PRM to sell into the market (curtailment therefore could potentially be exported)
- Included a $30/MWh adder to imports in every hour to limit times when imports might happen to take advantage of zero to negative energy prices
- Resource adequacy imports and exports were based on availability of resources across the West (see following section)

Palo Verde Hub Energy Prices (nominal dollars)



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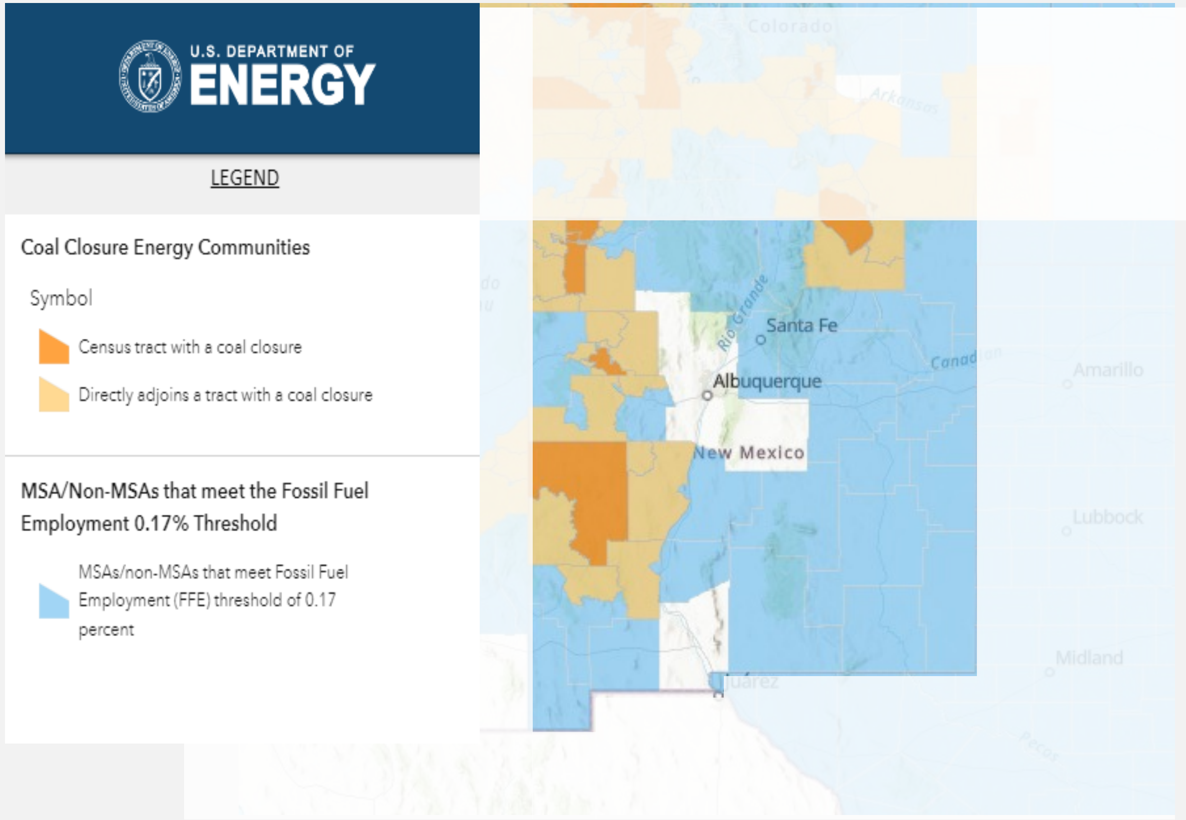
Candidate Resource Assumptions

Resources	Capital and Fixed O&M (1)	First Year Available	IRA (2)	Transmission Adder ($/kW) (3)
Solar	2022 NREL ATB*	2025	110% PTC	$150
Wind	2022 NREL ATB*	2025	110% PTC	$450
Battery Storage, 4-Hr	2022 NREL ATB	2025	40% ITC	No
Battery Storage, 10-Hr	2022 NREL ATB	2025	40% ITC	No
Multiday Storage, 100-Hr	CPUC IRP Zero-Carbon Technology Assessment(4)	2030	40% ITC	No
Geothermal	2022 EIA AEO	2027	40% ITC	No
Hydrogen CT	2022 NREL ATB	2030	40% ITC	No

1 Real costs were translated into nominal costs using a higher inflation rate to capture inflationary pressures (5% between 2025 and 2027 and then 3% thereafter). An additional cost adder was also included for wind and solar to reflect near term supply chain pressures.
2 The IRA assumptions include the Energy Community bonus adder and that projects meet labor and wage requirements.
3 The transmission cost adders were based on projects discussed in PNM's 2023 IRP Stakeholder Meetings although these values may be different in the final IRP.
4 https://www.cpuc.ca.gov/-/media/cpuc-website/divisions/energy-division/documents/integrated-resource-plan-and-long-term-procurement-plan-irp-ltpp/2022-irp-cycle-events-and-materials/cpuc-irp-zero-carbon-technology-assessment.pdf

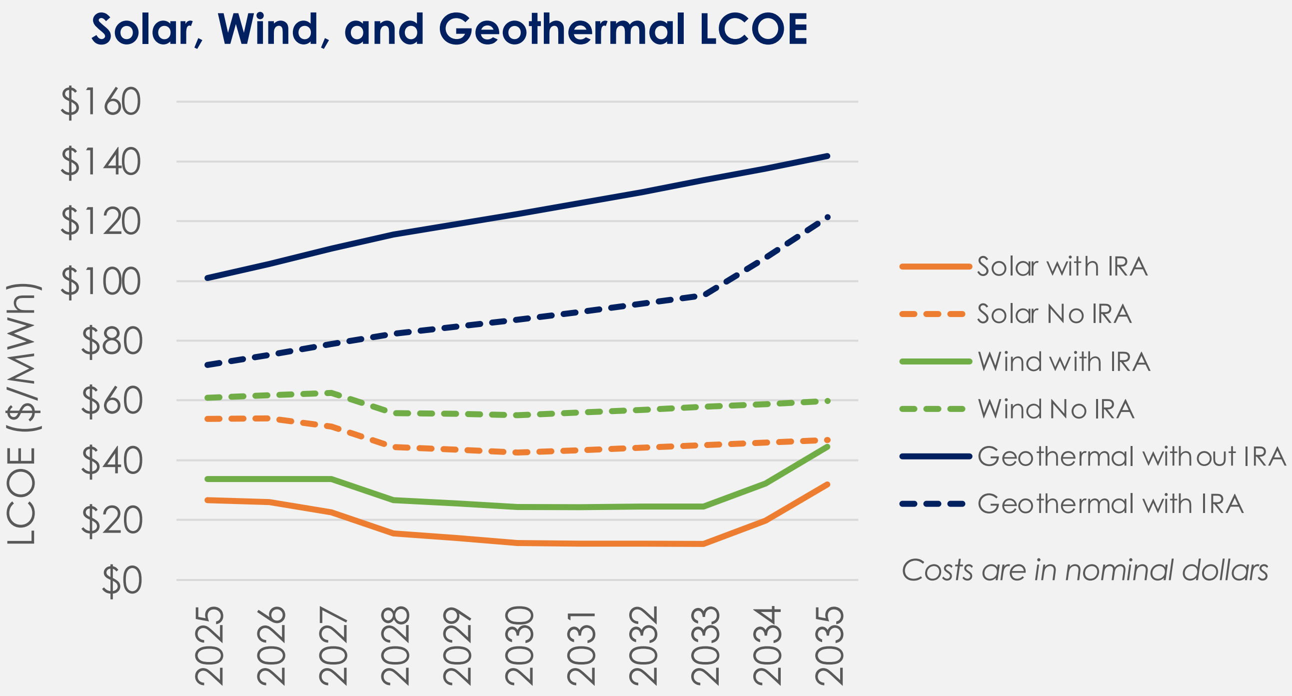
Incorporation of Inflation Reduction Act and Bonus Credits into capital cost assumptions



- The Inflation Reduction Act has a significant impact on the cost of clean energy resources
- A key part of our study was to incorporate these benefits in the form of tax credits which were converted into cost reductions, which were modeled as either a production tax credit (PTC) or a reduction to the capital cost (ITC)
- For New Mexico, we included the assumption that all projects would qualify for the Energy Community bonus adder (10%) based on projections of communities within New Mexico that would qualify
- Wind and solar resources were assumed to have 110% of PTC, all other resources assumed to have 40% ITC

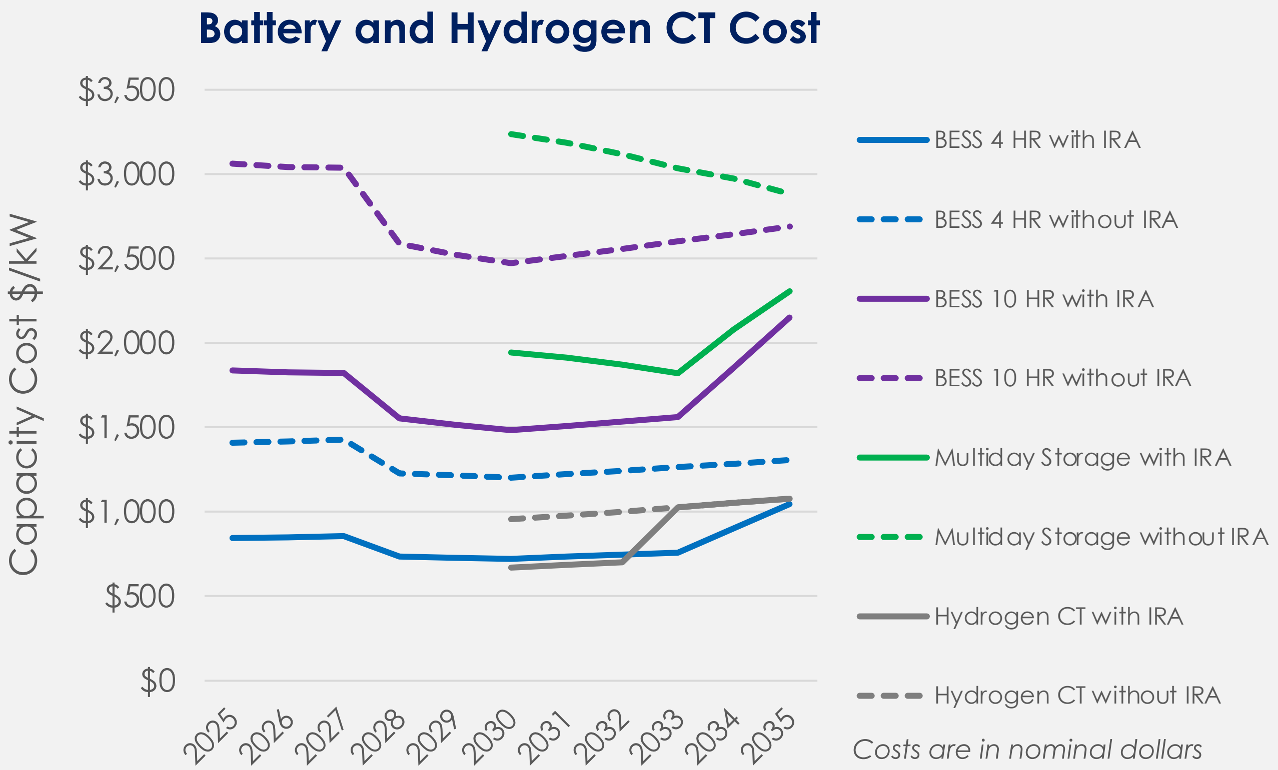
Capital Costs of New Wind, Solar, and Geothermal Resources

- We modeled wind, solar, and geothermal resources in LCOE format (vs. $/kW) in EnCompass to be reflective of a PPA price with the inclusion of the PTC from the IRA
- Because the PTC is in a $/MWh format and the resources do not have a fuel price this simplified the modeling for EnCompass
- The key observation to take from these figures is the significant impact that IRA has on costs



Capital Costs of New Wind, Solar, and Geothermal Resources

- For battery storage and hydrogen CT resources, capital costs were assumed in $/kW, with fuel costs (for H2 CTs) modeled endogenously
- Because utilization is based on system need, rather than predetermined profiles, an upfront capital cost method was used.



Costs are in nominal dollars

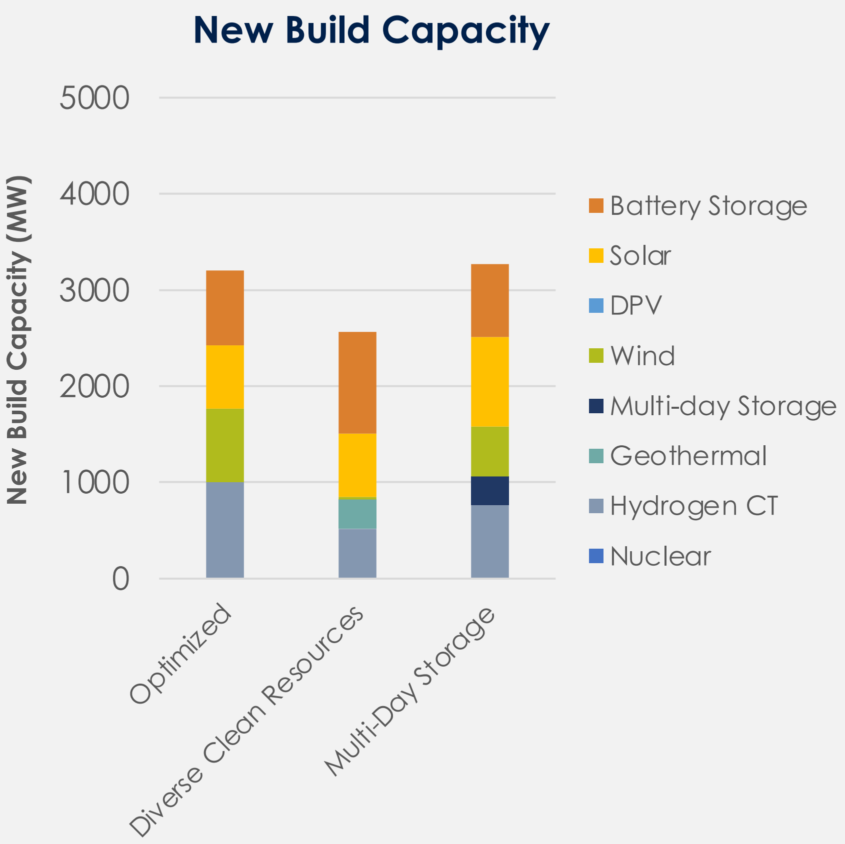
EnCompass Portfolios

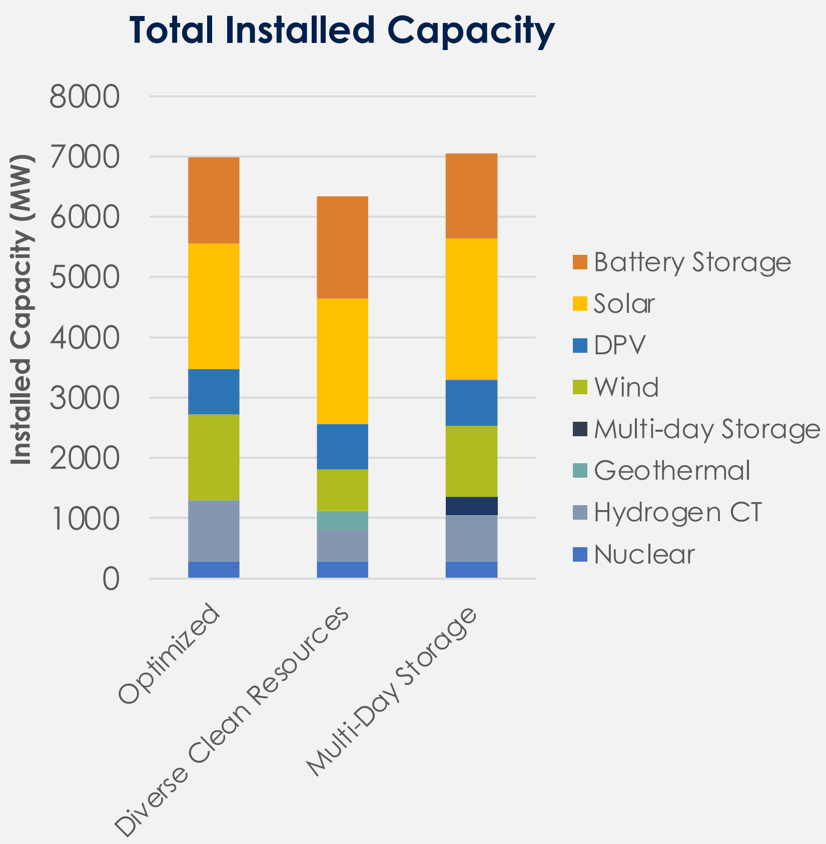
Portfolio	Description
Optimized*	Optimized based on best available assumptions Multiday storage could not be selected
Diverse Clean Resources*	300 MW Geothermal forced into the model Remaining resources optimally selected
Multiday Storage*	300 MW of 100-hour storage forced into the model Remaining resources optimally selected
Islanded**	Optimized based on best available assumptions No imports allowed in any hour
No Hydrogen CTs**	Optimized based on best available assumptions Hydrogen CTs not allowed to be selected

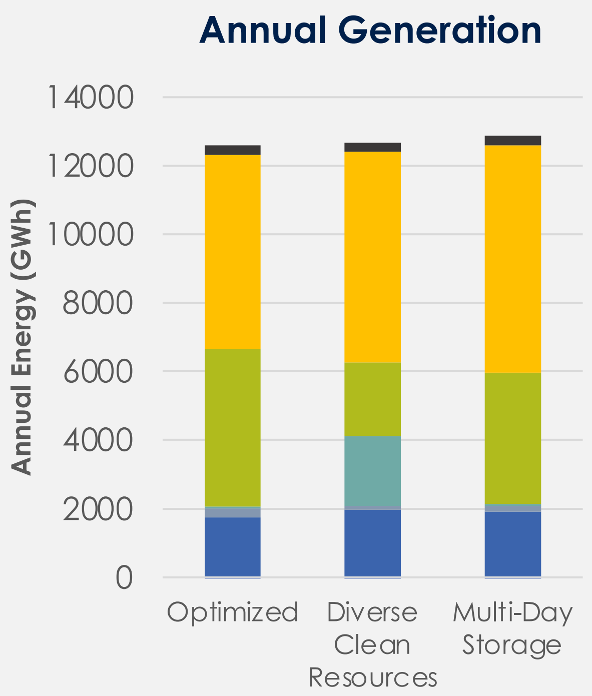
** Each portfolio was optimized for both the Baseline and High Electrification demand forecasts*

*** The Islanded and No Hydrogen CTs portfolios were developed as a secondary set of portfolio sensitivities to further understand how sensitive EnCompass modeling is to assumptions on import and hydrogen CT availability*

EnCompass Portfolio Comparisons
(Baseline Demand Forecast)

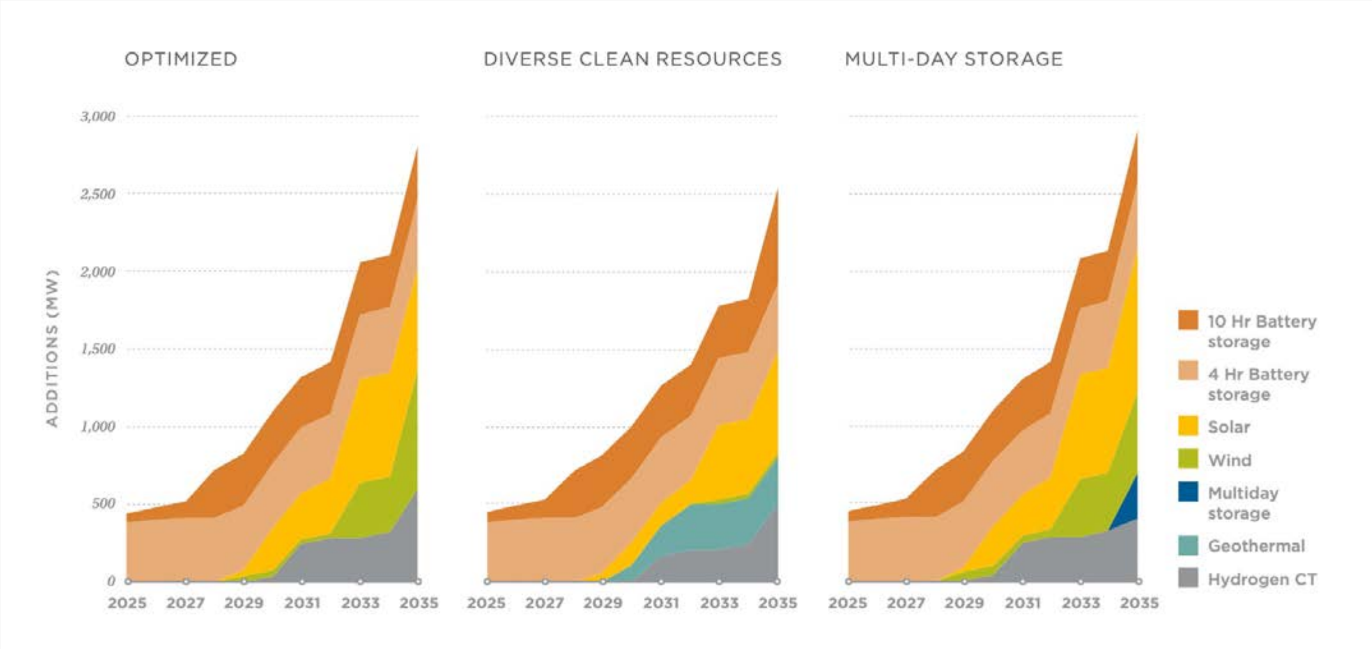






EnCompass New Build Comparisons

Baseline demand forecast



Similarities

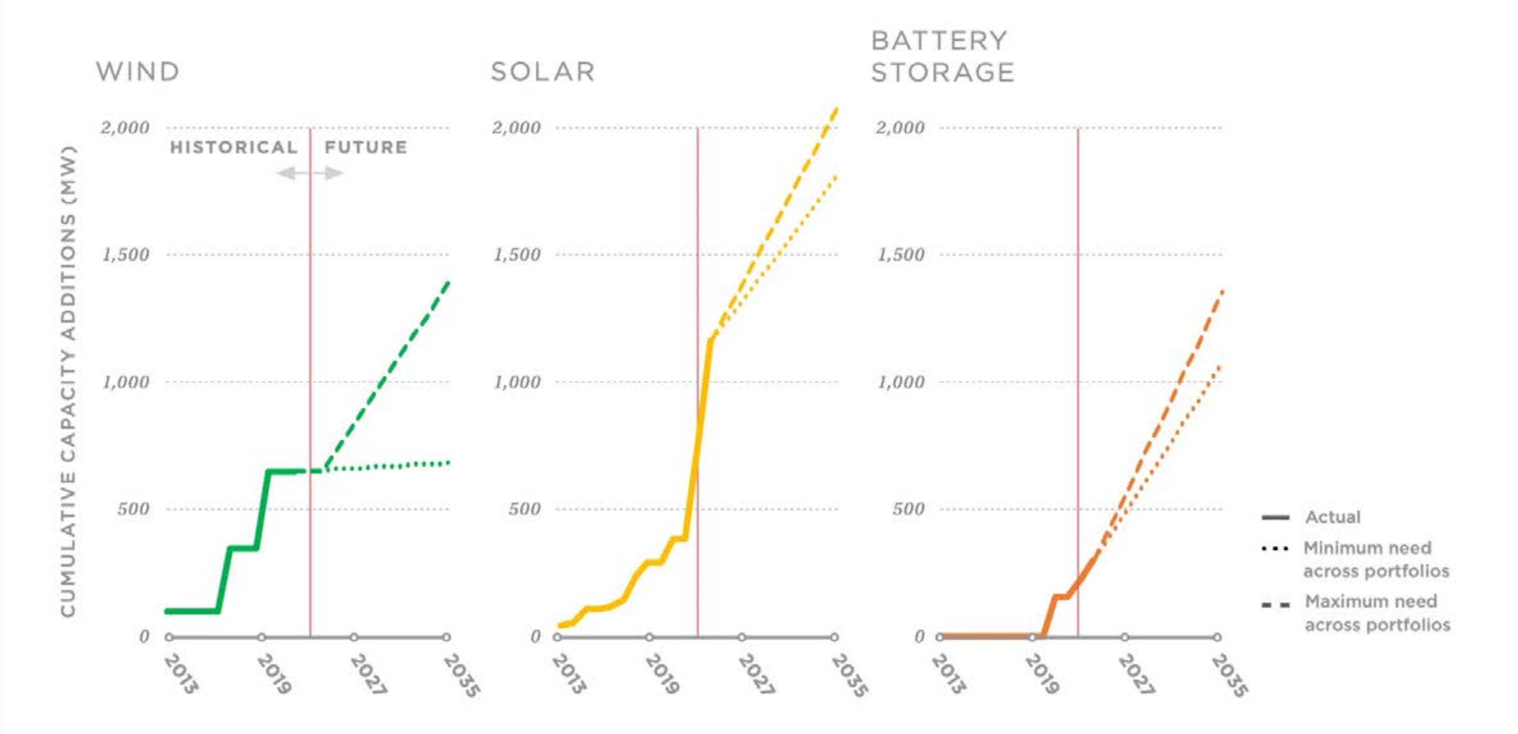
- Battery storage deployment through 2029 to meet PRM requirement, limited VRE
- Solar PV is the VRE primary energy resource
- H2 CTs (or other zero-carbon peaking resource) is the marginal RA capacity
- Battery storage saturates and is replaced by other firm zero-carbon resource for PRM requirement post 2030

Differences

- Wind provides energy in the optimized portfolio, replaced by geothermal
- Geothermal substitutes 1:1 the firm capacity of the H2 CTs
- LDES substitutes capacity of the H2 CTs, allows for more solar integration (less wind)

* *Portfolios do not include 32 MW of existing demand response programs. Load flexibility will be evaluated in future cases*

New Resource Builds Relative to Historical Additions



To achieve clean energy targets, PNM will have to accelerate deployment of clean energy resources relative to historical build rates, even without electrification, but this pace is line with the pace of development during some periods (i.e., wind during the 2015-2019 time period and recent solar procurements)

Detailed Portfolio Composition, Baseline demand

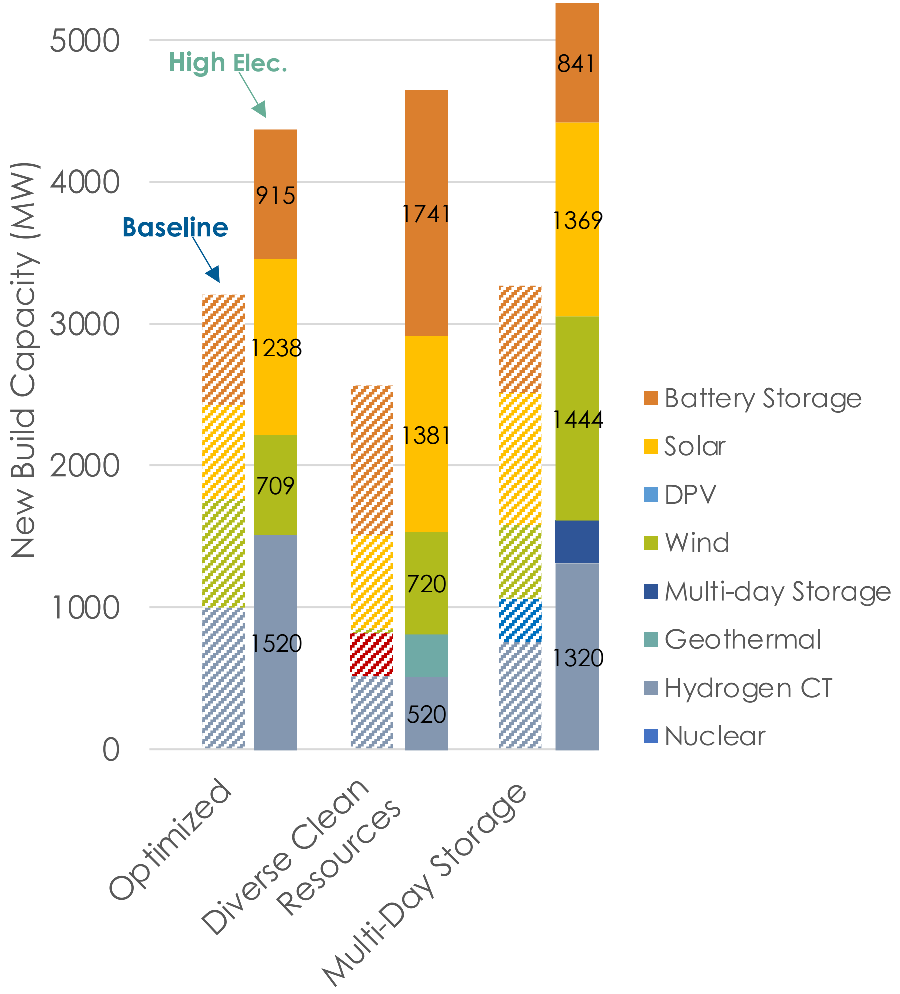
		Hydrogen CTs	Geothermal	Multi-day Storage	Wind	Solar	4-8 hour Battery Storage	Storage (MWh)	Storage (hrs)
Total Fixed Capacity pre 2025 (MW)	Total Existing	0	11	0	658	385	0	0	0.0
	Total Approved	0	0	0	0	1032	650	2600	4.0
	Total Fixed	**0**	**11**	**0**	**658**	**1418**	**650**	**2600**	4.0
New Build 2025-2035 (MW)	Optimized	1000	0	0	765	663	778	5156	6.6
	Diverse Clean Resources	520	300	0	32	657	1057	7948	7.5
	Multi-Day Storage	760	0	300	521	930	756	34993	33.1
	No H2 - Optimized	0	0	168	189	1459	1741	31588	16.5
	EnCompass Islanded	1000	0	0	945	670	759	5002	6.6
Total Installed Capacity by 2035 (MW)	Optimized	1000	11	0	1423	2081	1428	7756	5.4
	Geothermal	520	311	0	690	2075	1707	10548	6.2
	Multi-Day Storage	760	11	300	1179	2348	1406	37593	22.0
	No H2 - Optimized	0	11	168	847	2877	2391	34188	13.4
	EnCompass Islanded	1000	11	0	1603	2088	1409	7602	5.4

This table provides the fixed capacity (existing plus proposed projects) that was included in the EnCompass starting point database.

New build capacity represents incremental capacity additions selected by the model.

Total installed capacity shows the total 2035 capacity by resource type, including both fixed and new build resources

EnCompass Portfolios developed using the High Electrification demand forecast



Change to Baseline (MW)

	Hydrogen CT	Wind	Solar	Battery Storage	Storage (MWh)
Optimized	520	-56	575	137	1372
Diverse Clean Resources	0	688	724	684	6840
Multi-Day Storage	560	923	439	85	903

Change to Baseline (%)

	Hydrogen CT	Wind	Solar	Battery Storage	Storage (MWh)
Optimized	52%	-7%	87%	18%	27%
Diverse Clean Resources	0%	2164%	110%	65%	86%
Multi-Day Storage	74%	177%	47%	11%	3%

- **High electrification mainly implies we need to build clean resources more quickly**
- Larger increase in wind relative to the increase in solar (already built out significantly in the Baseline demand results)
- Still no economic additions for multi-day storage or geothermal resources
- Clean firm needs in the Geothermal case are unchanged

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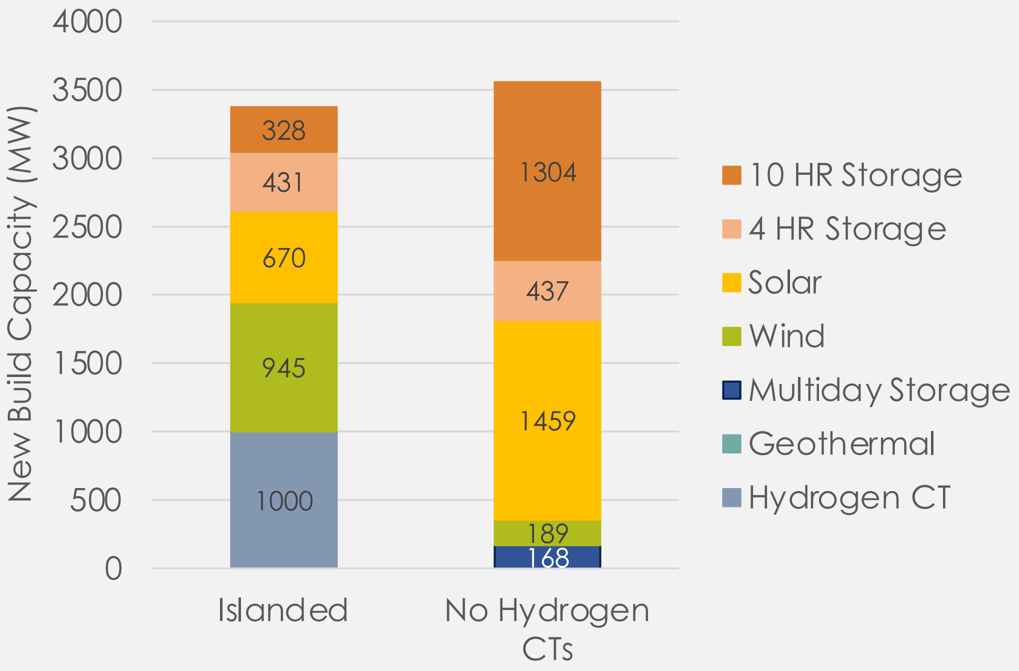
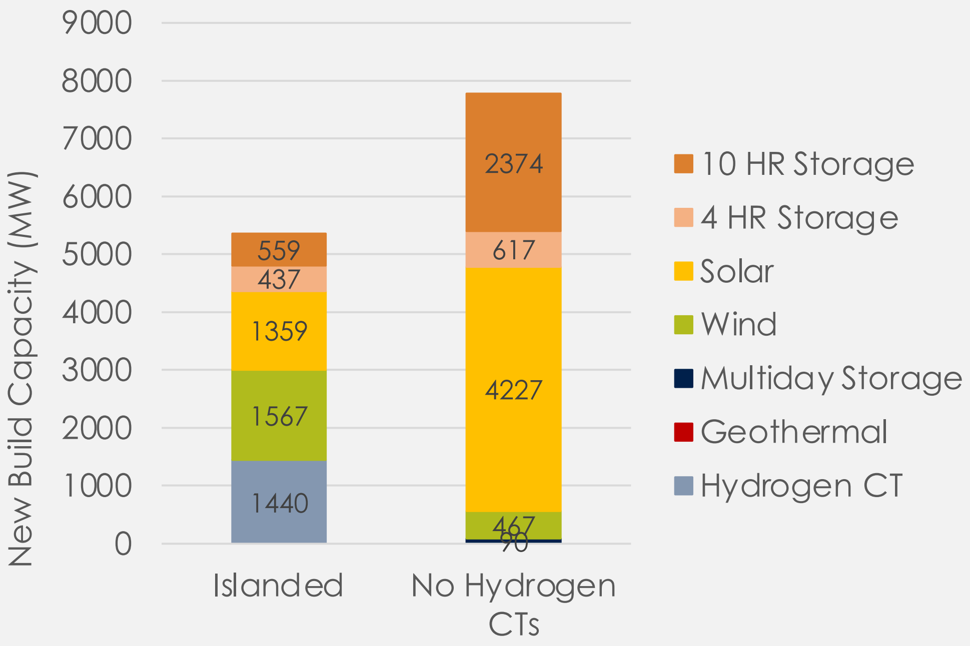
Sensitivity Analysis: Islanded and No Hydrogen CTs

Sensitivities were conducted assuming no market import capability in EnCompass (islanded), and without Hydrogen CTs as a resource candidate

Baseline demand



High Electrification demand



- In both demand cases, the availability of hydrogen CTs has a more direct impact than the availability of imports in terms of the resources required to meet the planning reserve margin.
- In both demand cases, the no hydrogen CT case requires more resources compared to the islanded case. The increase in resources is greater under high electrification demand assumptions, suggesting that increases in winter demand are driving up capacity requirements.
- In both demand cases, not having availability of hydrogen CTs increases the need for solar and batteries, but reduces the need for wind, likely because solar and batteries are more cost efficient in meeting the planning reserve margin.

EnCompass Portfolios: Net present value revenue requirement ($000)

Each of the portfolios was within 5% of one another on a PVRR basis, suggesting that there are multiple pathways available to achieve decarbonization targets at similar costs.

Comparing the present value revenue requirements shows that the differences in demand assumptions have a larger impact on PVVR compared to the differences in portfolio composition, suggesting a need for improved analysis and forecasting on electrification trends

Portfolio	Baseline demand	% change relative to Optimized portfolio	High Electrification demand	% change relative to Optimized portfolio	% change for each portfolio type between Baseline and High Elec demand
Optimized	$5,432,256	--	$5,952,505	--	10%
Diverse Clean Resources	$5,715,061	5%	$6,169,880	4%	8%
Multiday Storage	$5,432,961	<1%	$5,941,686	<1%	9%
Islanded Sensitivity *	$5,579,885	3%	$6,108,476	3%	9%
No Hydrogen Sensitivity *	$5,567,140	2%	$6,347,214	7%	14%

Note: present value revenue requirements do not reflect any market sales revenue since sales were not allowed in the model
** The Islanded and No Hydrogen CTs portfolios are sensitivities on the Optimized portfolios*

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Key modeling challenges and observations (1)

Time Sampling Trade Off

- Selecting a sampling period for capacity expansion modeling involves a trade off between simulation periods and model run time
- Selecting a “typical week” or modeling representative days with aggregated time blocks (i.e. splitting days into 4 blocks of time) may result in longer run times
- Sometimes trying to model every hour of every day of the planning period is not feasible and the model will not be able to solve
- Selecting representative days (i.e., 2 days as one on-peak and one off-peak) will result in shorter model runs, but can lead to some differences in sampling for renewable profiles and load when the representative days are mapped to the entire planning year

Uncertainty in Costs

- It is challenging to predict when the inflationary and supply chain pressures of the last few years will dissipate and the countereffect of the additional tax credits from the passage of the IRA (The IRA was introduced as this study was underway)
- Transmission costs also may be higher as additional wind and solar resources are brought online
- The combination of these three items make it challenging to make projections for resource costs into the future

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Key modeling challenges and observations (2)

Imports/ Exports

Imports

- Capacity expansion models typically include an input for "unserved energy"
- If the unserved energy cost is high enough, then the model will seek to build new resources to avoid the unserved energy costs
- When simulating a system without the ability to import, this means that the model will either choose to incur the unserved energy cost or build more resources
- We will typically see more resources added when imports are not available to meet the energy needs of the system

Exports

- Sometimes constraints have to be imposed (not allowing exports or limiting new resource builds) to prevent the model from overbuilding the system to take advantage of off-system sales to lower system costs

A tale of two capacity modeling tools

- The Moonshot study utilized two modeling suites: the practitioner toolkit, which is the focus of this appendix, and a regionally-coordinated capacity expansion modeling tool
  - The practitioner toolkit used EnCompass for capacity expansion.
  - The regionally-coordinated capacity expansion approach used SWITCH (SWITCH is described in detail in Appendix 2)
- These slides are included to help the reader understand the key differences between the EnCompass and SWITCH modeling exercises

Cross-walking between our two capacity expansion modeling results

- We used two capacity expansion models
  - Encompass (coupled with GridPath) is the "**practitioner**" approach (PRM approach)
  - SWITCH is a regional model that optimizes resources for the entire West (an idealized "**regionally-coordinated**" planning world) (uses 365 days/4 hr blocks)
- Contrasting the results:
  - **Encompass** prefers "emerging" technologies for reaching 100% clean (hydrogen, LDES)
  - **SWITCH** relies on current technologies exclusively (storage durations are generally short) and relies on exchange with the rest of the West (net importer in summer, net exporter in winter)
  - **Both tools** were tested in **"islanded mode"** and can achieve 100% clean systems by up-sizing renewables, with short duration storage, and with no reliance on exchanges

- While we don't have an appropriate economic comparison between Encompass and SWITCH portfolios, three core strategies to reach 100% emerge (these **are not** mutually exclusive):
  1. **Emerging technology approach** (e.g., hydrogen, long duration storage)
  2. **Upsizing existing technologies** (e.g., islanded case with solar, batteries, biomass)
  3. **Regionally coordinated planning** (e.g., West-wide capacity expansion planning)
- While the "regionally-coordinated" approach is idealistic, it speaks to the value of markets
- Policy makers may want to navigate these paths (most relevant to the last "mile" but not exclusively) based on risk mitigation

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Comparison of EnCompass and SWITCH models

	Encompass	SWITCH
Sampling and chronology	1 on peak and 1 off-peak day per month	365 days and 4 hour blocks
Geography	PNM focus with assumptions about imports/exports	WECC wide focus (using 50 zones) with PNM being its own zone
Capacity needs	Meets an annual PRM of 21.2%, based on ELCC values for renewables and storage, UCAPs for other resources	Does not explicitly model for capacity needs but ensures energy is met in all hours
Transmission	Models TX flow constraints between 3 zones within PNM's LSE. Outside imports/exports modeled as a 150 MW limit all hours.	Copper plate within PNM LSE. Existing transmission constraints between all 50 zones in WECC are enforced.
New candidate resources modeled	Solar, wind, batteries (4-hour, 10-hour, and multiday), generic H2, and geothermal	Solar, CSP, wind, offshore wind, storage (any duration), coal, thermal, nuclear, geothermal, and biomass
Wind and solar profiles	1 wind and solar profile based on a weighting of several sites for new resources	266 different wind and solar profiles within PNM zone

Details of the SWITCH model, which was used to conduct regionally-coordinated capacity expansion modeling, are shown in Technical Appendix 2.

Practitioner Toolkit:
Resource Adequacy Modeling using GridPath

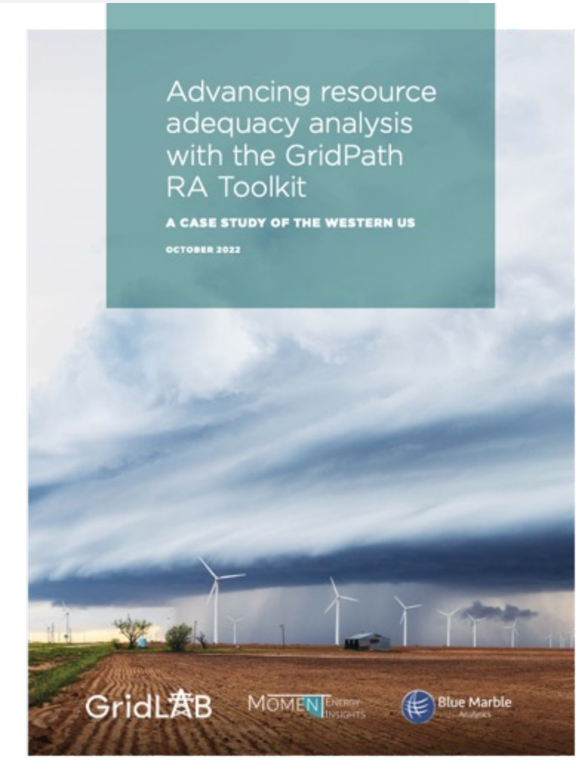
Foundation of the resource adequacy modeling

The resource adequacy analysis was conducted using GridPath. This modeling step used the resulting portfolios from the capacity expansion plan to determine whether they were reliable (achieved a 1-day-in-10-year loss of load expectation).

Unlike the capacity expansion modeling, this process included a more detailed representation of many weather years and interactions (imports and exports) with the rest of the Western Interconnection.

The starting point for resource adequacy analysis in this study is the GridPath RA Toolkit. The GridPath RA Toolkit (including the software and case study components) are described along with details about how the GridPath RA Toolkit is modified for this study.

GridPath RA Toolkit



Open-source Toolkit for conducting RA analysis in the Western US using publicly available data.

The Toolkit consists of:

- **GridPath**, Blue Marble's open-source power system platform, which includes capacity expansion, production cost, and RA modeling: https://github.com/blue-marble/gridpath
- **Accompanying code** to develop and post-process RA runs in GridPath: https://github.com/MomentEI/GridPath_RA_Toolkit
- **Western US Dataset**, which includes the load, resource, and transmission data for conducting RA assessments of the Western US in 2026: www.gridlab.org/GridPathRAToolkit

Users can customize the datasets to evaluate other systems, years, or portfolios. Users can also modify the code to leverage additional capabilities in GridPath or to create new functionality.

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GridPath RA Toolkit

Key features for RA analysis

Weather correlations

Two modes available for capturing key weather correlations between load and resource availability over very large geographical areas: Monte Carlo Simulation and Weather-Synchronized Simulation.

Energy-limited resources

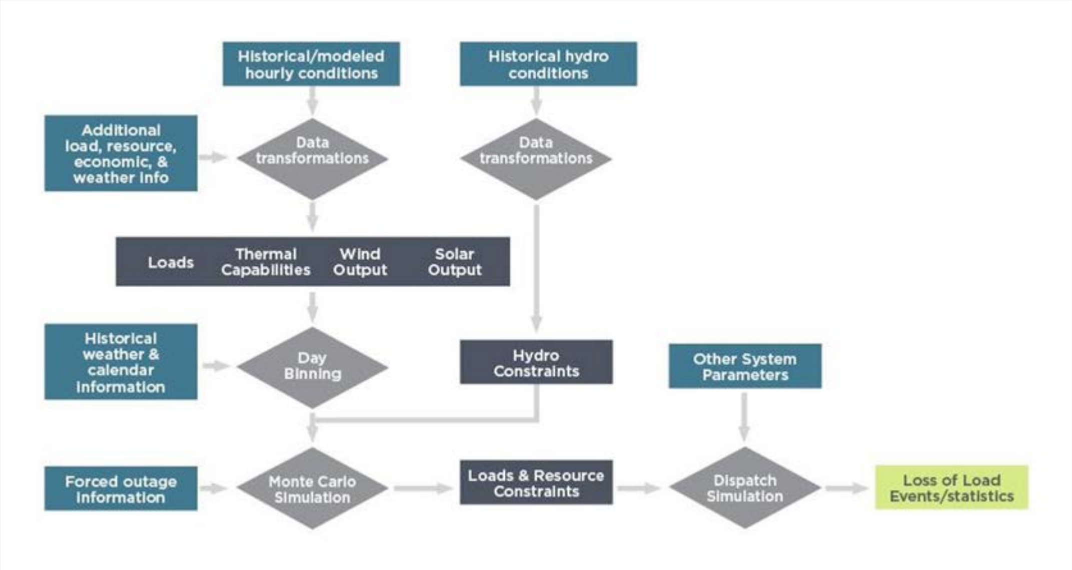
Dynamic dispatch of energy-limited resources, like hydropower, energy storage, and hybrid resources to avoid lost load.

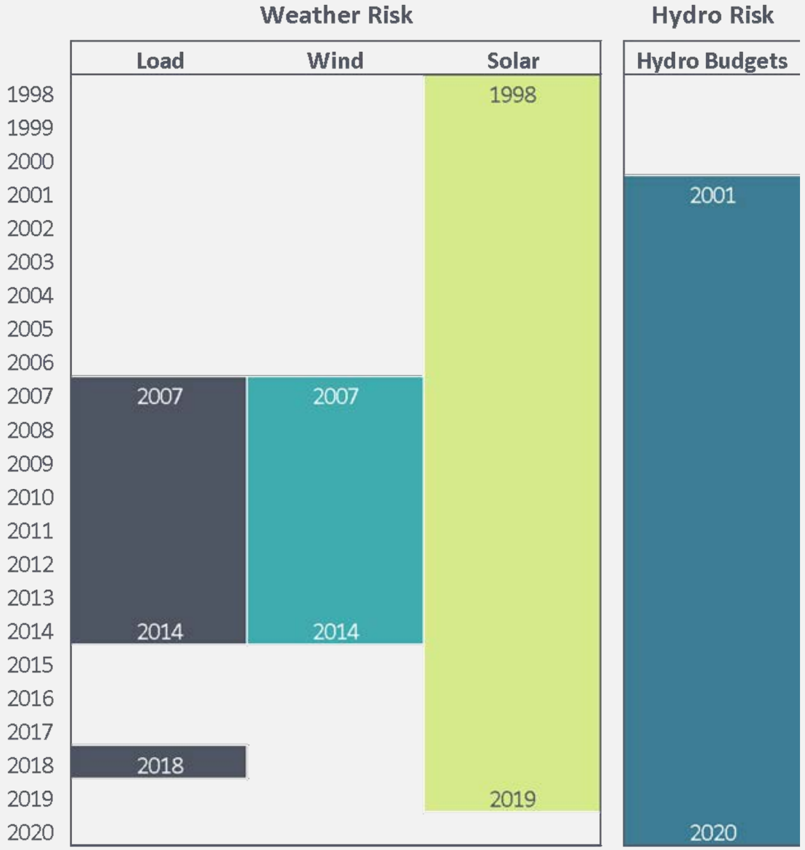
Transmission and regional coordination

Dynamic transmission flow modeling provides transparency into weather-coherent and transmission-constrained market availability.

GridLAB Monte Carlo Simulation

The GridPath RA Toolkit report described two simulation modes: Monte Carlo simulation and Weather- Synchronized simulation. The Moonshot study uses the Monte Carlo simulation approach described in this slide.





- Mixes and matches shapes from similar historical days
- Can generate many possible conditions, leading to high precision
- Conditions are not fully physically consistent and may not fully preserve all correlations

Optimization windows and storage modeling

- For portfolios without multiday storage, GridPath is configured to simulate hourly dispatch with perfect foresight over one-week optimization windows
  - Optimization minimizes total unserved energy plus the maximum observed unserved energy in each week
- Across all portfolios, energy storage is constrained so that the beginning state of charge is equal to the ending state of charge over each week (i.e., a periodic boundary constraint)
  - Ensures that energy is not "created" over the course of the simulation
  - Beginning and ending state of charge is selected by the model
- Weekly optimizations with periodic boundary constraints cannot capture the value of multiday energy storage because energy cannot be carried across weeks
- For multiday storage modeling in this study, GridPath was run with one-year optimization windows (perfect foresight) instead of one-week optimization windows
  - Applied periodic boundary constraint across the year
  - Applied very small penalty on any depletion below the maximum state-of-charge to encourage recharging while not compromising reliability (note: penalty was 0.01% of penalty applied to unserved energy)

Data Sources

Transmission topology

- Consolidated BAA-based zonal topology from the GridPath RA Toolkit (based on the WECC 2026 Common Case) into 5 Western regions, plus a separate region for PNM
- Constrained flows between SW region and PNM based on contractual constraints in PNM's IRP (see next slide)

Load shapes

- Hourly load by state for weather years 2007-2014 + 2018 from Evolved Energy Research (Baseline and High Electrification scenarios)
- Mapped to 5 Western regions and PNM using EIA Form 861 data
- These are described in the "Load forecasting" section of this appendix

West-wide resource portfolio

- Non-emitting resource portfolios reflect planned additions, based on a review of recent IRPs (published between 2020-2022)
- Emitting resources excluded and replaced with capacity- and energy-constrained proxy resources (more information on "Import Framework" slides)

Renewable shapes

- Existing resource shapes were taken from the GridPath RA Toolkit Western US Dataset
- BTM solar and planned and new-build solar and wind resources were developed as described in the "Renewable Generation Profiles used in the Practitioner Toolkit" section

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RA Model Topology

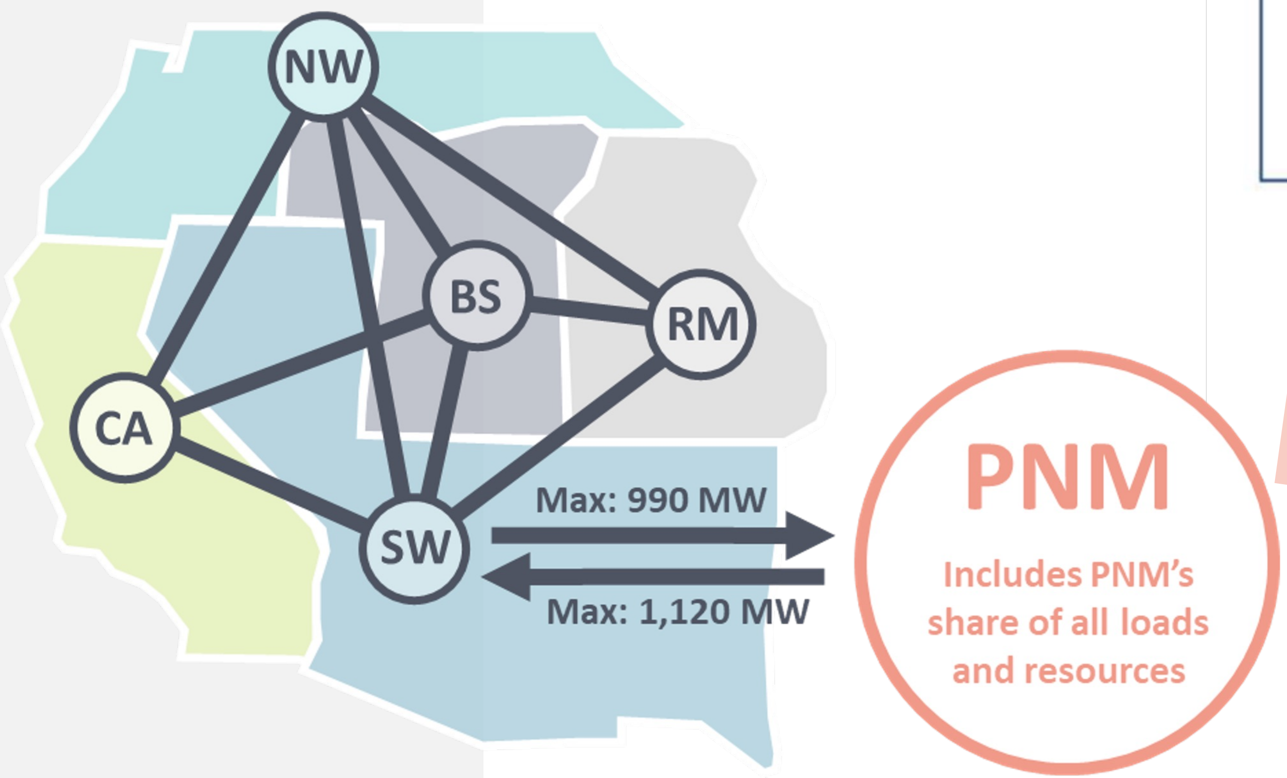
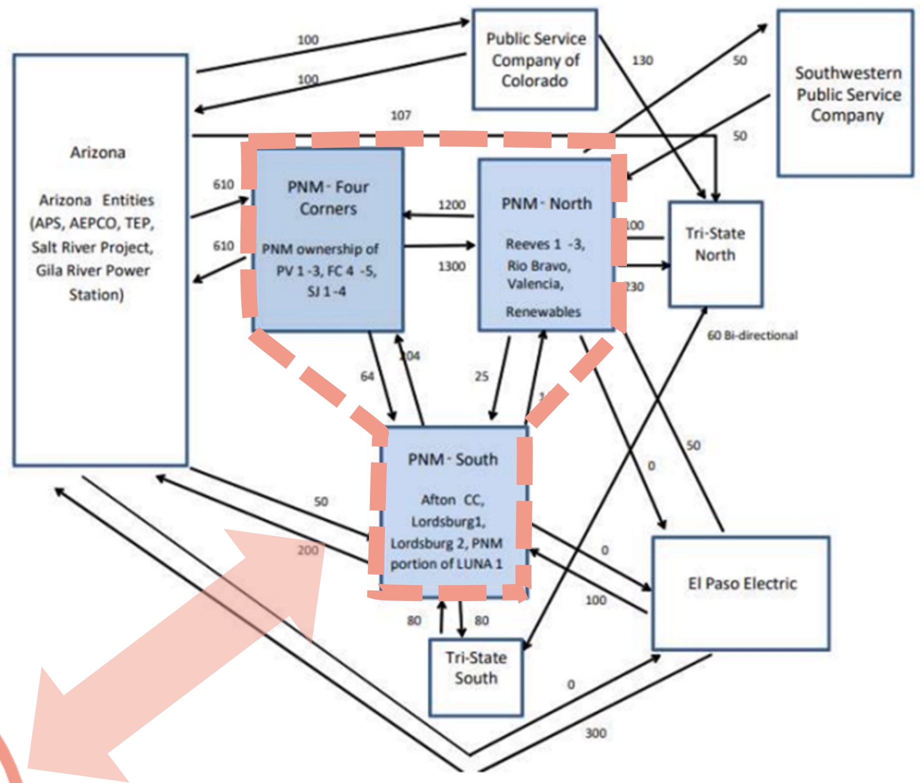


Figure 11: Study Topology and Market Assistance



- Simplified regional topology
- Converted to PNM contractual representation
- Approximated transmission constraints into/out of PNM – Four Corners, PNM – North, and PNM – South

Import Framework

Challenge in considering imports:

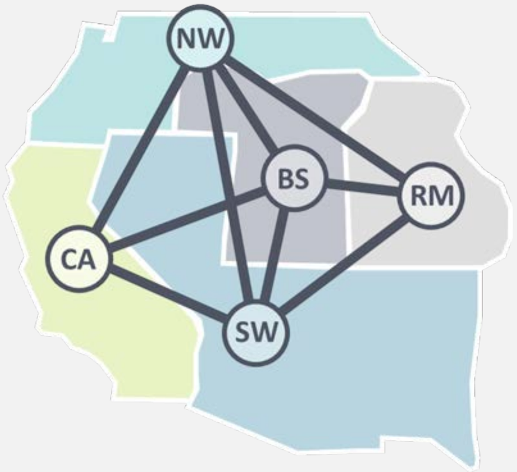
The study needed to develop a methodology to consider the potential benefits of importing excess renewable energy from neighboring systems without relying on imports of fossil-fuel resources. To accomplish this, the study developed a novel, four-step process to evaluate resource adequacy and availability of imports across the West.

Objectives:

- Account for coherent weather conditions across the West
- Capture regional load and resource diversity benefits
- Respect transmission constraints
- Avoid free-ridership and net reliance on fossil generation outside of PNM
- Avoid subsidizing RA for the rest of the West

Step 1. Add currently planned clean resources (based on IRPs) and remove all emitting resources across the West.

Step 2. Simulate operations in the West without PNM to identify shortages not associated with PNM.



Example January week results without PNM:

Total shortages:
3,830 GWh

Max shortage:
43,896 MW

Step 3. Add technology-agnostic energy-limited resources to the rest of the West to exactly avoid all unserved energy.

- **Example week:** Add **43,896 MW** of energy-limited resources that can provide up to **3,830 GWh** of energy in the example week. This is an 11.5-hour resource.

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Import Framework (continued)

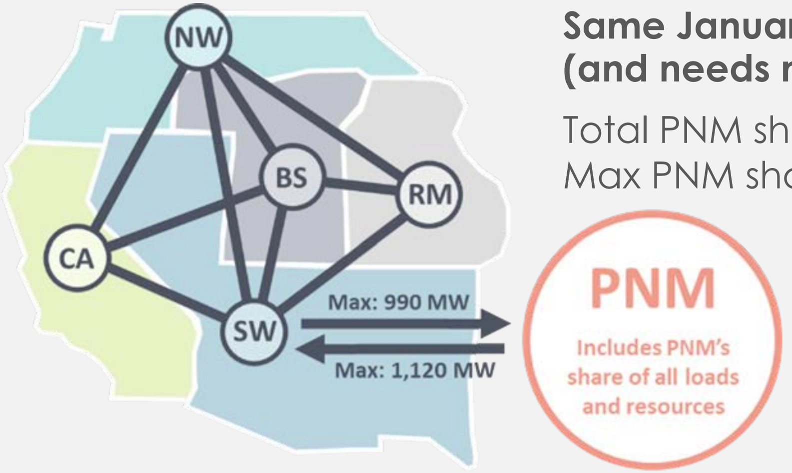
Outcome

The interchange between PNM and the rest of the West was evaluated across a wide range of coherent weather conditions experienced across the entire region. This included load variation as a function of temperature and wind and solar output consistent with real weather systems as they are experienced across the West.

The process allowed PNM to benefit from interregional coordination, while isolating the resource adequacy challenges specifically attributable to meeting PNM loads.

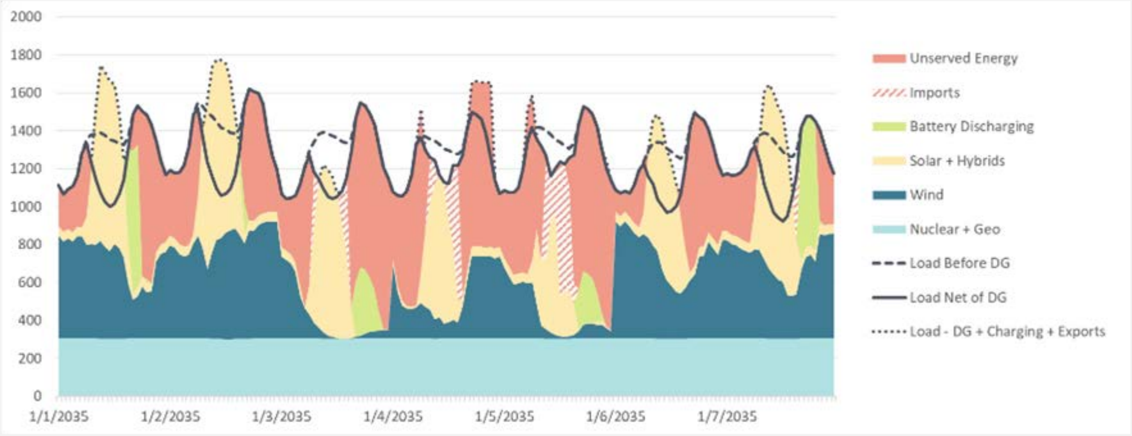
Sensitivity analysis was also conducted where PNM was islanded and had to meet resource adequacy requirements in isolation.

Step 4. Add PNM loads and resources back into the model and attribute any simulated shortages to PNM.



Same January week with PNM (and needs met in rest of West):

Total PNM shortages: **58.7 GWh**
Max PNM shortage: **868 MW**



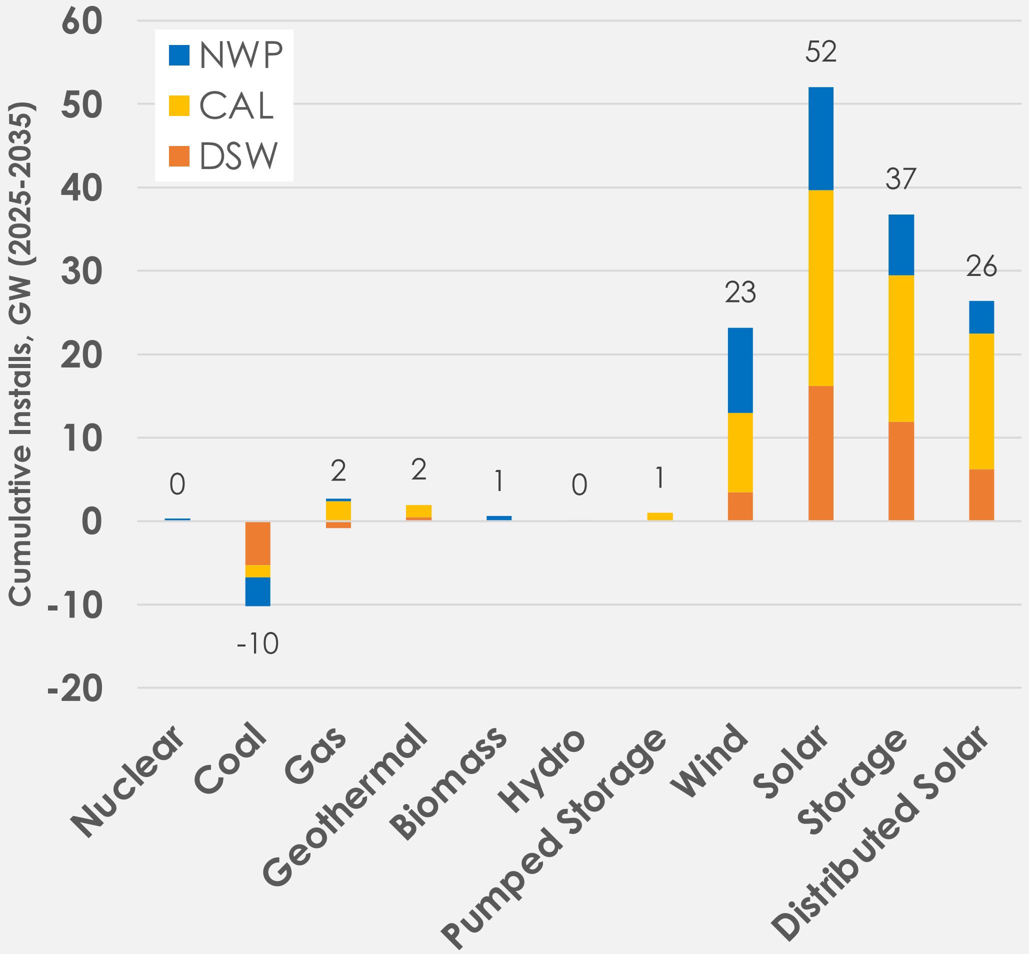
West-wide resource portfolio

West-wide IRP Review

- Utility preferred plans / reference scenarios (pre-IRA)
- Announced retirements and installations
- 80 GW of renewables, 37 GW of storage, -8 GW fossil

West-wide BTM-solar forecast

- +26 GW by 2035, zip-code granularity (details in backup)



GridLAB Baseline Scenario Results

These results quantify the PNM loss of load expectation across all three portfolios. Capacity and generation was also provided for the Hydrogen (H2) CT capacity as this resource serves as the marginal capacity resource (or resource of last resort) to meet demand, after accounting for variable renewables and storage. The hydrogen data quantifies both the capacity (MW) and energy (GWh and fuel requirement) needed for RA.

First the results are provided for the EnCompass portfolio directly, then the portfolio was iterated by reducing hydrogen CT capacity (in 100 MW blocks) until the RA criterion was met. This shows the amount of firm capacity that could be avoided while still meeting the RA criterion. This iteration is discussed further in Resource Adequacy & Capacity Expansion Iterations section.

	Optimized		Diverse Resources		Multi-Day Storage	
	EnCompass Portfolio (based on PRM)	GridPath Adjusted Portfolio (based on 0.1 days/year LOLE)	EnCompass Portfolio (based on PRM)	GridPath Adjusted Portfolio (based on 0.1 days/year LOLE)	EnCompass Portfolio (based on PRM)	GridPath Adjusted Portfolio (based on 0.1 days/year LOLE)
GridPath LOLE (days/year)	0.00	0.09	0.07	0.04	0.00	0.04
H2 CT Capacity (MW)	1000	600	520	500	760	400
H2 Generation (GWh)	511	508	410	402	371	445
H2 Capacity Factor (%)	5.8%	9.7%	9.0%	9.2%	5.6%	12.7%
H2 Fuel Offtake (metric tons H2/yr.)[1]	36,504	36,289	29,289	28,717	26,503	28,574
H2 Renewable Capacity Need (MW)[2]	626	622	502	492	454	490
H2 Water Usage (million gallons)[3]	171	170	137	134	124	134
H2 Water Need (% of current PNM use)	6%	6%	5%	5%	4%	5%

[1] *Hydrogen fuel offtake is based an H2 LHV of 33.33 kWh/kg H2 and a 42% efficient combustion turbine*
[2] *Renewable capacity needed is based on a 50/50 wind solar split and annual CFs of 42% (wind) and 32% (Solar)*
[3] *H2 water usage is based on an 18 L H2O/kg H2 conversion of the fuel offtake needed*

Baseline Scenario Results (continued)

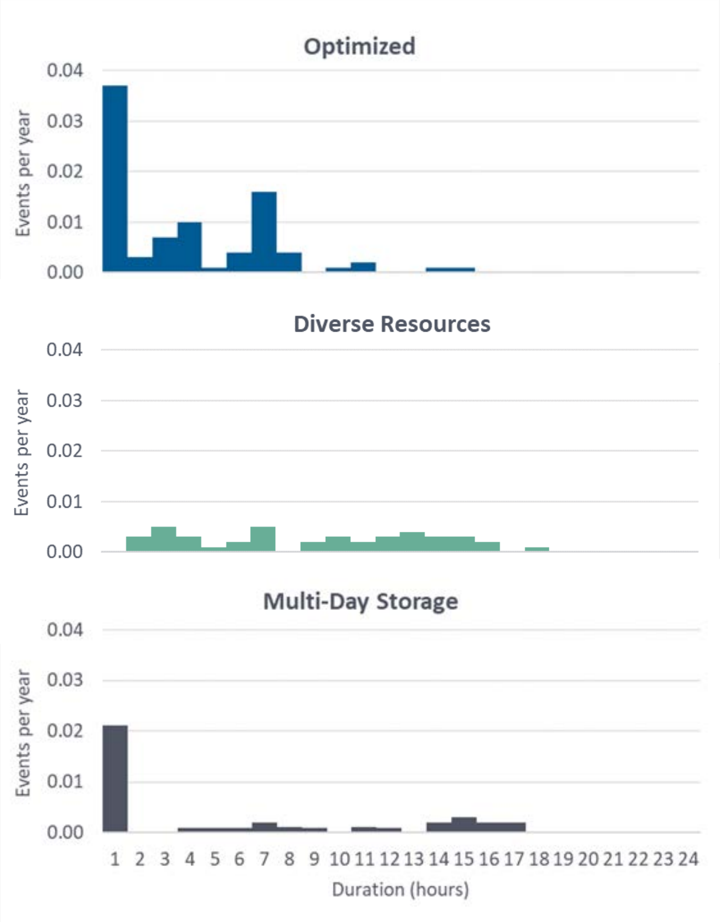
A complete set of resource adequacy results are provided in the table for the portfolios where the hydrogen CT capacity was adjusted so that the LOLE below the 0.1 days/year reliability criterion.

Interestingly, the Diverse Resources portfolios shows relatively low LOLE (0.4 days/year) but the highest average event size and duration, likely driven by times where the geothermal resource was unavailable. This highlights the importance of using multiple metrics to evaluate resource adequacy.

The multi-day storage portfolio, in contrast, saw the highest frequency of short during shortfalls (1-hour) relative to the longer duration shortfalls.

	Optimized	Diverse Resources	Multi-Day Storage
LOLE (days/year)	0.09	0.04	0.04
LOLH (hours/year)	0.34	0.38	0.23
EUE (MWh/year)	29	25	13
NEUE (ppm)	2.4	2.1	1.1
Average event size (MWh per loss of load day)	330	597	325
Average hourly shortage (MWh per loss of load hour)	85	66	55
Average event duration (hrs)	3.9	9.1	5.9

Event duration distributions

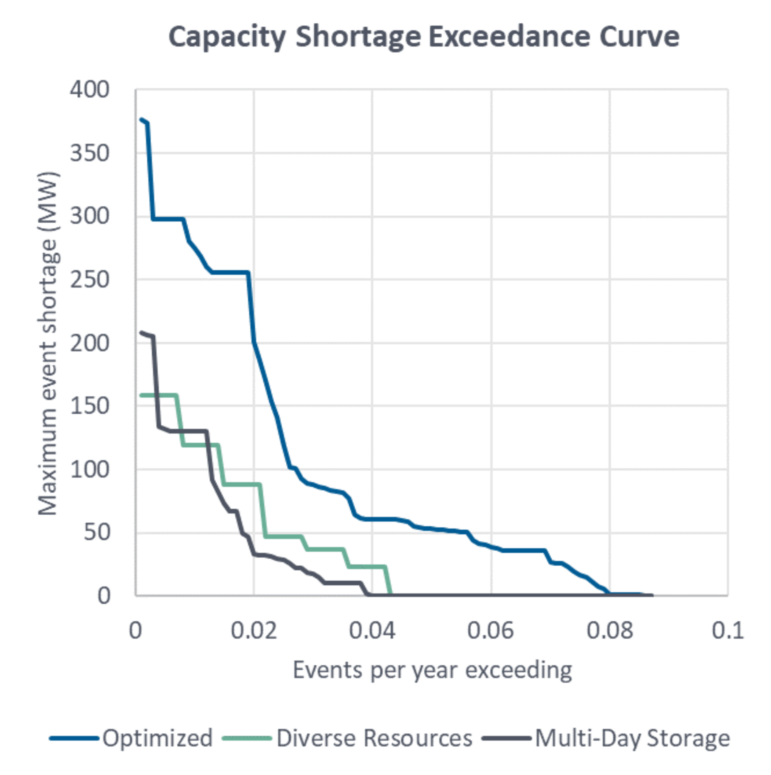


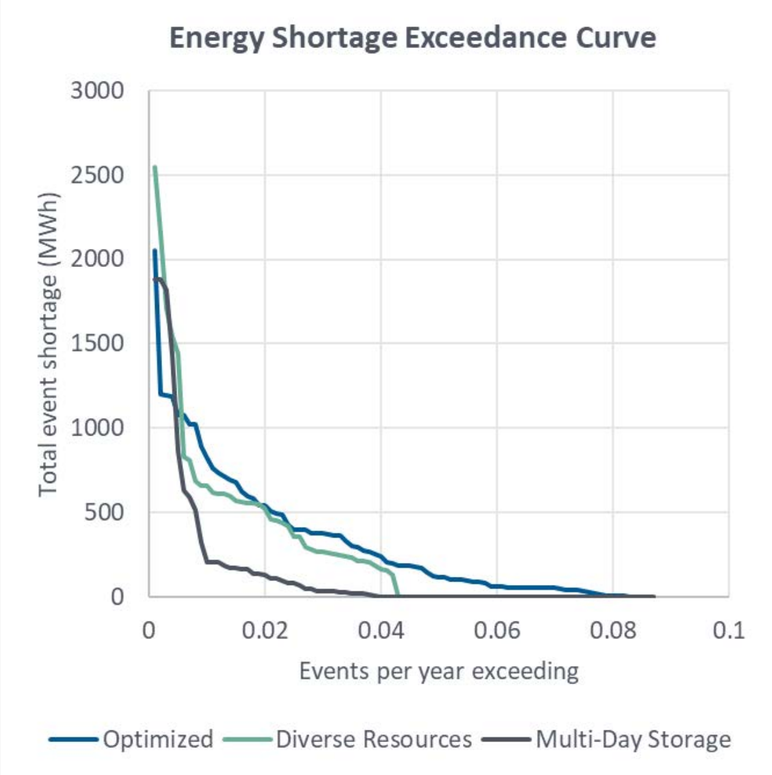
Baseline Case Results

The exceedance curves shows the frequency of shortfall events exceeding a certain size in terms of capacity or MW (left) and energy or MWh (right)

This helps better characterize the *individual* shortfall events rather than the averages presented in the previous slide.

This information can be used to help identify the potential size of resources or imports that would be required to mitigate additional risk, or to understand the potential magnitude and impacts associated with shortfall events.

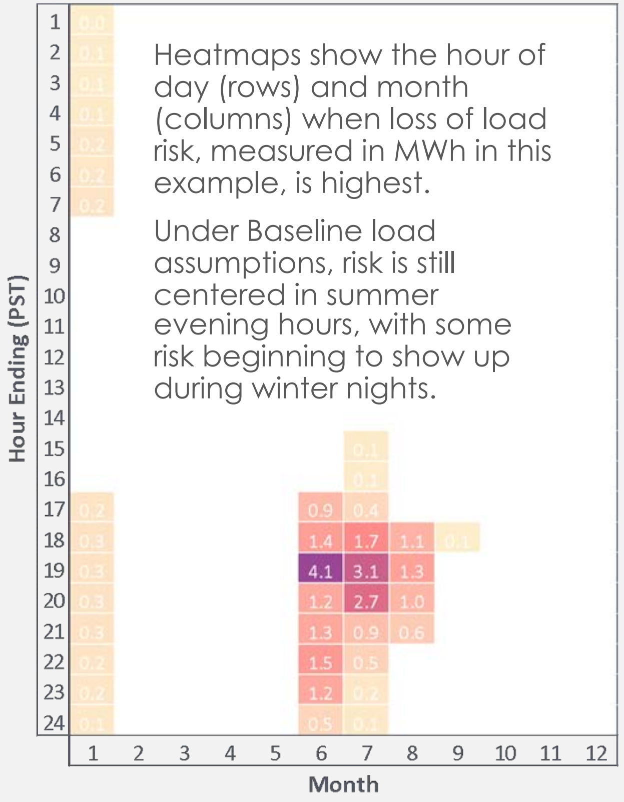




GridLAB

Baseline Case EUE (MWh) by month-hour

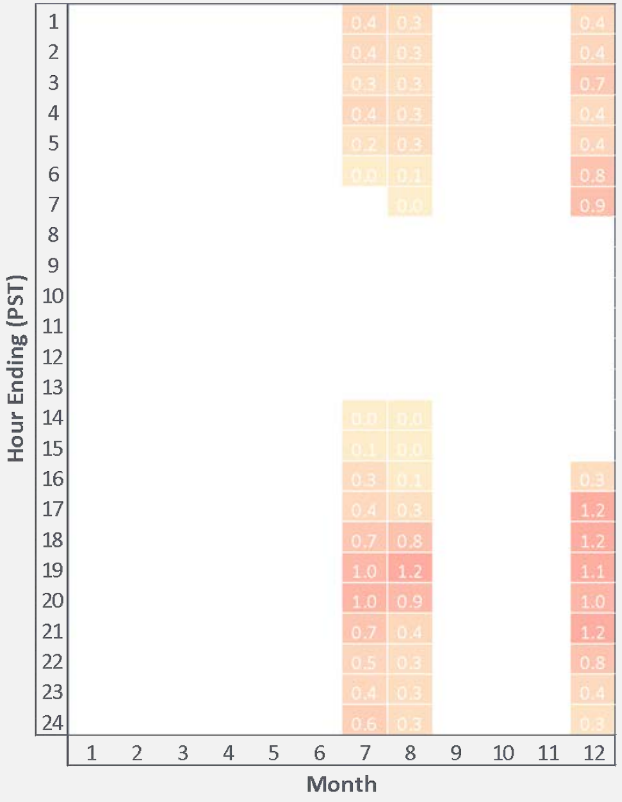
Optimized



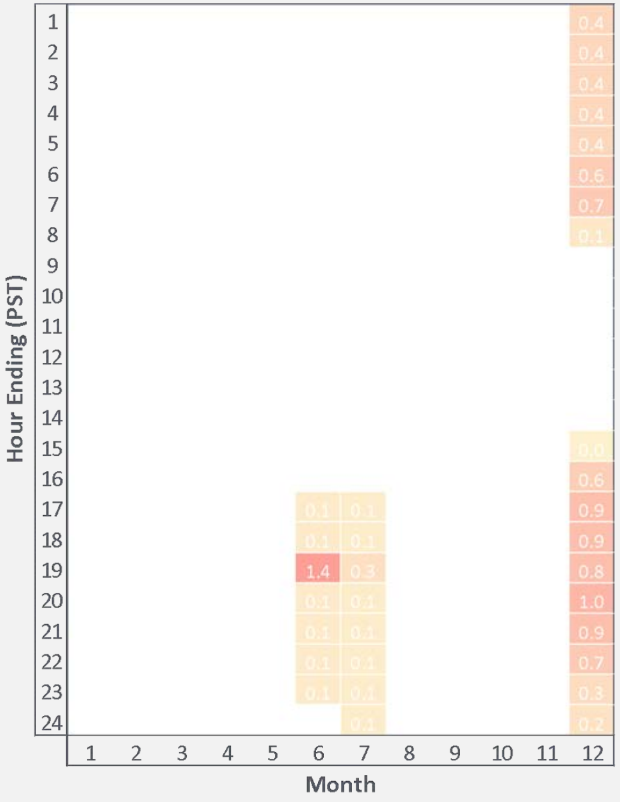
Heatmaps show the hour of day (rows) and month (columns) when loss of load risk, measured in MWh in this example, is highest.

Under Baseline load assumptions, risk is still centered in summer evening hours, with some risk beginning to show up during winter nights.

Diverse Resources



Multi-day storage



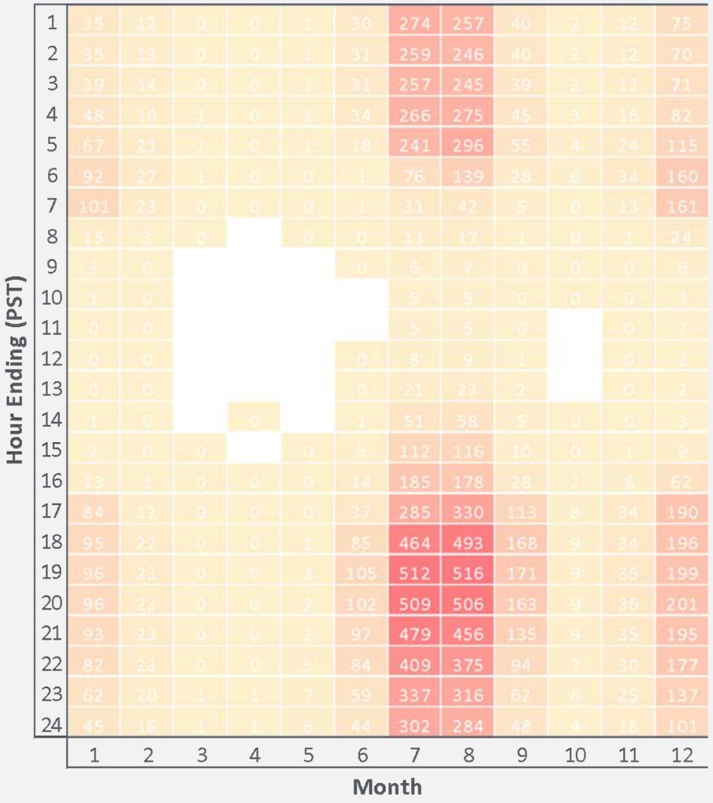
Baseline Case H2 Dispatch (avg MW) by month-hour

Heatmaps of the average hydrogen dispatch show similar findings as the previous slide.

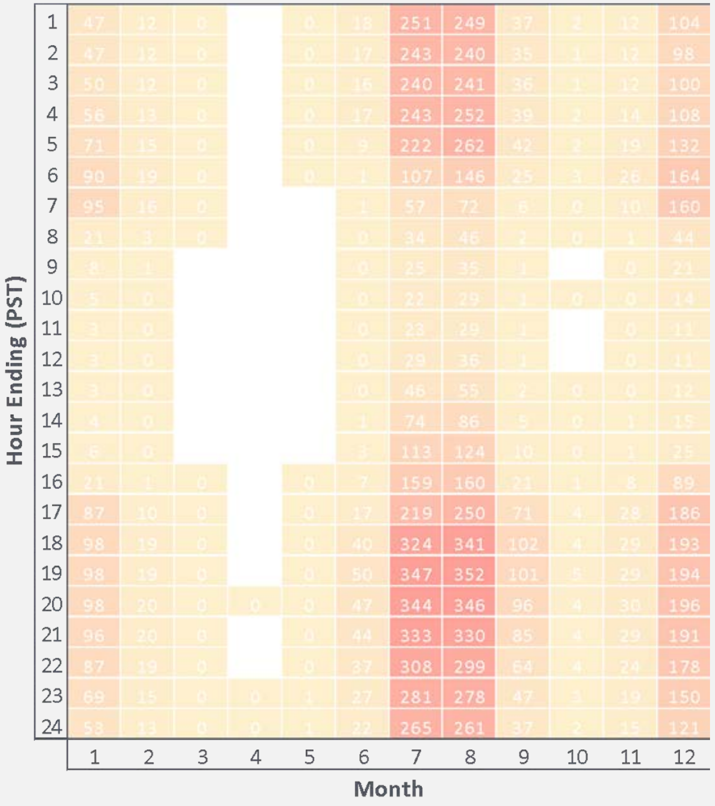
They hydrogen CT capacity is needed most during summer evenings and early morning hours, as well as winter nights.

The heatmaps of the average dispatch can be used to help determine when hydrogen fuel may be needed and to what magnitude. This can be helpful when contracting for hydrogen fuel and evaluating fuel storage needs.

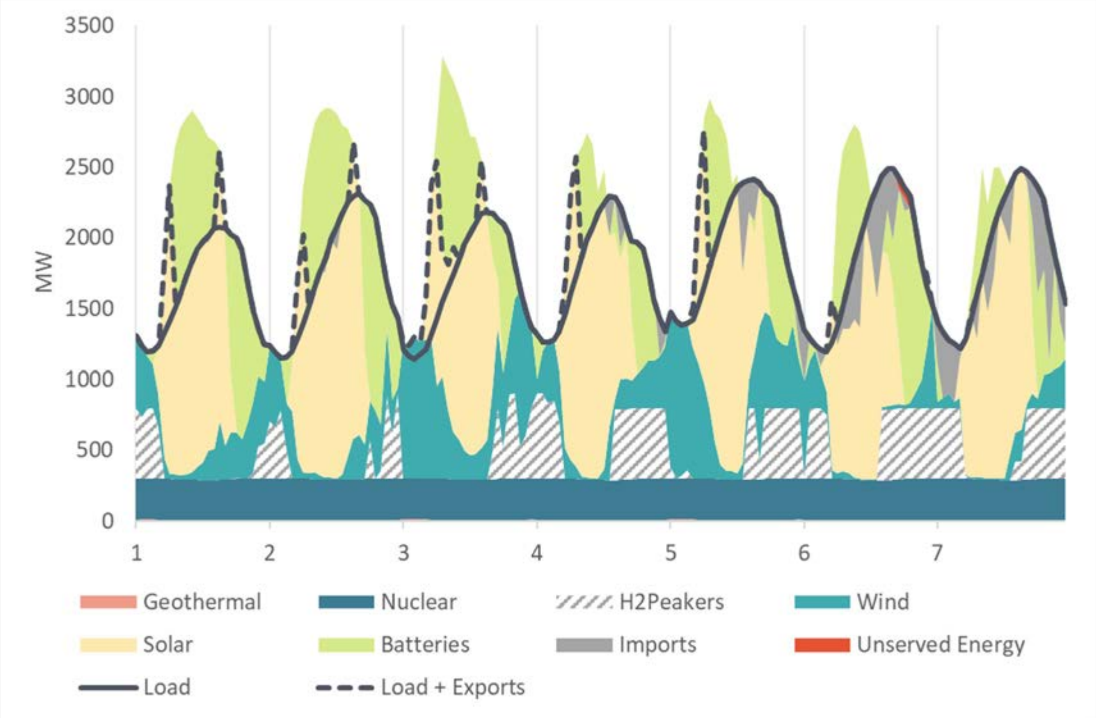
Optimized



Multi-day storage



Optimized Portfolio – Example Week



Observations

- This is a challenging week – small amount of unserved energy observed on day 6
- Most excess solar is used to charge battery storage
- Some excess solar is exported around sunrise and sunset
- H2 Peakers are running mostly during evenings and overnight
- Imports are available during the day (excess solar in the rest of the West) and occasionally at night

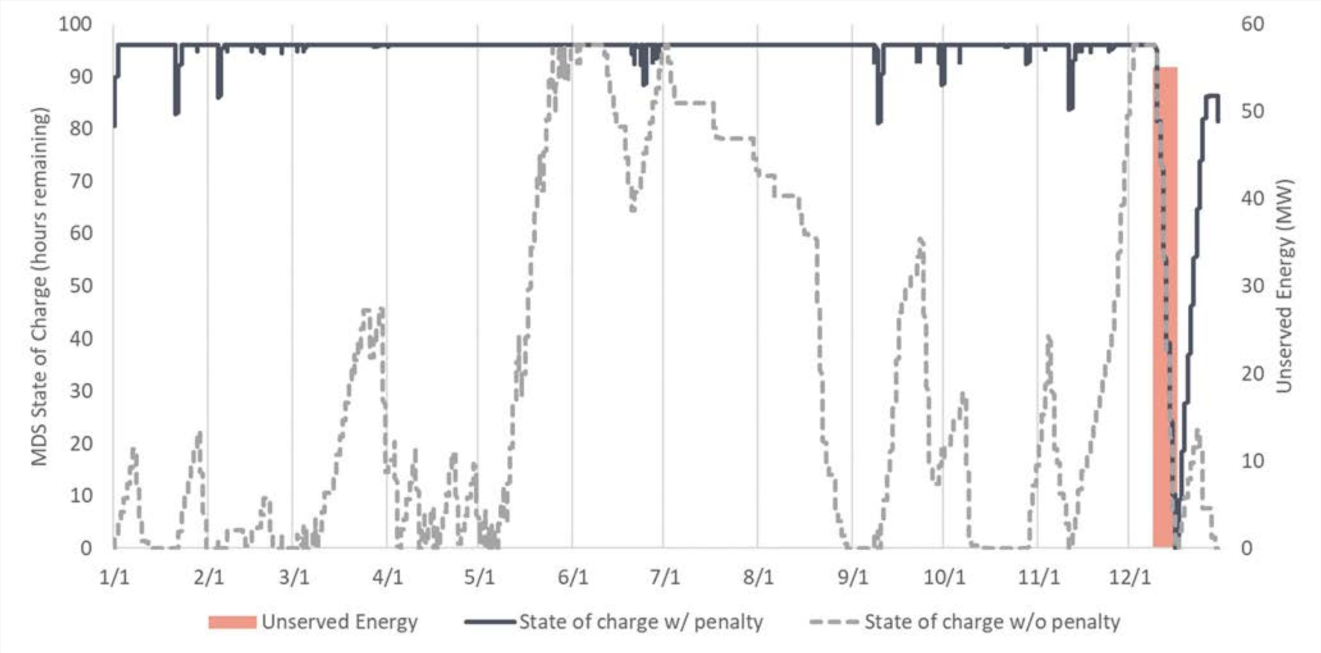
Multi-day storage modeling

The study evaluated multi-day storage (100-hour) scheduling for resource adequacy. This raised important questions about how to manage state of charge given uncertainty in future conditions over days, weeks, and months.

GridPath did not attempt to optimize storage dispatch for economics. Depending on how future dispatch decisions account for uncertainty in future loads, renewable output, hydro, and outages over days to months, economic dispatch of energy storage could lead to lower storage availability during constrained periods and more shortages than are identified in this study. Instead, the study approximates a conservative operating strategy in which multiday storage is only discharged when needed to avoid lost load. During all other circumstances, the study assumes that the operator prioritizes charging multiday storage to maximize the state of charge in case it is needed. To approximate this operating strategy while maintaining energy balance, GridPath was run with the following settings:

- Optimized over a full year with perfect foresight. This increased the problem size, led to longer runtimes, and overestimated forecast accuracy.
- Applied a periodic boundary constraint on the state of charge across the year to ensure energy balance.
- Applied a penalty to any depletion of the state of charge from the maximum level, so that it would only discharge if needed to avoid a larger penalty (i.e., unserved energy).

Multi-Day Storage Utilization



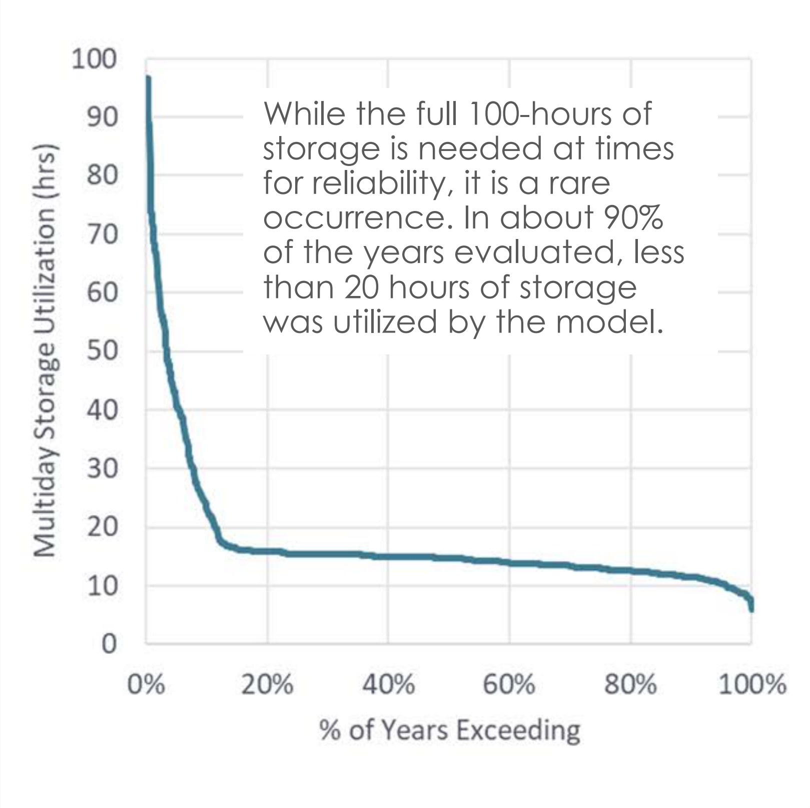
This chart shows the multi-day storage state of charge across an entire year of operation with and without the state of charge depletion penalty (described on the previous slide).

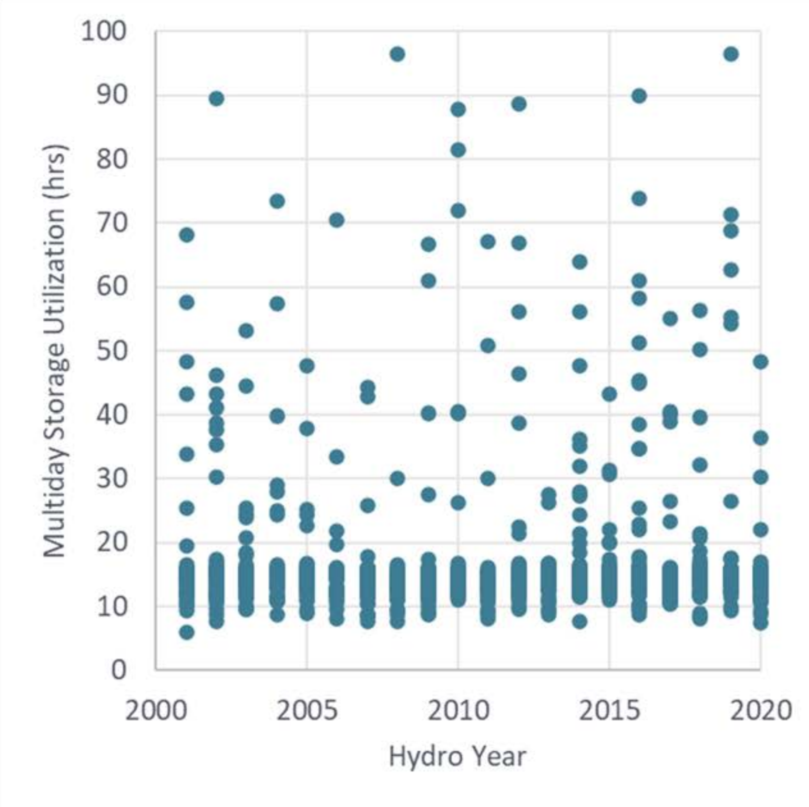
Without the penalty (dashed grey line), multi-day storage has a low state of charge throughout the winter months until over-supply from wind and solar in the spring increases state of charge. The storage is depleted during the summer peak conditions (August) and then quickly recharges at the end of the year to be available during a December RA event.

With the penalty (dark solid line), multi-day storage stays fully charge except when needed most for reliability.

GridLAB

What duration of storage is actually used?





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Baseline Case Sensitivity to Imports

A sensitivity was conducted on the Optimized portfolio to assess the impact of imports on resource adequacy.

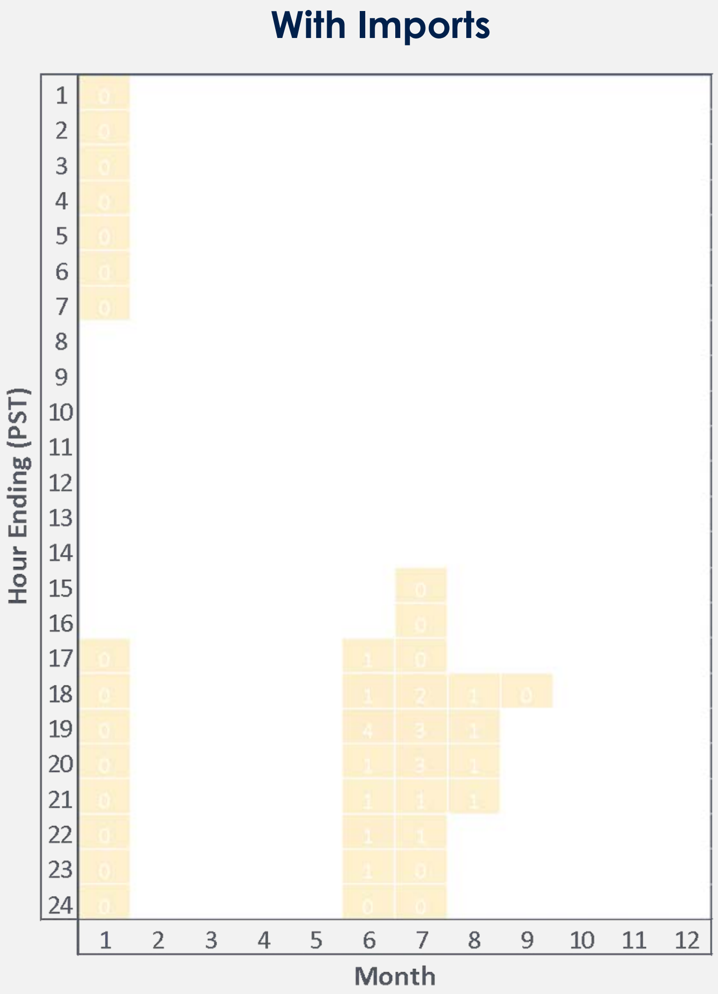
Both the original EnCompass portfolio (prior to removing surplus hydrogen (H2) CT capacity) and the GridPath Adjusted portfolio were evaluated without any imports available.

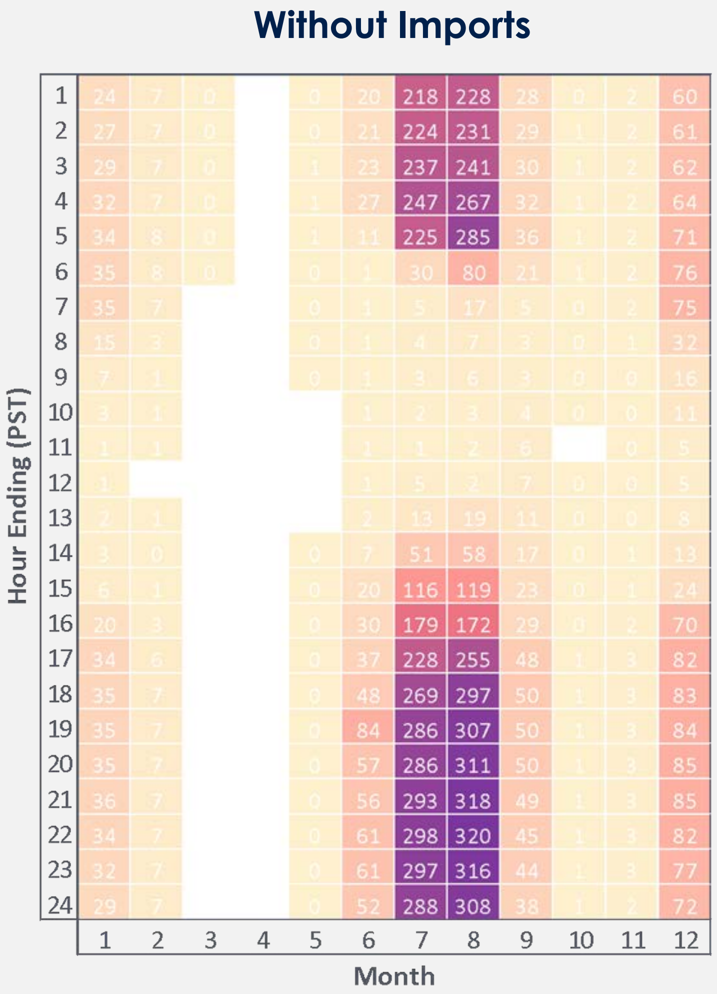
The results showed that the original EnCompass portfolio remained resource adequate (0.07 days/year LOLE), but the iterated portfolio became significantly unreliable (13 days/year).

This illustrates the tradeoff between increased interregional coordination and "going it alone." Both are options available to meet resource adequacy requirements, but without imports an additional 400 MW of hydrogen CTs are required (>$250 million in capital costs) to maintain resource adequacy without fully leveraging imports

	Optimized (with imports)		Optimized (without imports)	
	EnCompass Portfolio (based on PRM)	GridPath Adjusted Portfolio (based on 0.1 days/year LOLE)	EnCompass Portfolio	GridPath Adjusted Portfolio
GridPath LOLE (days/year)	0.00	0.09	0.07	13.3
H2 CT Capacity (MW)	1000	600	1000	600
H2 Generation (GWh)	511	508	889	884
H2 Capacity Factor (%)	5.8%	9.7%	10.1%	16.8%

Optimized Portfolio EUE (MWh) by month-hour





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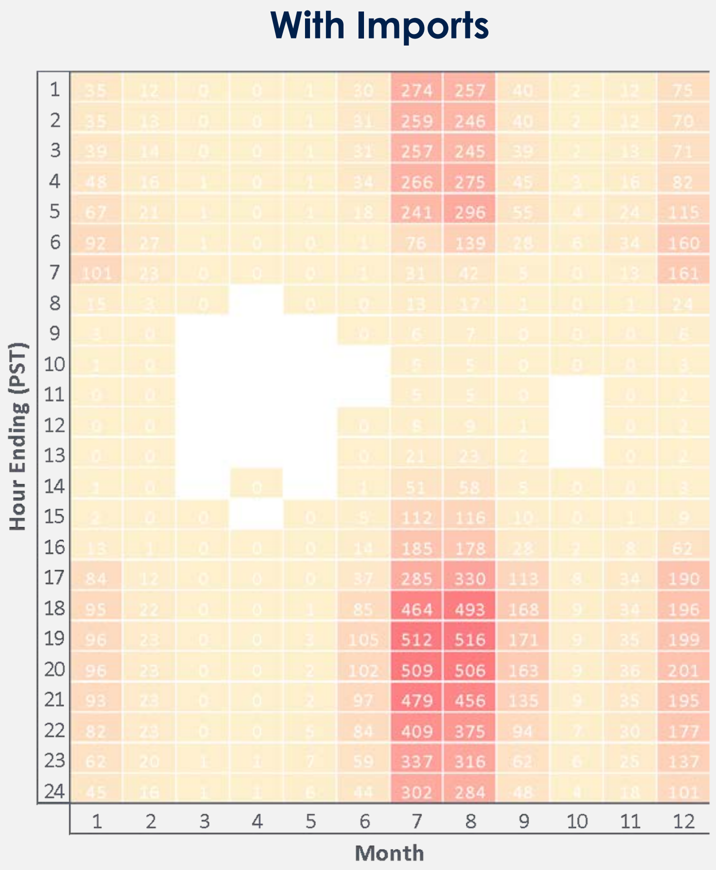
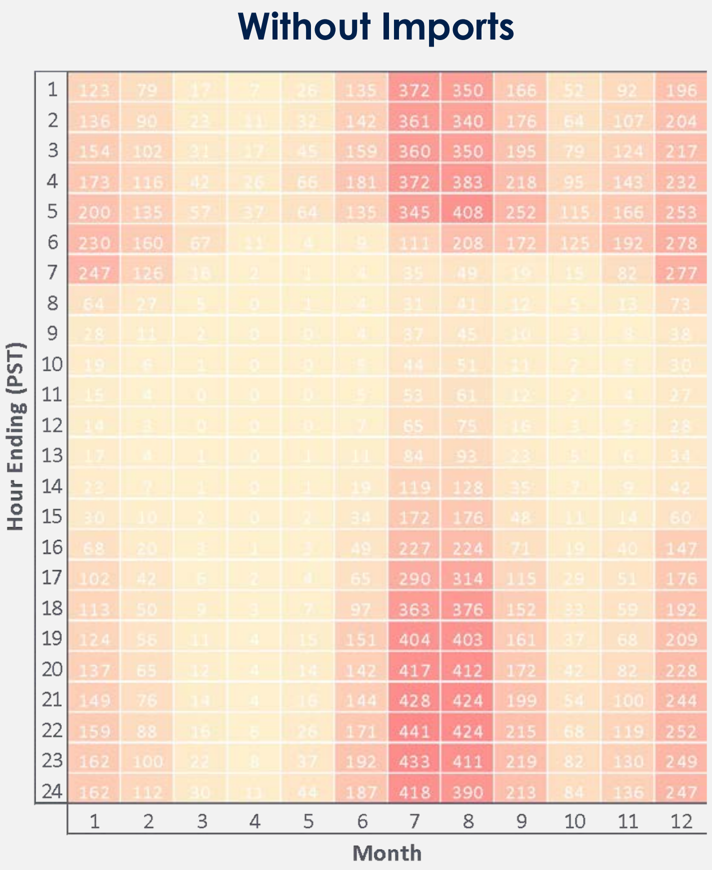
Optimized Portfolio H2 Dispatch (average MW) by month-hour





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High Electrification Demand Results

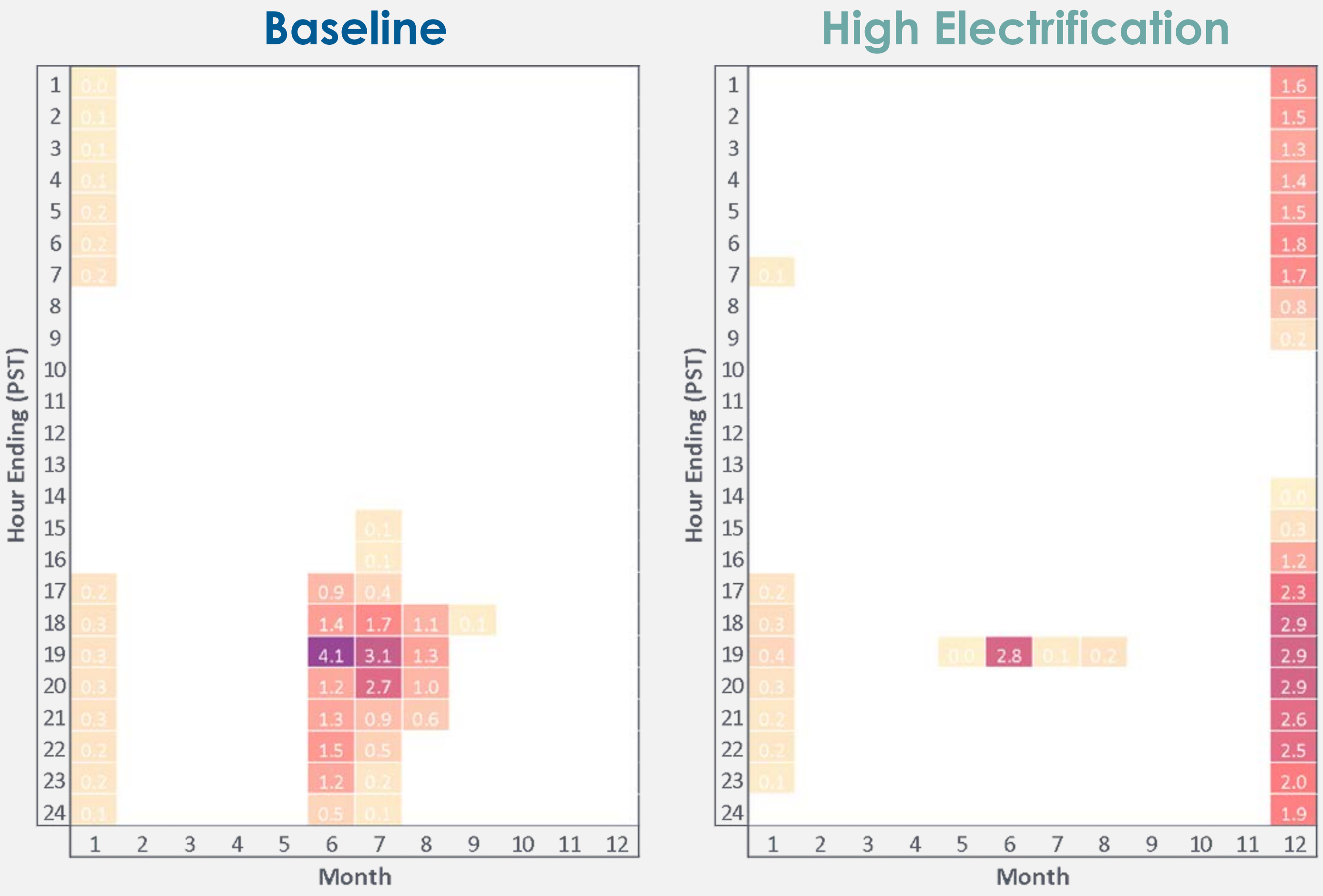
	Baseline Demand Forecast (Optimized)		High Electrification Forecast (Optimized)	
	EnCompass Portfolio (based on PRM)	GridPath Adjusted Portfolio (based on 0.1 days/year LOLE)	EnCompass Portfolio (based on PRM)	GridPath Adjusted Portfolio (based on 0.1 days/year LOLE)
LOLE (days/year)	0.00	0.09	0.00	0.05
LOLP (% of years)	0.0%	5.9%	0.0%	2.2%
LOLH (hrs/year)	0.00	0.34	0.00	0.42
EUE (MWh/year)	0.0	28.7	0.0	38.1
H2 CT Capacity (MW)	1000	600	1520	1000
H2 Generation (GWh)	511	508	927	922
H2 Capacity Factor (%)	5.8%	9.7%	7.0%	10.5%

- EnCompass overbuilds the portfolio, using the High Electrification forecast, similar to the Baseline forecast result
- The High Electrification based portfolio requires both more capacity and energy from the Hydrogen (H2) CTs, relative to the Baseline based portfolio
- The High Electrification based portfolio experiences **fewer years with shortages**, but slightly more **unserved energy** and **more loss of load hours**, even though it has a smaller LOLE

Baseline vs. High Electrification Risk Periods

- **Seasonal shift** – winter becomes the highest risk period
- Remaining RA risk under High Electrification is more concentrated on winter days
- Winter events may span most of the day due to energy shortages
- Some summer evening risk remains

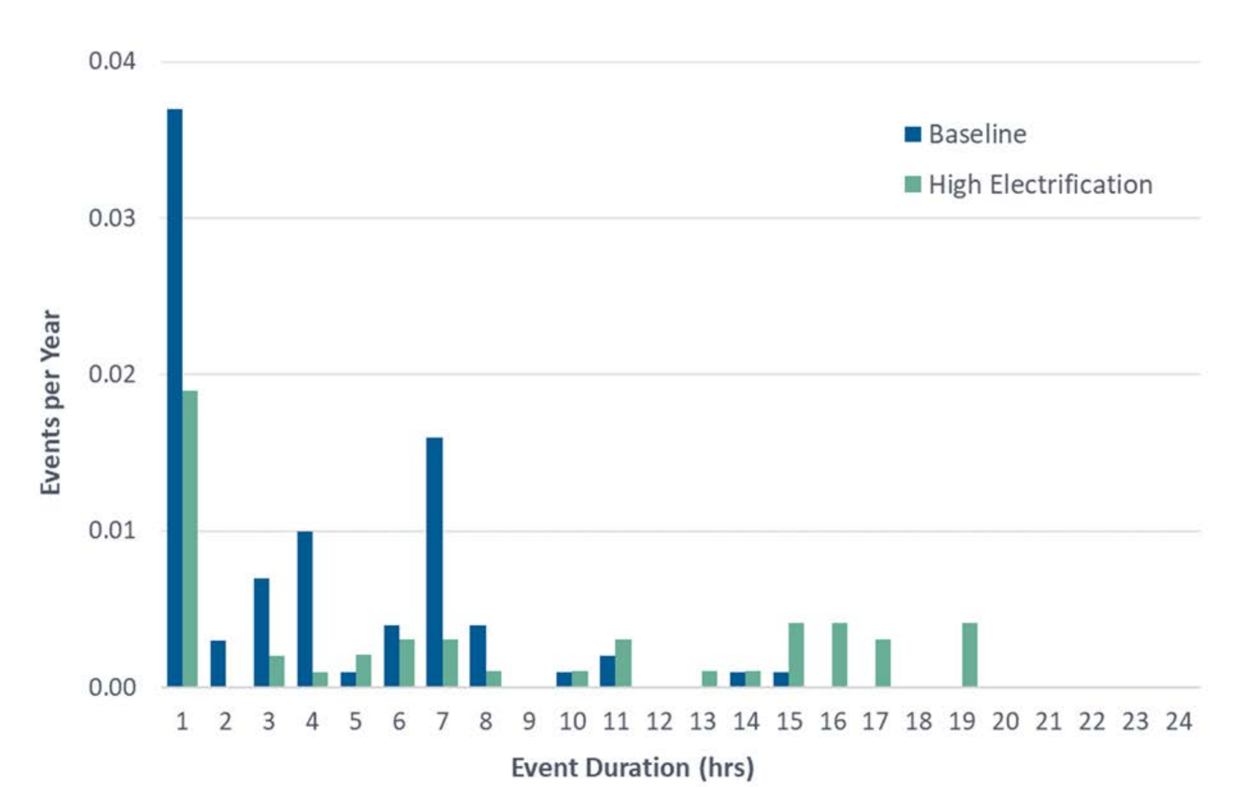
EUE (MWh/yr.) by month/hour bins



Baseline vs. High Electrification Event Duration

- Remaining events under High Electrification tend to be longer, but still less than 24-hours
- Energy constraints become more pronounced in winter, high electrification scenarios

Distribution of event durations



Load Flexibility Modeling

Flexible load formulation:

- End use load shapes developed using EnergyPATHWAYS were assumed to represent timing and magnitude of energy services demand
- Load can be experienced on the grid in advance and "stored" until the energy services are demanded (e.g., pre-cooling)
- Model applies losses to demand "stored" in each hour and further constrains:
  - Maximum dispatched load (fixed value equal to the maximum of the original end use load)
  - Maximum "stored" demand (value varies hourly, derived based on the demand shape and duration parameter)

Flexible load parameters were designed to align with the 2035 flexible load treatment in the NREL Electrification Futures Study[1]:

	% Flexible	Duration (hrs)	Hourly Losses[2]	Max Load (MW)
Res. HVAC	35%	1	20%	269
Res. Water Heating	35%	8	2.5%	78
Com. HVAC	34%	1	20%	80
Com. Water Heating	34%	4	2.5%	14
Light Duty Vehicles	38%	8	0%	169
Maximum simultaneous flexible load (MW)				505

[1] https://www.nrel.gov/docs/fy20osti/73336.pdf and https://www.nrel.gov/docs/fy21osti/79094.pdf
[2] Hour-to-hour losses are estimated

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Load Flexibility Results

- Flexible load reduced the need for battery storage by about 600 MW and 3,500 MWh
- Flexible load did not reduce the need for H2 CTs, as these provide both capacity and energy to the system

	Portfolio Without Flexible Load	Portfolio With Flexible Load
H2 CT Capacity (MW)	950	950
Storage MW	1,565	950
Storage MWh (MW x duration)	9,155	5,626
LOLE (days/year)	0.07	0.10
EUE (MWh/year)	17.0	15.3

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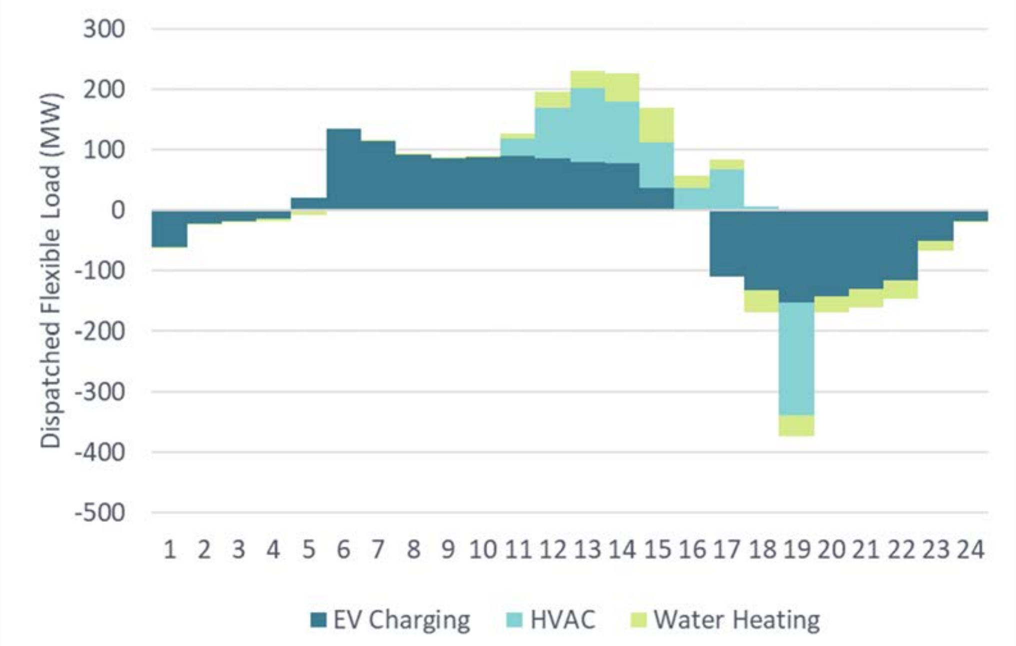
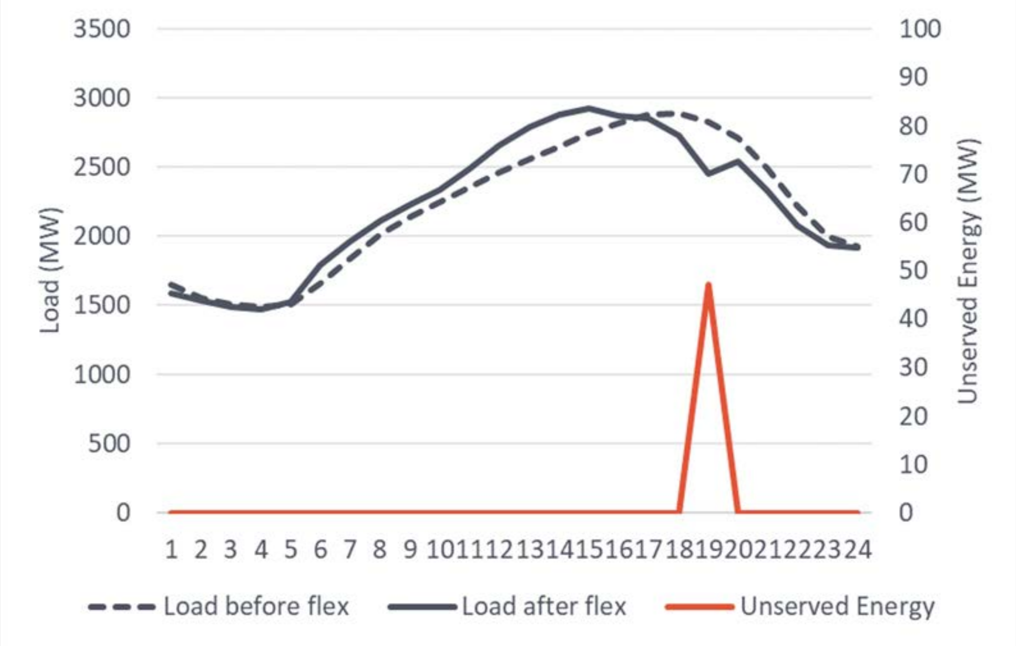
Load Flexibility Results

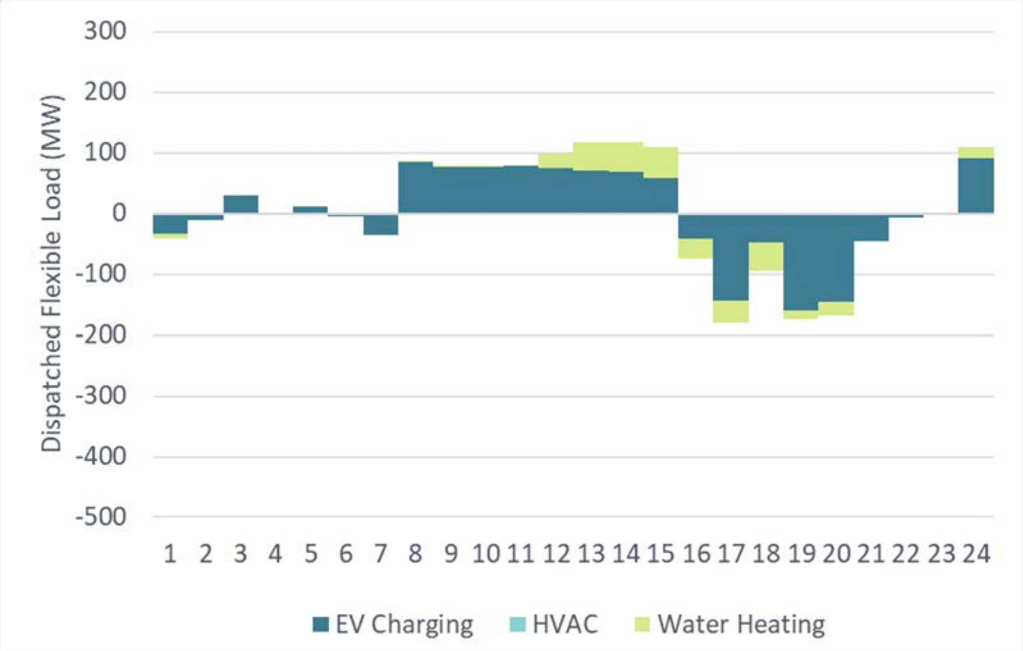
- On summer days with capacity constraints, flexible loads offer a good substitute for batteries by shifting demand away from brief periods of RA risk

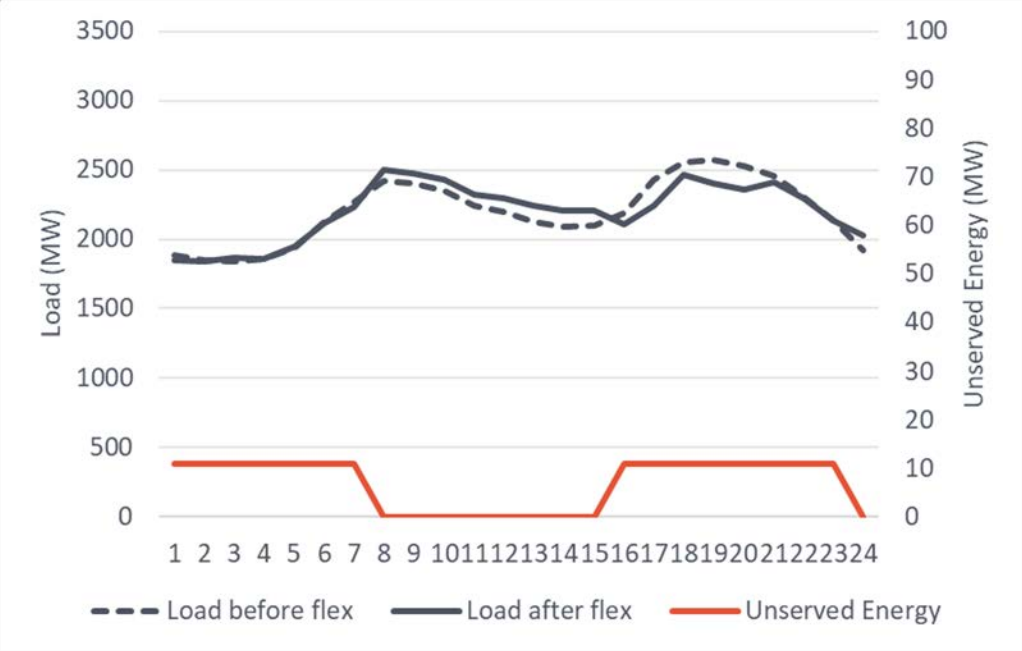




Load Flexibility Results

- On winter days with energy shortages, daytime charging and water heating flexibility provide value, but HVAC flexibility is not utilized, likely due to losses





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Key modeling challenges and observations (1)

RA metrics in storage-dependent systems

- There are many ways to experience unserved energy and the shortages observed in storage-dependent systems will depend on the specifics of the objective function
  - Energy storage losses can result in more unserved energy, so if the model only cares about minimizing unserved energy, it may not use the storage and instead see very large MW shortages in some hours, though fewer MWh overall
  - A penalty term on the maximum shortage helps to avoid these very large events, but results in more MWh overall
- RA metrics can be quite different for the same system, depending on the objective function
  - Adding a penalty to the maximum unserved energy will tend to increase EUE, LOLH, event durations, and potentially LOLE, but will decrease the size of capacity shortages
  - The differences seems greatest in energy-short systems (i.e., when we tested the portfolios without capacity additions, which bring both capacity and energy to the system)
  - As a result, capacity shortages observed in the base runs (i.e., without capacity additions) were not always a good indicator of how much capacity was needed to achieve the LOLE target
- In the final runs:
  - Objective function equally weighed total unserved energy and maximum unserved energy in each optimization window to avoid unnecessarily large capacity shortages. This may have resulted in slightly higher EUE.
  - Iterated on capacity additions to achieve LOLE < 0.1 days per year, rather than relying on base simulation results to estimate capacity needs

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Key modeling challenges and observations (2)

Multi-day energy storage modeling

- Weekly optimizations with periodic boundary constraints could not carry energy across weeks and therefore could not appropriately value multi-day energy storage
- Annual optimizations required much longer runtimes and may risk overstating the value of multi-day energy storage due to the assumption of perfect foresight
- Initial tests were frequently drawing down the multi-day storage state of charge and it was not clear if this was ***needed to*** avoid unserved energy or if it was just ***possible while*** avoiding unserved energy
  - To better understand what was needed from multi-day storage, we applied a small penalty (0.01% of unserved energy penalty) to any depletion of the state of charge below the maximum state of charge
  - This significantly reduced multi-day storage dispatch. It approximated an operational strategy in which the storage is kept full when possible, in order to be prepared for unforeseen events.
- Storage/thermal and multi-day storage/battery co-optimization were important strategies for ensuring that capacity could be utilized during events
  - Example: using thermal resources or multi-day storage to charge batteries in advance of events
  - GridPath was not run in economic mode for this project and did not consider forecast errors, so it is unclear whether these operational practices would arise in more realistic scheduling and dispatch simulations or in real systems

Resource Adequacy & Capacity Expansion Iterations

What is “round-trip modeling,” and why is it required?

Traditional Treatment of Resource Adequacy in Planning Studies

Consistent Inputs & Assumptions

Demand Profiles
EnergyPATHWAYS Baseline & High Electrification
WECC-wide, multi-weather year

Renewable Profiles
NREL NSRDB & WindToolkit
WECC-wide, multi-weather year

Resource Adequacy
Current or potential future portfolios

PRM & ELCC estimates

Capacity Expansion
Portfolio meeting a PRM requirement

Portfolio of resource additions

Final Portfolio

- Planning Reserve Margin (PRM) and Effective Load Carrying Capability (ELCC) are estimated ***before*** the capacity expansion model and used as an ***input*** into the modeling process
- Portfolio effects and saturation effects can change the PRM and ELCC values depending on the make-up of the portfolio, load profile, and other interactions
- If the capacity expansion portfolio differs from the one evaluated in the PRM and ELCC study, the resulting portfolio from the capacity expansion may not be resource adequate
- This creates two potential errors: 1) the system may not be reliable, despite meeting the PRM, or 2) the system may be overbuilt, investing too much money in new capacity
- In this process, the planner and regulator have no insight into whether or not an error exists or how large of an error it might be.
- The process implicitly relies on the input PRM and ELCC to ensure resource adequacy, without backchecking the final portfolios.
- This is common practice in most IRPs across the country today.

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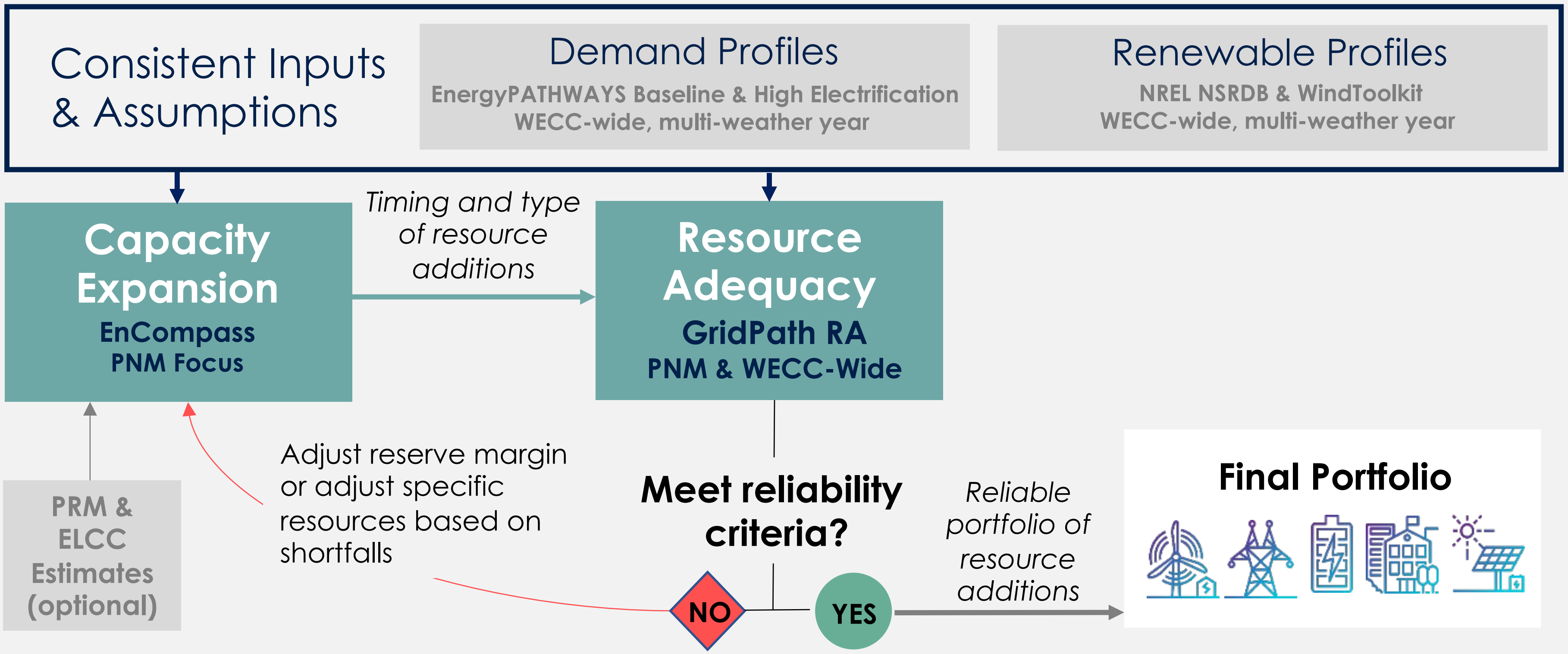
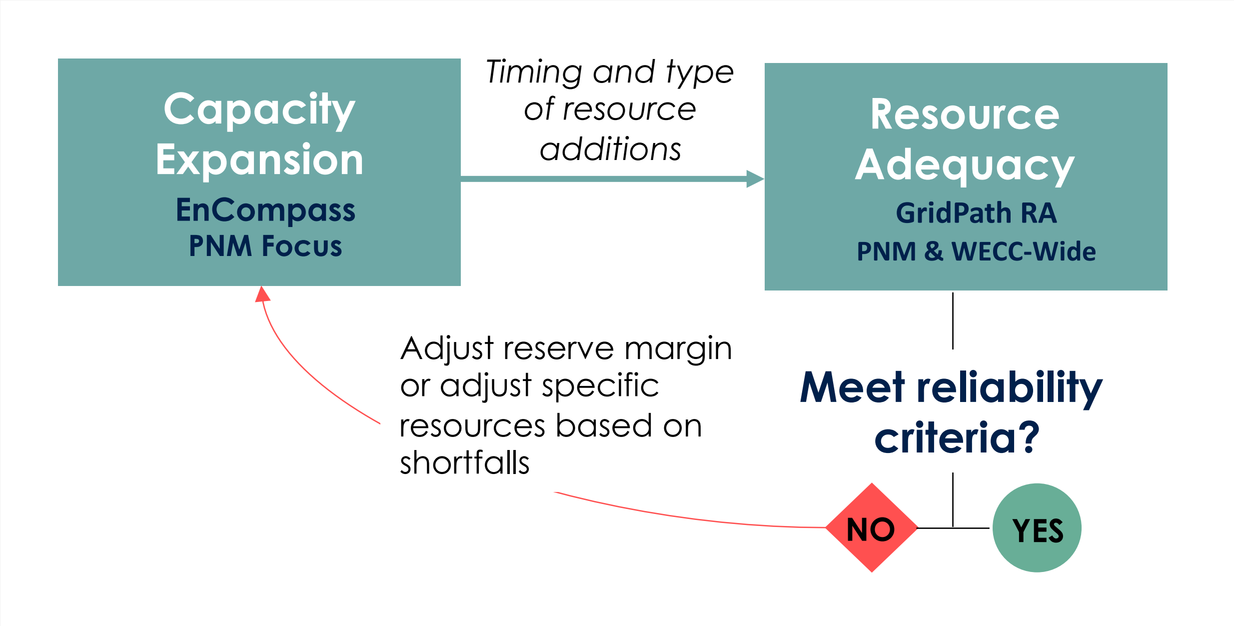
Proposed solution: "round-trip" modeling

- PRM and ELCC estimates can be used to seed the model, but less attention is required
- Resource adequacy analysis is conducted after the portfolios are developed (portfolio and saturation effects are known)
- The modeling process is iterated until the resource adequacy metric is achieved (see the following slide)

Iterative Modeling in Resource Adequacy and Capacity Expansion Planning



Round-trip modeling iteration options



If the portfolio dos not meet the reliability criteria:

- **Option 1:** Increase the PRM
- **Option 2:** Adjust ELCC of resources
- **Option 3:** Pairing of energy & capacity resources
- **Option 4:** Reliability backstop with specific resource (marginal capacity resource)

In this study the marginal capacity resource was determined to be a hydrogen CT and as such, the hydrogen CT capacity was iterated until the resource adequacy criteria was met.

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Benefits of an iterative, round-trip modeling approach

- Less time and effort required to develop initial PRM and ELCC estimates (can avoid creating N-dimensional surfaces of ELCC as a function of various resource combinations)
- The resulting portfolio is guaranteed to be resource adequate — the planner does not need to rely solely on the PRM for reliability
- Portfolio and saturation effects of ELCC are explicitly captured
- Planners and regulators have better insights into the costs associated with meeting the resource adequacy criteria.
- Limitations: requires a smooth process to iterate between two different modeling approaches (capacity expansion and resource adequacy), requires the modeler to know or assume what the marginal resource is, does not extend easily to scenarios in which a combination of additional resources may outperform the identified "marginal" resource

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Results of round-trip modeling: Balancing reliability and costs through iteration

	Optimized		Geothermal		Multi-Day Storage	
	EnCompass Portfolio (based on PRM)	GridPath Adjusted Portfolio (based on 0.1 days/year LOLE)	EnCompass Portfolio (based on PRM)	GridPath Adjusted Portfolio (based on 0.1 days/year LOLE)	EnCompass Portfolio (based on PRM)	GridPath Adjusted Portfolio (based on 0.1 days/year LOLE)
GridPath LOLE (days/year)	0.00	0.09	0.07	0.04	0.00	0.04
H2 CT Capacity (MW)	1000	600	520	500	760	400
H2 Generation (GWh)	511	508	410	402	371	445
H2 Capacity Factor (%)	5.8%	9.7%	9.0%	9.2%	5.6%	12.7%

- Each of the three portfolios developed by EnCompass exceeded the resource adequacy criterion.
- This is likely due to two reasons: 1) more accurate inclusion of imports in GridPath, and 2) the ELCC curves for solar, wind, and storage, did not consider portfolio effects.
- To resolve the overbuild, the hydrogen (H2) CT capacity — determined to be the marginal capacity resource built to meet the PRM requirement — was iterated down in 100 MW increments until the RA criterion (1-day-in-10-year LOLE) was met, but not exceeded.
- Results showed that 400 MW of hydrogen CT capacity could be avoided (~$250 million in savings), but total energy and fuel needs remain largely unchanged.