Power Shift: How Virtual Power Plants Unlock Cleaner, More Affordable Electricity Systems

Technical Appendix

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Introduction

Power Shift: How Virtual Power Plants Unlock Cleaner, More Affordable Electricity Systems explores the role that virtual power plants (VPPs) can play in reducing costs and emissions from the grid. The report includes two novel analyses that explore VPPs' potential impacts across different scopes, levels of detail, and operational assumptions. **VPPs' Role in Affordable, Reliable Decarbonization** uses a detailed model of a case study power system in 2035 to understand how VPPs inform cost-effective portfolios. **VPPs' Nationwide Carbon Savings Potential** uses forecasts of load, VPP enrollment, and grid emissions rates to simulate VPP operations and calculate a nationwide emissions reduction potential. These analyses apply novel approaches to surface new insights about VPPs' economic and emissions potential; **VPPs' Role in Affordable, Reliable Decarbonization** compares key outcomes of modeled real-world power systems using well-defined VPP technologies; **VPPs' Nationwide Carbon Savings Potential** is the first analysis we're aware of that calculates a greenhouse gas emissions impact potential estimate for virtual power plants across the United States over the next decade.

These analyses find the following:

- In the **VPPs' Role in Affordable, Reliable Decarbonization**, we find:
    - The VPP-Enabled portfolio includes 6.7 GW of cost-effective VPPs across a variety of technologies.
    - VPPs almost eliminate the need for new gas capacity, with a 75% or 1.5 gigawatt (GW) reduction in new gas capacity compared to the Baseline portfolio.
    - VPPs relax the need to procure additional utility-scale battery storage, although storage plays a complementary role with VPPs on the system and the model still adds over 500 MW compared to today's levels.
    - VPPs are key for integrating additional renewables procured 2023–2035 and can help reduce the costs of complying with anticipated carbon policies.
    - Compared to the Baseline portfolio, the VPP-Enabled portfolio further reduces carbon emissions while saving 20% in generation costs — about $140 per household per year.
- **VPPs' Nationwide Carbon Savings Potential** shows that by shifting load toward low-emissions resources, VPP demand flexibility could reduce 2035 US emissions by 12–28 million metric tons, 2%–4% of project power sector emissions.

This technical appendix accompanies the main *Power Shift* report and provides an overview of the data sources, methods, and assumptions analyses.

Role of VPPs in Affordable, Reliable Decarbonization

Overview

To evaluate the impacts of incorporating VPPs into planning, we model optimal resource portfolio development — with and without carbon policy and VPPs — for an example Mountain West state in 2035.[i] We model four distinct portfolios:

- **Baseline:** A counterfactual portfolio in which the Mountain West state does not include a carbon emissions signal in resource planning and does not have access to VPPs.
- **VPP-Enabled:** A portfolio that allows resource planning software to select VPPs.
- **Baseline, CO_2 Policy:** A portfolio where a carbon policy is included in planning, but VPPs are not available as a candidate resource.[ii]
- **VPP-Enabled, CO_2 Policy:** A portfolio that includes the carbon policy and allows resource planning software to add VPPs.

Each portfolio begins with the same set of existing resources. A capacity expansion optimization algorithm then identifies resource procurements, retirements, and hourly operations that meet load and reliability at least cost. We compare system-level outputs across portfolios, including resource mix, generation production costs, and emissions to characterize the impacts of including carbon policy and VPPs in resource planning. All economic figures are reported in 2021 dollars, with past annual inflation adjustments sourced from the US Federal Reserve and a future inflation projection of 2.5% per year.[1]

We use GenX, an open-source capacity expansion model, to simulate the power system and identify optimal scenarios and operations.[2] GenX is a configurable electricity resource capacity expansion model, developed by researchers at MIT and Princeton, to support analyses of power sector investment. GenX software supports many of the functions essential to resource planning, including simulating hourly grid operations, accounting for hourly production costs and emissions, and identifying the least-cost portfolio of resources to provide power and meet reliability requirements.

We populate our GenX model with inputs from a selection of high-quality, independently validated, and industry-standard data sources, including the Energy Information Administration's Form 860,[3] the National Renewable Energy Laboratory (NREL)'s Annual Technology Baseline (ATB),[4] and NREL Cambium data.[5] Many of these data sets are processed for use in GenX through PowerGenome,[6] an open-source tool that aggregates and manages publicly available data for use in capacity expansion models. Specific sources and assumptions, including those generated by PowerGenome, are provided through the rest of this section.

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[i] Generally, we used data from Colorado as the representative Mountain West state for this analysis. However, this analysis uses several simplifying assumptions for modeling purposes and therefore is not suitable for drawing specific insights or making specific recommendations for Colorado's energy system.

[ii] We model a carbon dispatch signal, based off Xcel's FERC-approved policy in Order Accepting Tariff Revisions re Public Service Company of Colorado under ER23-158 et al., *FERC*, 2023, https://elibrary.ferc.gov/eLibrary/filelist?accession_number=20230117-3032.

The Representative System

First, we establish the demand profile for the 2035 Mountain West System. We provide key parameters and their sources in
Table 1, below:

Table 1. Sources for Key Inputs, Mountain West system.

Parameter	Source
Hourly Load Shape	FERC Form 714
Annual Non-Electrification Load Growth	Energy Information Administration Annual Energy Outlook – Reference Case
Electrification Load Growth	NREL Electrification Futures Study
Gas Fuel Cost	From EIA 2023 Annual Energy Outlook – Reference Case
Coal Fuel Cost	From EIA 2023 Annual Energy Outlook – Reference Case

We use PowerGenome to generate hourly load data in 2035 for the case study system. PowerGenome bases its load profiles off historical hourly shapes reported in FERC Form 714 data.[7] PowerGenome's load data methodology uses 2012 as a base year, then applies load growth assumptions based on the US Energy Information Administration (EIA)'s Annual Energy Outlook (AEO) Reference Case.[8] Load growth due to electrification is represented using load shapes from the NREL Electrification Futures Study (EFS), using the "high" electrification scenario with moderate technological advancement.[9] NREL EFS does not produce results for the year 2035; for this analysis, we used 2030 outputs for load growth and changing load shapes from electrification.

We used a selection of hours from the 2035 analysis year to manage computational demands for this analysis. In this case, we use a sample time series of 12 weeklong continuous periods (including 2,016 hours, or about a quarter of all hours in the year), including the hourly peak demand day. PowerGenome creates representative time periods by using a k-means clustering algorithm to identify and assign weights to custom-sized sample periods. Our testing indicated that this sample is large enough to capture the full variation in net load, including *dunkelflaute* periods of protracted low wind and solar output. We use fuel price projections from the EIA AEO 2023 Reference Case, Mountain Region.[10] We assume fuel prices remain constant throughout the year.

Table 2. Sources for Key Inputs, Existing Generation

Parameter	Source
Existing Generators: Capacity	From EIA Forms 860 and 923
Existing Generators: Operations & Maintenance Costs	US EIA National Energy Modeling System[11]
Distributed Generation Forecast	NREL 2022 "Low Renewable Energy Cost" Standard Scenario[12]

Table 2, above, shows sources for key parameters for existing resources. PowerGenome uses EIA Forms 923 and 860 to enumerate existing generators and uses EIA's National Energy Modeling System (NEMS) and NREL ATB to estimate operation and maintenance costs.[13] We assume that existing generators comply with announced retirements dates.[14] For distributed generation (i.e., rooftop solar), we assume a trajectory based on NREL's 2022 "Low Renewable Energy Cost" Standard Scenario.[15]

Table 3. Sources for Key Inputs, Policy Inputs.

Parameter	Source
Carbon Policy	Xcel Colorado January 2023 Social Cost of Carbon
Investment Tax Credit	Inflation Reduction Act
Production Tax Credit	Inflation Reduction Act
Planning Reserve Margin	Xcel 2021 Energy Resources Plan

Federal and state policies, along with planning requirements, are summarized above in Table 3. We represent relevant policies at the state and federal levels. In the scenarios that use carbon policy, we use a social cost of carbon proposed by Xcel Colorado and approved by FERC in January 2023.[iii] To incorporate the impact of the Inflation Reduction Act, we assume any new builds of battery storage, geothermal, and nuclear receive a 30% investment tax credit (ITC), represented as a reduction in capital cost.[iv,16] We assume wind and solar developers opt for the production tax credit (PTC) instead, which results in a benefit of $28.82 per megawatt-hour (MWh) applied to all generation from new builds.[v,17] We use a planning reserve margin (PRM) of 18%, consistent with other Mountain West utilities.[18] GenX enforces the reserve margin constraint on an hourly basis, yielding stricter reliability requirements than a planning reserve margin assessed over peak hours only.

Capacity Expansion: Candidate Utility-Scale Resources

We include seven candidate utility-scale resources: gas-fired combined cycles (gas CC), gas-fired combustion turbines (gas CT), advanced nuclear, advanced geothermal, battery storage, wind, and solar. Key technical and financial assumptions, along with their sources, are shown in Table 4, below. Additional operational inputs are sourced through PowerGenome,[19] supplemented with NREL ATB.

Table 4. Candidate Utility-Scale Resources

Name	Description	Unit Capacity (MW)	Capital Cost ($/kW) *	Capital Recovery Factor (%/y)†	Fixed O&M ($/kW-y)*	Variable O&M ($/MWh)*

[iii] We model a carbon dispatch signal, based off Xcel's FERC-approved policy in Order Accepting Tariff Revisions re Public Service Company of Colorado under ER23-158 et al., *FERC*, 2023, https://elibrary.ferc.gov/eLibrary/filelist?accession_number=20230117-3032.
[iv] Assuming prevailing wage and apprenticeship requirements are met.
[v] 2.75¢/kWh, adjusted for inflation.

Gas Combined Cycle (CC)	Combined cycle F-Frame	500	$1,172	8.88%	$29.0	$1.86
Gas Combustion Turbine (CT)	Simple cycle F-Frame	100	$1,058	8.88%	$23.0	$6.44
Nuclear	AP1000 pressurized water reactor	500	$5,515	8.08%	$152.1	$2.47
Geothermal	Hydrothermal Flash.	25	$4,252	8.88%	$107.9	$0
Battery	Lithium Ion	1[vi]	$418[vii]	11.68%	$7.4 (plus $6.3 per MWh-y)	$0
Wind	Land-based, Class 4	1	$1,198	8.88%	$27.6	$0
Solar	Utility-scale, Class 4	1	$1,080	8.88%	$18.5	$0

Source: 2023 Annual Technology Baseline (ATB), NREL, 2023.
** Consistent with GenX methodology, values are averaged between 2023 and 2035 analysis year. Capital cost values reflect investment tax credit for nuclear, geothermal, and energy storage capital costs. Variable O&M values do not reflect production tax credit for wind and solar.*
† Calculated using an 8% discount rate.

Capacity Expansion: Virtual Power Plants

We also include virtual power plants as a selectable resource for capacity expansion. We model eight types of sector-specific flexible demand (e.g., residential space heating and cooling), using operational characteristics from PowerGenome and NREL EFS.[20] We supplement PowerGenome and NREL EFS technical inputs with cost assumption data from the Brattle Group's Real Reliability report and other sources. We also apply a *de minimis* variable cost ($1/MWh) to all technologies, which limits frequency of VPP dispatch. We also model behind-the-meter (BTM) battery storage as an available technology for virtual power plants. We assume 500 MW of three-hour duration storage is available to the case study system. To arrive at this number, we first estimate cumulative national BTM battery storage installations of 36.4 GW by 2035, interpolating the 2023 and 2028 forecasts provided in Wood Mackenzie's March 2024 *US Energy Storage Monitor*,[21] holding annual additions constant after 2028. We scale this availability down to 500 MW, using Colorado's approximate share of national retail energy sales.[22] We apply a *de minimis* variable cost to storage charge and discharge, consistent with that used for utility-scale storage. Table 5 below shows the key operational assumptions made for each VPP technology.
Table 5. VPP Technical Potential and Operational Characteristics

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[vi] Due to the modular nature of battery storage, wind, and solar, we assume procurement is possible to the nearest megawatt.
[vii] Based on capital costs of $206/kW plus $177/kWh (taken from NREL ATB 2023 v2, Moderate Technology Innovation Scenario, net of the ITC). *Electricity Annual Technology Baseline (ATB) Data Download*, NREL, https://atb.nrel.gov/electricity/2023/data.

Name	Technical Potential (MW)	Shiftable Demand (GWh per year)	Potential Demand Shift (hours)[23]
Residential Space Heating And Cooling	1,324	5,439	2
Residential Water Heating	284	2,119	8
Commercial Space Heating and Cooling	743	1,623	2
Commercial Water Heating	9	72	4
Light-Duty Vehicle Managed Charging	3,548	8,315	8
Medium-Duty Vehicle Managed Charging	118	739	7
Heavy-Duty Vehicle Managed Charging	234	1,466	4
Bus Managed Charging	5	32	4
BTM Battery Storage	500 MW/ 1,500 MWh	n/a	n/a

Source: Sun et al., Electrification Futures Study, 2020

Table 6 below shows key financial assumptions made for each VPP technology. To model VPPs in capacity expansion context, we derive annualized per-MW costs for each measure (comparable to the annualized capital cost of a conventional generator) following the methodology used in the Brattle Group's *Real Reliability* report.[24] We group VPP demand flexibility technologies into three buckets: space heating and cooling, water heating, and vehicle managed charging. We begin with annualized program costs, given in $ per participant per year. These costs are assumed to be constant over the measure lifetime. Next, we calculate the peak-coincident per-participant demand reduction from each measure. Dividing per-participant program cost by per-participant gross peak-coincident demand reduction yields the annual gross cost of peak-coincident demand reduction, in dollars per kilowatt-year. We assume that each kilowatt of peak demand reduction capacity also reduces costs associated with transmission and distribution (T&D) system investments. Subtracting T&D benefits from the cost of demand reduction yields net cost of peak-coincident demand reduction.

Finally, we adjust the denominator from peak-coincident demand reduction capacity to non-peak-coincident demand reduction capacity to be consistent with cost expressions for other technologies. We do this by using a peak coincidence factor, which is each technology's available capacity at the system's peak demand hour divided by each technology's maximum single-hour available capacity in the evaluation year.

Table 6. VPP Economic and Financial Inputs by Technology

Parameter	Space Heating and Cooling	Water Heating	Vehicle Managed Charging	BTM Battery Storage
Program Cost[25] ***($/participant-y)***	$64.9	$81.1	$93.5	$610.7
Peak-Coincident Demand Reduction *(kW/participant)*	1.00[viii,26]	0.51[ix,27]	0.96[x]	7.00
Gross Cost ($/peak-coincident kW-y)	$64.9	$159	$97.8	$87.2
T&D Deferral Benefit[xi] **($/peak-coincident kW-y)**	$45.0	$45.0	$45.0	$45.0
Net Cost[xii] **($/peak-coincident kW-y)**	$19.9	$114.0	$52.8	$42.2
Peak Coincidence Factor[xiii]	48%	49%	100%	100%
Net Cost[xiv] **($/non-coincident kW-y)**	$9.5	$55.9	$52.8	$42.2

GenX Configuration

We run capacity expansion using GenX version 0.3.5, modeling linearized unit commitment and not explicitly modeling operating reserves. We use the open-source HiGHS solver.[28]

To manage computational load for optimization, we reduce the hours evaluated in the analysis year using PowerGenome. PowerGenome uses a clustering algorithm to construct a representative sample of twelve weeklong periods, rather than running the model for every hour of the year. Each period is weighted and aggregated up to annual results. The sample includes the peak load hour.

Limitations

We discuss some limitations of this analysis below.

[viii] We assume a summer-peaking system.
[ix] We assume high-end load reductions.
[x] Consistent with *The Value of Virtual Power Volume II: Technical Appendix*, The Brattle Group, 2023, https://www.brattle.com/wp-content/uploads/2023/04/Real-Reliability-The-Value-of-Virtual-Power-Technical-Appendix_5.3.2023.pdf, we use the US Department of Energy's EVI Pro Lite tool to generate EV charging load profiles, https://afdc.energy.gov/evi-pro-lite. We use Colorado data, assuming 75% of the EV fleet is all-electric and 90% of participants respond to calls for load shifting.
[xi] Assuming T&D deferral benefits of $50/kW-y, adjusted downward to account for imperfect VPP availability.
[xii] Gross cost minus T&D deferral benefit.
[xiii] Calculated as measure output (% of capacity) during system peak hour.
[xiv] For modeling, net cost must be converted from peak-coincident kW in the denominator to non-coincident peak kW (analogous to converting from $/kW UCAP to $/kW ICAP).

GenX Capabilities

- GenX is primarily a bulk-scale power modeling system, and this analysis does not explicitly consider operations and investments in the distribution and transmission systems. We have represented transmission and distribution system benefits indirectly by using an average per-kilowatt T&D benefits value and accounting for T&D benefits in the net cost of VPPs. However, additional analysis on a case-by-case basis would be necessary to evaluate T&D benefits posed by VPPs.
- GenX does not explicitly conduct reliability assessments; instead, reliability is ensured by portfolio resources meeting a planning reserve margin every hour. GenX credits each resource's contribution to the resource adequacy requirement as the resource's nameplate capacity, multiplied by its energy availability, multiplied by its outage availability. For variable energy, demand flexibility, and energy storage resources, their contribution to resource adequacy is represented as the generation in each hour multiplied by an outage availability factor. The sum of resource adequacy contributions across all resources must be greater than or equal to system energy demand plus the planning reserve margin in every analysis hour. Table 7 shows each resource's contribution to the resource adequacy requirement.

Table 7. Resource Adequacy Contribution by Resource (Percent Nameplate Capacity).

Resource	Average Hourly Energy Availability	Outage Availability Factor
Gas Combined Cycle (CC)	100%	95%
Gas Combustion Turbine	100%	95%
Nuclear	100%	97%
Geothermal	100%	95%
Battery	Variable[xv]	90%
Wind[xvi]	28%-45%	97.5%
Solar	28%-29%	97.5%
Residential Space Heating and Cooling[xvii]	22%	90%
Residential Water Heating	32%	90%
Commercial Space Heating and Cooling	12%	90%
Commercial Water Heating	52%	90%
Light-Duty Vehicle Managed Charging	27%	90%

[xv] For batteries, average energy availability is dynamic, depending on state of charge.
[xvi] We use PowerGenome's built-in wind and solar generation profile aggregation tools to capture the diversity of wind and solar resources across Colorado. We sort potential sites into bins based on resource quality. Each bin is constrained in capacity expansion by maximum MW additions. As shown, the quality of wind resources varies across the state (from 29% to 48% annual capacity factor), while solar is much more consistent (27%–28% annual capacity factor).
[xvii] VPP measure hourly availability comes from PowerGenome's analysis of NREL *Electrification Futures Study* data. We assume a 90% outage availability factor (i.e., that 10% of available resources participating in a VPP will fail to respond to a given call for capacity).

Medium-Duty Vehicle Managed Charging	72%	90%
Heavy-Duty Vehicle Managed Charging	72%	90%
Bus Managed Charging	72%	90%
BTM Battery Storage	Variable%	90%

Sources: PowerGenome and RMI analysis.

Scenario Definition

- The GenX model considers only the least-cost annualized system in 2035 and does not consider the least-cost pathway to 2035 or any requirements or considerations after the year 2035. We also assume that planners have perfect foresight into market conditions in this model.
- The modeled Mountain West state is an islanded system, without transmission interconnections to neighboring regions.

Detailed Results

Table 8 and Table 9 below show detailed results across the analytical scenarios.

Table 8. 2035 Capacity Mix (MW), by Portfolio

	2024	**2035**			
	Existing System	**Baseline**	**VPP-Enabled**	**Baseline, CO_2 Policy**	**VPP-Enabled, CO_2 Policy**
Coal	3,804	0	0	0	0
Gas CC	3,306	5,306	3,806	4,806	3,306
Gas CT	3,498	3,016	3,016	3,016	3,016
Biomass	12	11	11	11	11
Hydro	531	545	545	545	545
Wind	5,136	15,099	16,486	19,514	20,858
Utility Solar	2,874	4,952	3,787	5,958	5,045
Distributed Solar	746	1,995	1,995	1,995	1,995
Pumped Storage	581	581	581	581	581
Utility-Scale Battery Storage	240	3,855	839	4,254	1,269
VPPs (Residential)	0	0	1,609	0	1,609
VPPs (Commercial)	0	0	753	0	753
VPPs (Transportation)	0	0	3,809	0	3,809
VPPs (BTM Battery Storage)	0	0	500	0	500

Source: RMI analysis.

Table 9. Generation Costs and Emissions by Scenario

	Baseline	VPP-Enabled	Baseline, CO_2 Policy	VPP-Enabled, CO_2 Policy
Net Production Costs *($ million/y)*	$2,016	$1,619	$2,115	$1,682
Carbon Emissions *(MMT CO_2/y)*	5.35	4.97	3.08	2.81

Source: RMI analysis.

VPPs' Nationwide Carbon Savings Potential

Overview

In the **VPPs' Nationwide Carbon Savings Potential** analysis, we use third-party projections to estimate VPP capacity by technology and state across the Continental United States from 2024 to 2040. Then, we use a simplified model of grid operations and VPP dispatch to identify shifts in demand from VPP dispatch that would avoid the most carbon emissions compared to a status quo without shifts in demand. We use emissions-minimizing VPP operations across states from 2024 to 2040 to estimate VPP emissions reduction potential from 2024 to 2035. This analysis provides directional insights into the magnitude of emissions reduction potential for VPPs and provides an opportunity to explore how VPPs' role might shift across years, seasons, and regions.

The **VPPs' Nationwide Carbon Savings Potential** study takes the following steps:

1. **Project VPP Capacity:** We use hourly sub-sector load for each state in the Continental United States in 2024, 2030, and 2040 from the National Renewable Energy Laboratory (NREL)'s Electrification Futures Study.[29]
2. **Define VPP Potential:** We characterize flexible demand as a portion of total subsector demand, which varies as a function of study year, increasing over time.
3. **Project Grid Emissions Signals:** We use hourly, state-level emissions rates from NREL Cambium's "95 percent decarbonization by 2050" scenario to define the dispatch signal and emissions factor for this analysis.[30]
4. **Identify Demand Shift that Maximizes Avoided Emissions:** We use a dispatch algorithm to shift demand to reduce power sector emissions, within constraints that reflect broader power system requirements.
5. **Calculate Total Emissions Reduction, 2024–2035.** We calculate emissions savings for analysis years 2024, 2030, and 2040 and interpolate between these years to provide annual emissions savings.

This analysis takes several foundational data inputs from the National Renewable Energy Laboratory's *Electrification Futures Study* (EFS), a 2017–2021 study that explored the impacts of widespread electrification and demand flexibility on the US economy.[31] As described below, NREL EFS datasets inform the underlying hourly load data and provide demand flexibility capabilities used in this analysis.

We elaborate on each of these steps below, then describe the simplifying assumptions of this analysis.

NREL EFS includes projections for 2018, 2020, 2024, 2030, 2040, and 2050. Across all the steps below, we conduct our analysis using the 2024, 2030, and 2040 analysis years, then linearly interpolate outputs between analysis years. Results reported for 2035 are linearly interpolated between analysis outputs in 2030 and 2040.

Project VPP Capacity

For this analysis, VPP technologies fall into two categories. The *flexible demand* category contains all technologies that typically represent electric load, but can shift the time and nature of that demand (for the purposes of this study, we examine managed electric vehicle charging only and not electric vehicle discharge onto the grid; for that reason, we place it in the *flexible demand* category). The *distributed storage* category contains only distributed storage installations. We project potential VPP capacity across US states through 2040 with distinct methods for flexible demand technologies and distributed storage technologies.

Flexible Demand

We use hourly load profiles defined at the state and sub-sector (e.g., residential heating, ventilation, and air conditioning) developed by NREL for *Electrification Futures Study: Methodological Approaches for Assessing Long-Term Power System Impacts of End-Use Electrification,* which in turn uses a combination of reference load forecasts from the 2018 release of NREL's Regional Energy Deployment System (ReEDS) and demand-side flexibility and electrification forecasts using the EnergyPATHWAYS tool.[32] These load profiles represent the maximum amount of load for each subsector that could theoretically be managed by a virtual power plant, subject to the limitations described in ***Define VPP Potential*** below. NREL EFS includes profiles for the following sub-sectors:

- Commercial
    - Space Heating and Cooling
    - Water Heating
    - Other
- Industrial
    - Machine Drives
    - Process Heat
    - Other
- Residential
    - Space Heating and Cooling
    - Water Heating
    - Clothes and dish washing/drying
    - Other
- Transportation
    - Light-duty vehicles
    - Medium-duty vehicles
    - Heavy-duty vehicles

Together, the load profiles represent total hourly load for each state, which may be shifted by charging and discharging distributed storage under a VPP. For this analysis, we use NREL EFS's "High" electrification and "Moderate" technology advancement scenario to examine a highly electrified future scenario, while using a central projection on end-use technologies. This scenario results in a 1.6% compound annual growth rate of electricity load, 2016–2050,[33] with transportation representing most of the increase in annual electricity demand. NREL *Electrification Futures Study* load scenarios provide hourly load at the state- and subsector-level, which allows for a detailed, state-level characterization of daily, seasonal, and sub-sector dynamics across states and regions. To manage computational requirements for this analysis, we calculate average load for each hour of the day to construct an "average day" for each month, state, and analysis year. These "average days" also yield loads and dispatch patterns that are more representative of typical power sector dynamics of the month, state, and year, rather than representing weather on a single day.

Distributed Storage

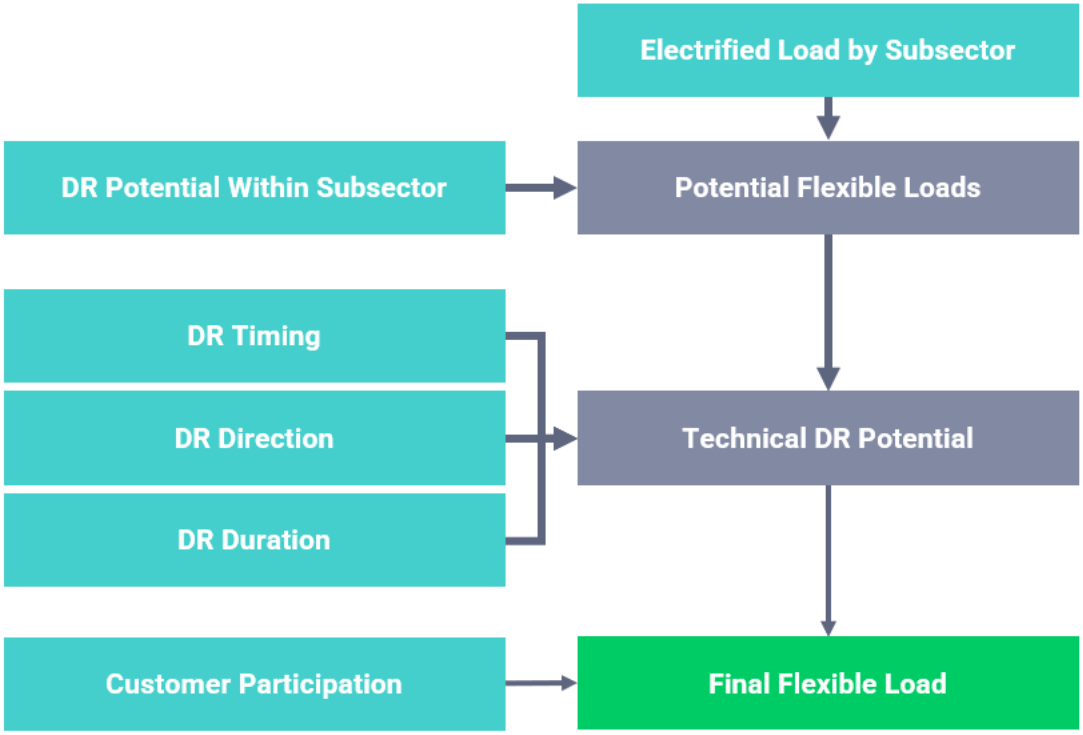
NREL EFS does not project distributed storage deployment. We project distributed storage using Wood Mackenzie's *U.S. Energy Storage Monitor 2024 Q1*, assuming that the projected annual distributed storage deployment in 2028 is sustained through 2040.[34] We allocate distributed storage across US states, weighted against each state's share of total US load in NREL Cambium's "95 percent decarbonization by 2050" mid-case scenario.

Define VPP Potential

Flexible Demand

Starting from subsector-level hourly load defined in the previous section, we calculate the proportion that is technically capable of being managed through a VPP, the limits and characteristics of VPP dispatch across technologies, and the trajectory of VPP deployment across states and over time. Figure 1, below, provides a flow chart showing assumptions applied to subsector load to yield flexible demand at the sub-sector level.

Figure 1. Flow Chart of Assumptions Used to Determine Final Flexible (VPP-Enrolled) Load Used in Modeling.



Source: Adapted from Sun et al., Electrification Futures Study, 2020, p. 30.

Below, we provide a description for each of the data elements included in Figure 1.

Electrified Load by Subsector

Hourly subsector load, described in the *Project VPP Capacity* section above.

Demand Response (DR) Potential within Subsector

We apply a factor representing technical potential for flexibility for each sub-sector (expressed as a percentage of subsector load) based on the specific technical and behavioral considerations of that technology. For example, electric vehicle charging can be relatively easily shifted, but space heating and cooling is more limited. Technical potential for each sub-sector does not vary over time or across geographies.

DR Timing

We characterize the window of time each day when each sub-sector is capable of shifting demand. For this analysis, we assumed VPP flexible demand technologies were capable of shifting demand at all hours.

DR Direction

We set the direction that load can be shifted: Depending on the sub-sector, demand may only be able to be delayed or only brought forward in time, or either.

DR Duration

We identify the maximum duration of the shift in demand possible for each sub-sector. Depending on the sub-sector, demand may be shifted from one up to eight hours.

Customer Participation

Finally, we define the portion of all customers that have enrolled in a virtual power plant for each sub-sector, which is the percentage of technically flexible demand for each sub-sector that is actually available to shift load. This analysis uses the "Enhanced" customer participation scenario from NREL EFS, where participation increases linearly from 5%, 6%, or 7% in 2018 (depending on sub-sector) to 60% or 90% in 2050.[35]

Equation 1, below, shows the steps needed to calculate each state, year, and sub-sector's hourly flexible load profile from its total load profile.

Equation 1. Calculating sub-sector flexible load profiles

$$For\ each\ year\ y, state\ s, subsector\ t, month\ i, and\ hour\ j,$$

$$Flexible\ load\ (MWh)_{y,s,t,i,j} = Total\ load\ (MWh)_{y,s,t,i,j} * Technical\ availability\ (\%)_t * VPP\ Enrollment\ (\%)_{t,y}$$

Table 10, below, shows each of these parameters by sub-sector. We add one more parameter, called "DR allowed peak factor" that constrains the ability for demand shifts to exceed existing subsector-level peak demand. This parameter will be discussed in greater detail in the *Execute Demand Flexibility Dispatch* section, below.

Table 10. VPP Demand Flexibility Parameters by Subsector

Sector	Subsector	DR Technical Potential	DR Direction	DR Duration	Allowed Peak Factor	VPP Enrollment		
						2018	2050, Sustained Enrollment	2050, Slow Enrollment
Commercial	Space Heating & Cooling	100%	Both	2*	1.25	5%	60%	20%
Commercial	Water Heating	100%	Both	4	1.25	5%	60%	20%
Commercial	Other	5%*	Backward only	1*	1.25	5%	60%	20%
Industrial	Machine Drives	36%	Both	1	1	7%	60%	20%
Industrial	Process Heat	60%	Both	1	1	7%	60%	20%
Industrial	Other	25%*	Both	1*	1	7%	60%	20%
Residential	Clothes and dish washing/drying	100%	Both	8	1.5	6%	60%	20%
Residential	Other	5%*	Both	2*	1.5	6%	60%	20%
Residential	Space heating & cooling	100%	Both	2*	1.25	6%	60%	20%
Residential	Water heating	100%	Both	8	1.5	6%	60%	20%
Transportation	Light-duty vehicles	75%	Both	8	1.25	6%	90%	20%
Transportation	Medium-duty trucks	100%	Forward only	6.5	1.25	5%	60%	20%

Transportation	Heavy-duty trucks	100%	Forward only	4.4	1.25	5%	60%	20%

Source: Sun et al., Electrification Futures Study, 2020, Table 2, Table D-2, Table D-3, Table D-4, Table D-5.
** For technical parameters of "Other" subsectors, we made conservative assumptions based on available sector-wide information. We also made selected reasonable adjustments to DR duration for specific subsectors.*

We use flexible demand profiles for each sub-sector to calculate projected VPP capacity by sub-sector and technology. VPP capacity represents the greatest single hour of demand (not coincident with any system peak demand) for that sub-sector across month-average hours in the analysis year. This is a more conservative approach than reporting the greatest single hour of demand across all hours in the analysis year and is more consistent with the rest of our analysis.

Distributed Storage

We assume that distributed storage enrollment in VPPs is roughly consistent with other technologies in 2024 (6%), and enrollment linearly increases to 60% by 2050, in line with NREL EFS's "Enhanced" enrollment trajectory. We assume that distributed storage installations have an average duration of three hours, coincident with the Brattle *Real Reliability* study and the approximate duration of the Tesla Powerwall.[36] We assume that distributed storage is available to dispatch at all hours.

Project Grid Emissions Signals

Emissions rates reflect the amount of greenhouse gas emissions emitted (typically in kilograms of CO_2-equivalent greenhouse gas) per megawatt-hour generated or consumed.

We use hourly grid emissions rates from NREL's 2022 Cambium data set.[37] We use the "95 percent decarbonization by 2050" scenario for US power sector emissions, which generally results in declining emissions rates over time.

We use three hourly emissions rates from NREL Cambium data:

- **Average Emissions Rate (AER):** The average emissions rate is calculated by dividing total generation in each hour by total greenhouse gases emitted in that hour. This value reflects hourly total energy mix but does not provide information on the impact changes to demand would have on the generation mix.
- **Short-Run Marginal Emissions Rate (SMER):** The short-run marginal emissions rate represents the emissions impact of increasing or decreasing demand by a marginal amount, which would result in either increasing or decreasing generation from the marginal unit based on merit dispatch order at that time. The marginal unit is often, but not always, the most expensive and most carbon-intensive unit currently generating electricity. The short-run marginal emissions rate is equal to the emissions rate of the marginal unit before any VPP-driven shifts in demand.
- **Long-Run Marginal Emissions Rate (LMER):** The long-run marginal emissions rate has been recently developed by NREL and is "an estimate of the rate of emissions that would be either induced or avoided by a change in electric demand, taking into account how the change could influence both the operation as well as the structure of the grid (i.e., the building and retiring of capital assets, such as generators and transmission lines)."[38] Put another way, the long-run marginal emissions rate includes the marginal change in load's impact on how the grid operates

today and its impact on the most economic portfolio of future resources to be built. This emissions rate assumes that changes to load are fixed and permanent.

Choosing a Dispatch Signal and Emissions Factor

We use emissions rates in this analysis to perform two distinct functions:

- The **dispatch signal** is used by the dispatch algorithm to identify the most emissions-effective shift in demand.
- The **emissions factor** is used to calculate total emissions before and after demand shift and quantify the total amount of emissions avoided through use of demand flexibility.

These functions can be played by the same emissions rates or different emissions rates, depending on the goals and priorities of the analysis. An analysis might use different dispatch signals and emissions factors to reflect the challenges of communicating about grid conditions to VPPs in real time. Information used to direct dispatch must be available to the VPP in real time, must be simple enough to calculate and communicate, and may ultimately differ from the aggregated impacts to emissions based on shifting demand. For most of our analysis outputs, we use the same emissions rate as the dispatch signal and emissions factor.

A robust scholarly discussion continues around the identification of the most appropriate emissions signal to use for real-time emissions accounting and unit dispatch.[39] We do not resolve that discussion, and a detailed discussion of the relative advantages and disadvantages of these emissions rates is outside of the scope of this technical appendix. This analysis is, however, responsive to the following dynamics:

- Average emissions rates do not accurately reflect the implications of increases or decreases to demand, in part because zero-marginal-cost resources such as renewables are not responsive to marginal shifts in demand. This issue grows more pronounced as renewables become a greater part of the electricity mix.
- Evaluating demand shifts against a short-run marginal emissions rate (and to a lesser extent an average emissions rate) may drive VPP operations that reduce emissions based on the grid's state today, but may not reduce emissions if adopted in the long run. For example, shifting vehicle charging from evening peak demand to overnight hours may reduce emissions by avoiding the use of high-emissions peaking plants, but overnight hours may be more difficult to decarbonize in the long run than mid-day hours. Where possible, this analysis attempts to model demand shifts that have short- and long-term emissions benefits by using long-run marginal emissions rates as dispatch signals.
- Marginal emissions rates become less accurate for characterizing changes in demand as the magnitudes of changes to demand increase. In this analysis, flexible demand can reach up to 15% of hourly demand. Marginal emissions rates may not adequately describe the change to system dynamics applied by shifting demand at this magnitude.
- Long-run marginal emissions rates may not be appropriate for estimating emissions reductions in the short term, because virtual power plants may not yet be integrated into resource portfolio development decisions.

We develop multiple emissions reduction estimates, using multiple sets of emissions signals and dispatch factors, to execute VPP dispatch and quantify emissions reductions. **Error! Reference source not found.**, below, summarizes our dispatch signal and emissions factor approach for low, moderate, and high estimates.

Table 11. Dispatch Signal and Emissions Factor by Estimate Level, 2024–2040.

Estimate Level	2024		2030		2040	
	Dispatch Signal	**Emissions Factor**	**Dispatch Signal**	**Emissions Factor**	**Dispatch Signal**	**Emissions Factor**
Low	AER	AER	AER	AER	AER	AER
Moderate	LMER	LMER	LMER	LMER	LMER	LMER
High	SMER	LMER-SMER average	SMER	LMER-SMER average	LMER	LMER-SMER average

Source: RMI Analysis.

We made the following decisions in defining our approach to low, moderate, and high estimates for emissions impact.

- The low estimate uses an average emissions rate (AER) for the dispatch signal and emissions factor in 2024–2040. This approach represents a reasonable minimum estimate for emissions impacts of VPPs.
- The moderate estimate uses long-run marginal emissions rates (LMER) for the dispatch signal and emissions factor in 2024–2040. This approach represents a reasonable expectation of emissions impact of VPPs when VPPs are integrated into power sector operations and planning.
- The high estimate uses the short-run marginal emissions rates (SMER) for 2030 and a long-run marginal emissions rate (LMER) in 2040, and an average of LMER and SMER as emissions factors from 2024 to 2040. This approach represents an attempt to incorporate the ability for smart demand flexibility dispatch to continue to target high-emissions units and the grid planning value of additional available demand flexibility.

Identify Demand Shift that Maximizes Avoided Emissions

This analysis uses different methods for shifting demand using demand flexibility and distributed storage. Demand flexibility shifts load, followed by distributed storage.

Flexible Demand

We use a dispatch algorithm, based on that used in NREL EFS's *Operational Analysis of U.S. Power Systems with Increased Electrification and Demand-Side Flexibility* and developed specifically for this analysis,[40] to simulate emissions-minimizing shifts in demand by VPP demand flexibility and distributed storage. The algorithm shifts flexible demand under several constraints:

- **System Peak**. Shifts in demand from VPPs cannot create a new annual state-level peak in demand (all-subsector flexible load plus inflexible load). Load in every hour after all demand has been shifted by VPPs must be less than or equal to the existing annual peak.
- **Subsector Peak.** Shifts in demand from VPPs can create a peak in sub-sector demand but cannot exceed the allowed peak factor shown above in Table 10. This is to prevent the predicted capacity of devices from being exceeded in a given hour.
- **Demand Flexibility Characteristics.** For each subsector, demand shifts are subject to the specific DR Direction and DR Duration described in Table 10. The DR Duration constraint is applied using the inequality shown in Equation 2.

Equation 2. DR Duration constraint for each subsector.

$$DR\ Duration\ (hours) \geq \sum_{For\ each\ hour\ i=1}^{24} \frac{Flexible\ Load\ Shifted\ from\ Hour\ i\ (MWh) * Number\ of\ Hours\ Shifted(hours)}{Original\ Flexible\ Load\ in\ Hour\ i\ (MWh)}$$

To simulate grid operations with active use of demand flexibility, we assume two flexibility calls daily for each technology.

For a given state, year, and month, the optimization algorithm evaluates the emissions effectiveness for every possible demand shift for a single subsector (e.g., shifting water heating load from 5 p.m. to 4 p.m., 6 p.m. to 8 p.m., or any other shift). The definition of emissions effectiveness is provided in Equation 3, below.

Equation 3. Emissions effectiveness of shifting load from one hour to another.

$$For\ shifting\ demand\ in\ hour\ a\ to\ hour\ b:$$

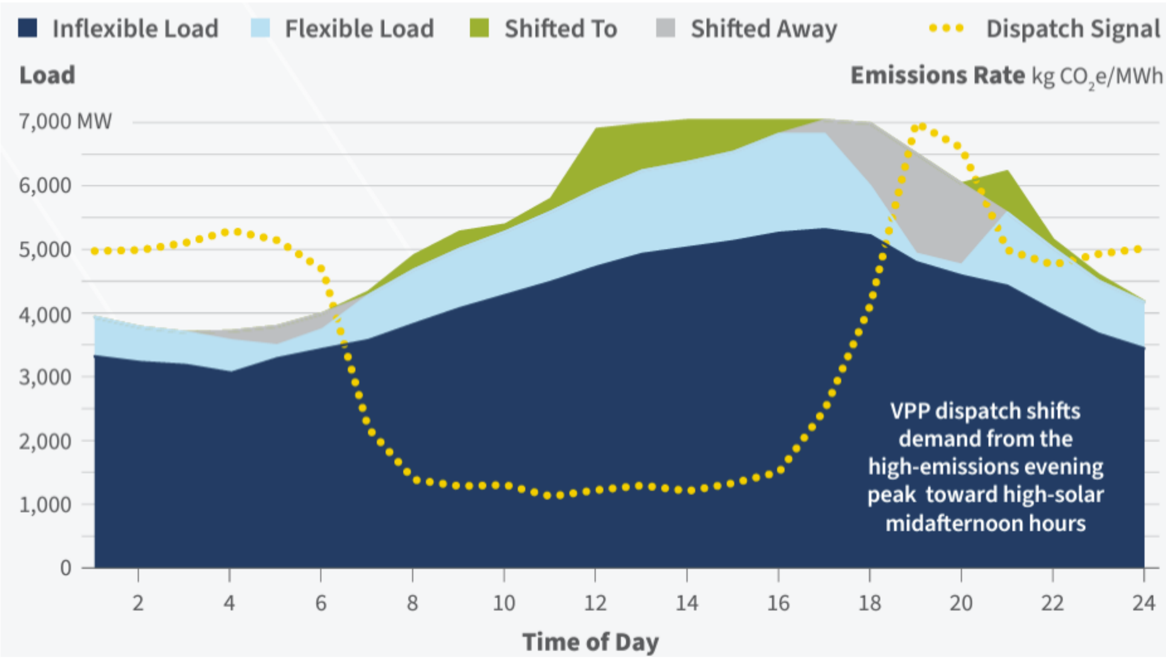
$$Emissions\ Effectiveness_{a,b} = \frac{\Delta\ Emissions\ intensity_{a,b}\left(\frac{kg\ CO_2e}{MWh}\right) * Flexible\ load\ available_a(MWh)}{Distance\ between\ hours_{a,b}(hours\ shifted)}$$

By executing demand shifts with the highest effectiveness, the VPP maximizes avoided emissions under the constraints described in Equation 2. Emissions effectiveness is weighted by flexible load available because the duration constraint on shifting demand applies to the number of *hours* that demand is shifted, rather than the amount of energy shifted across hours. Emissions effectiveness identifies demand shifts with a large difference in emissions rates, hours with a large amount of demand available to shift, and demand shifts that are relatively close together across time.

For each subsector, the VPP shifts demand based on the identified hour-to-hour with the highest effectiveness until reaching one of the constraints described above (e.g., the DR Duration constraint is reached, or any additional shifting would create an unacceptable system or sub-sector peak). The VPP then attempts the demand shift with the next-highest emissions effectiveness. The VPP iterates through emissions-effective demand shifts, from most effective to least effective, until the DR Duration constraint is reached for that subsector, and no more shifts are possible. Then, we proceed to the next VPP subsector in the current state, year, and month. For each state-year-month, VPP demand shifts begin with subsectors with lower DR Duration (e.g., space heating and cooling) and progresses to the subsectors with higher DR durations (e.g., managed electric vehicle charging).

Figure 2, below, shows projected system load and VPP dispatch in New Mexico in August 2040.

Figure 2. Projected System Average Hourly Load and VPP Dispatch (New Mexico, August 2040).



Sources: Pieter Gagnon, Brady Cowiestoll, and Marty Schwartz, Cambium 2022 Data, NREL, 2023; and RMI analysis.

The dispatch signal, which in this case is the long-run marginal emissions rate, is shown in yellow. It shows a dip in daylight hours, when solar energy is more plentiful, and a narrow peak in the evening during system peak net demand. The dark blue area shows inflexible load, which is load that is either technically not capable of shifting with VPP dispatch or is not enrolled in a VPP. The light blue area shows load available for shifting because it's enrolled in a VPP. Gray areas represent demand that has been shifted to a different time of day, and green areas show where the demand has been shifted to. Together, the VPPs shift load from the evening peak toward afternoon daylight hours while avoiding the creation of a new system-wide peak. Some mid-evening demand is also shifted to later in the evening and some morning demand is shifted into high-solar daylight hours.

Distributed Storage

Unlike flexible demand VPP technologies, which shift demand associated with their own usage, distributed storage instead charges and discharges from the grid. In this analysis, distributed storage shifts aggregated demand based on available capacity and incorporating all planned flexible demand VPP shifts.

The methodology for shifting grid demand with distributed storage is relatively simple compared to flexible demand VPP technologies. Distributed storage charges at its nameplate capacity (increasing total grid demand) during the three least emissions-intensive hours in the average day for each state and month, and discharges (decreasing grid demand) during the three highest-emissions hours in the average day. Three hours of charging and discharging at nameplate capacity correspond to the modeled storage duration of three hours. If distributed charging would exceed the existing system peak demand, distributed charging is spread across up to the five least emissions-intensive hours, decreasing the amount charged in each hour to maintain the same total energy charged.

Calculate Total Emissions Reduction, 2024–2035

We calculate total emissions reduction by identifying the total net change in load in each hour based on VPP shifts in demand, then multiplying by the appropriate emissions factor. We do this for all states and months in each analysis year and perform VPP dispatch and emissions calculations separately for each estimate level identified above in **Error! Reference source not found.**.

We interpolate subsector load and total distributed storage deployment across analysis years and use the enrollment trajectories identified in Table 10 to calculate enrolled VPP flexible demand load and distributed storage capacity in each year 2024–2035. To interpolate the amount of emissions avoided by VPP dispatch, we calculate an annual average realized emissions savings for each per MWh of flexible demand load enrolled in a VPP and per MW of distributed storage capacity enrolled in a VPP, with units $^{kg\ CO_2e}/_{MWh}$ and $^{kg\ CO_2e}/_{MW}$, respectively. We calculate average realized emissions savings separately for each sub-sector and state.

Using average realized avoided emissions values, we calculate total emissions reduction in each year 2024–2035 using

Equation 4 below.

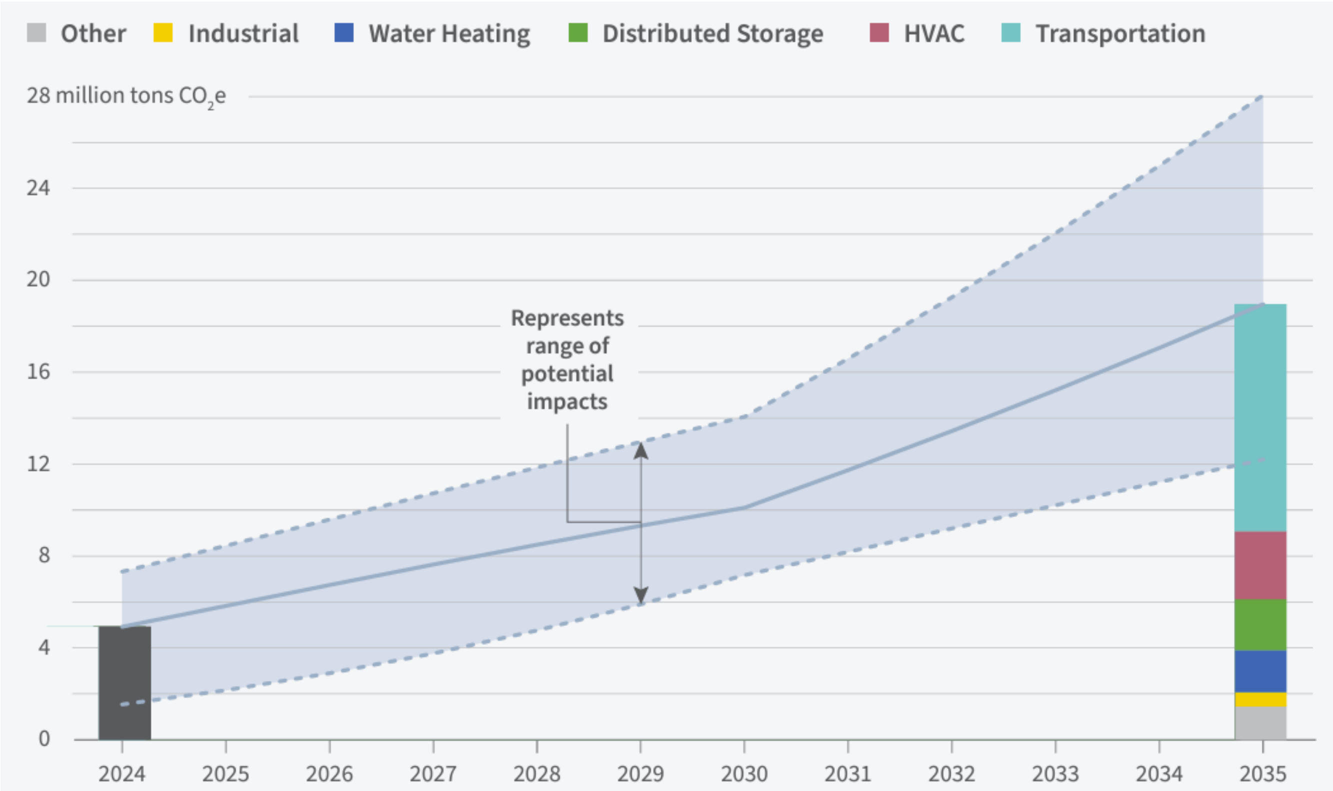
Equation 4. Total Annual Emissions Reduction.

$$
\begin{aligned}
&For\ each\ year\ y, state\ s, and\ subsector\ t,\\
&\qquad Total\ emissons\ reduction_y\ (kg\ CO_2e)\\
&\qquad\qquad = \sum_{s,t} \Big(VPP\ enrolled\ load_{y,s,t} (MWh)\\
&\qquad\qquad * average\ flexible\ demand\ realized\ savings_{y,s,t} \left(^{kg\ CO_2e}/_{MWh} \right) \Big)\\
&\qquad\qquad + \sum_{s} \Big(VPP\ enrolled\ storage_{y,s} (MW)\\
&\qquad\qquad * average\ storage\ realized\ savings_{y,s} \left(^{kg\ CO_2e}/_{MW} \right) \Big)
\end{aligned}
$$

We compare total annual emissions reduction from VPPs with NREL's Cambium data set of future US power sector scenarios, specifically using the "95 percent decarbonization by 2050" scenario.

Figure 3, below, shows aggregate emissions reduction from demand flexibility for each estimate level over the analysis period.

Figure 3. Annual VPP Emissions Reduction Potential for the United States, 2024–35, 2024–2040.



Source: RMI analysis.

Limitations

This analysis is a directional estimate of emissions reduction potential by virtual power plants. We make several simplifying assumptions in our analytical methods, consistent with our goal of providing an understandable, reasonable, and computationally tractable analysis using available data sets. We list several simplifying assumptions and limitations below and discuss potential opportunities for future analyses to further refine approaches to demand flexibility.

Accurately Modeling VPP Operations

- We do not model any specific mechanism for dispatching demand flexibility (e.g., time-varying rates, demand response tariffs or programs, or VPP platforms). We assume instant, perfect participation from end-users who have enrolled in a VPP without considering fatigue or end-user over-rides. Further analysis could include definition of VPP programs and consideration of multiple participant priorities.
- The **VPPs' Nationwide Carbon Savings Potential** analysis does not include an economic or cost-effectiveness assessment of VPP operations, and it does not include consideration of trade-offs between other grid-services beyond emissions reduction that might be provided beyond carbon reduction. Some grid services, (e.g., meeting peak demand) may be partially or completely aligned

with reducing emissions, but future analyses could better characterize trade-offs and synergies with provision of other VPP grid service offerings.

- We assume perfect demand shifting coordination between VPP technologies to avoid creating new system peak demands.
- We assume that shifting demand through VPP operations is perfectly efficient and requires the same amount of energy as demand without shifting. Further analysis could integrate dissipation rates for specific technologies (e.g., water heated will cool over time, leading to additional required energy to provide the same level of heated water) and other behavioral rebound effects.
- VPP operations are conducted with perfect foresight in terms of hourly emissions, and the long-run marginal emissions rate assumes knowledge of future build actions based on shifts in demand. This is appropriate for a long-run estimate of emissions reduction potential but may not capture the nuances of determining marginal short- and long-run emissions rates in real time.
- We assume flexible demand VPP technologies based on observed demand flexibility ability in 2018, and do not introduce any advanced demand flexibility technology or methods. Data center demand flexibility, for example, is not included in this analysis.
- We assume that participation consistently increases over time.

Estimating Load

- We use a combination of inputs to conduct this analysis, including load forecast and demand flexibility from NREL's Electrification Futures Study "High electrification, moderate technology advancement, enhanced participation" scenario and marginal and average emissions rates from the NREL Cambium "95 percent decarbonization by 2050" scenario.[41] These data sets and scenarios make different assumptions about future power sector conditions (including different load profiles), and the discrepancy between projected load and flexibility from NREL EFS and projected emissions rates from the 2022 NREL Cambium "95 percent decarbonization by 2050" scenario could potentially distort results.
- We examine average hourly load for each month, and do not analyze variation in demand or demand flexibility between days in a single month. While conducting this analysis using average hourly load days provides a better sense of general patterns for a given state and month, this analysis is not able to investigate the potential for VPP demand flexibility to address opportunities and risks created by any single particular weather or renewable generation pattern, including particularly high- or low-renewables days. Average annual days may also dilute the emissions impacts of wind energy because they are less concentrated during the same hours every day compared to solar energy. We also assume that demand flexibility is called every day of the year.
- We only examine intra-day flexibility, rather than demand flexibility between days or across multiple days. These options could potentially identify more effective shifts in demand.

Emissions Rates

- For the purposes of using long-run marginal emissions rates, we assume that resource planners can treat demand shifts as fixed and permanent. Future analyses could recognize that, while demand shifts are not fixed and permanent, additional flexibility provided by VPPs allows for a wider range of potential cost-effective resource portfolios.

- We assume that emissions rate estimates provided by the short- and long-run marginal emissions rates are reliable in cases where demand shifts may exceed the definition of "marginal," with demand shifts changing hourly demand by 15% or greater. More advanced approaches to measuring and projecting grid emissions are in active development.[42]

Endnotes

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