July 7, 2021

PGE DER and Flexible Load Potential – Phase 1

Portland General Electric

Developed For

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Section 1 Executive Summary

This report outlines work conducted to understand the potential adoption and impacts of distributed energy resources, flexible loads, and electrification for Portland General Electric (PGE) in support of its Integrated Resource Plan and ongoing Distribution System Planning as outlined in UM 2005. This work was undertaken by Cadeo in close collaboration with Ethan Goldman (independent), the Brattle Group, and Lighthouse Consulting (hereafter, the "Cadeo team").

To meet the evolving needs of PGE and its stakeholders, the Cadeo team worked closely with PGE to develop an open modeling framework. The framework integrates true bottom-up modeling of the building and vehicle stock with market-level adoption forecasts to create a rich, integrated view of how different DER and electrification technologies complement and compete under different conditions. The AdopDER model that we developed with PGE represents a paradigmatic shift in how potentials are modeled and lays the foundation for continued evolution in planning processes across the energy system.

This report outlines Phase I of a two-phase process to estimate potentials. In this phase, we estimated system-wide potential to inform the integrated resource plan. In Phase II, we will estimate locational adoption of these resources, fine-tune adoption models to account for different demographics, energy use patterns, built infrastructure, and cluster effects that are known to impact the distribution of DERs on the system. Phase II results will be used to inform PGE's forthcoming Distribution System Plan and program planning efforts.

This study presents results following estimated adoption, peak impacts (by season), and energy impacts for 2021-2050 from the following adoption pathways:

- **Programmatic adoption:** simulates measure adoption through PGE programs.
- **Market adoption:** simulates naturally occurring measure adoption for building electrification, transportation electrification, solar, storage, and smart devices technologies.

We modeled this adoption for the following technology groups:

- **Flexible loads**: programmatic adoption of opt-in direct load control and pricing measures, including peak time rebates, smart water heater controls, smart thermostats, and curtailable tariffs.
- **Solar and storage**: market and programmatic adoption of behind-the-meter solar and battery energy storage in residential, commercial, and industrial, including applications of microgrids for critical facilities.
- **Transportation electrification**: market and programmatic adoption of electric vehicles and accompanying charging infrastructure across all sectors and vehicles classes.

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We estimated forecast adoption and potential for the following categories:

- **Market forecast**: represents the expected adoption of resources given no programmatic intervention from PGE. This forecast excludes purely programmatic measures, such as demand response and pricing (excepting some enabling technologies, like smart thermostats, that might be adopted without intervention).
- **Technical potential**: provides a theoretical upper limit of adoption, showing what would happen if all feasible technologies were adopted in each year.
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For achievable technical and economic achievable potential, we estimated adoption and impacts under 9 different scenarios, looking at each possible combination of 3 load and 3 DER adoption scenarios. This provides us with a range of potential impacts and grounds the analysis in similar assumptions to those being used by the broader Integrated Resource Planning (IRP) effort.

Our final analysis outputs provide a rich view of different possible net load conditions. AdopDER provides hourly load and measure shapes down to the site level for each scenario and year over the 30-year planning horizon. It additionally provides anticipated costs and benefits for programmatic measures and estimated cost-effectiveness ratios using the Total Resource Cost (TRC) and Program Administrator Cost (PAC) tests, using an approach consistent with that PGE's Flexible Load Plan[1] adopted in May 2021. AdopDER also provides levelized costs and supply curves for dispatchable resources at the measure and program levels, to provide a more nuanced input into portfolio construction.

1.1 The AdopDER Model

The AdopDER model is a comprehensive modeling framework built in Python that is used to estimate the adoption of distributed energy resources, electrification, and flexible loads dynamically and stochastically under different programmatic and market conditions. AdopDER differs from traditional potentials analysis in several ways:

- **Open framework**: The AdopDER model is built using open-source tools and the entire codebase has been provided to PGE to be used in perpetuity, including

[1] UM 2141 Portland General Electric Company Flexible Load Plan available at https://edocs.puc.state.or.us/efdocs/HAS/um2141has132229.pdf

components that were previously proprietary to the Cadeo team. The inputs to the model are all either internal to PGE or publicly available, so that PGE is empowered to share and engage with commission staff, stakeholders, and communities wherever possible.

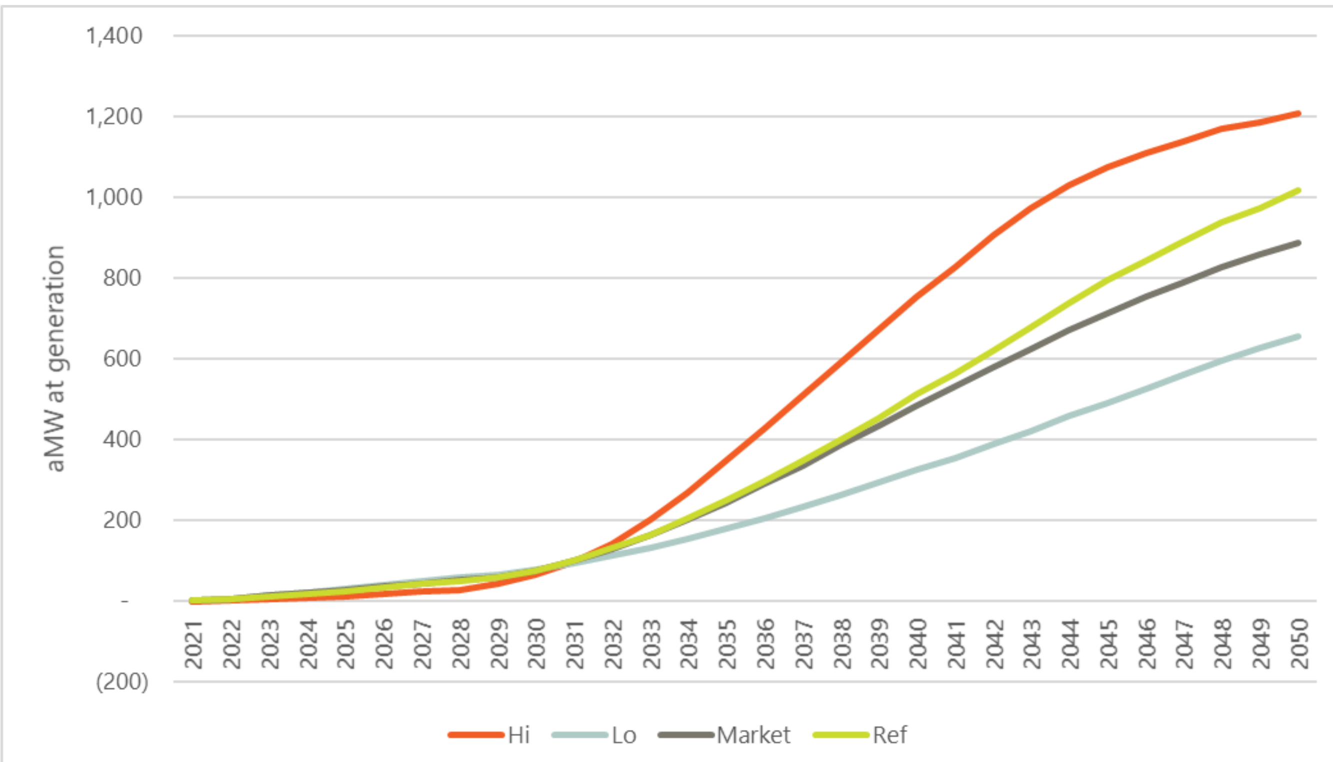
- **Scalable granularity**: While there is often a debate between bottom-up and top-down approaches, there is almost always a mix of the two based on the appropriateness of the model and the availability of data. Where more granular data is available and needs warrant, AdopDER can model down to the individual site level. However, where that is not available, it augments missing data stochastically, simulating missing fields or applying average values, as necessary.
- **Agent-based approach**: AdopDER is natively agent-based, meaning that it starts with the individual site as the unit of analysis and models its feasibility and adoption decisions over time, considering outside system-level factors such as weather, rates, costs, and product availability. This is critical for an integrated view of DER adoption as many resources compete or complement each other for limited customer spending, available site ampacity, or program participation opportunities.
- **Explicit, time-variant modeling of feasibility**: AdopDER uses a stock turnover approach to update site-level characteristics over time, which in turn updates the site-level feasibility for each technology over time. The dynamic nature of feasibility in AdopDER leads to findings that would be missed in a study that holds current trends static. For instance, forecasts for Level 2 home charging often assume that current trends hold through the forecast period, however, when looking at high levels of EV adoption that the Cadeo team expects in later years, it becomes apparent that a large portion of the residential population cannot install this charging due to lack of available parking and/or panel ampacity.
- **Differentiation of technologies and programs**: The model explicitly models the hierarchy that exists between measures, programs, and specific bundles of measures delivered through a program. For instance, smart thermostats can be adopted either in the market or through a program, but the latter has a timeline and specific set of criteria around it. By decoupling program delivery from specific measures, AdopDER allows PGE to model specific program portfolios and see how that changes adoption in the market and between different program offerings.
- **Integration of industry-leading tools**: Because AdopDER is built on an open framework, we can readily incorporate other open tools into the model framework. For instance, for this study, we incorporated data and analyses from NREL's REOpt Lite, PVWatts, DGen, and EVI-Pro Lite tools into AdopDER to provide a robust set of adoption forecasts for solar, storage, microgrid, and EV charging measures.

A critical element of this work is the flexibility it provides PGE to respond to changing conditions. As system planning relies increasingly on the distribution system and input from communities, and within this context technology and regulation are rapidly evolving, it is critical that utilities can rapidly update their models with new information. In creating an open codebase upon which PGE can develop new tools, we have enabled PGE and its communities to capitalize on new opportunities more rapidly for shared benefits on the distribution system.

1.2 Findings

In aggregate, the confluence of solar, storage, transportation and building electrification, and flexible loads is set to have a dramatic impact on PGE's system and its customers. The graph below shows the expected energy impacts (in aMW at generation) through 2050 under the different adoption scenarios.

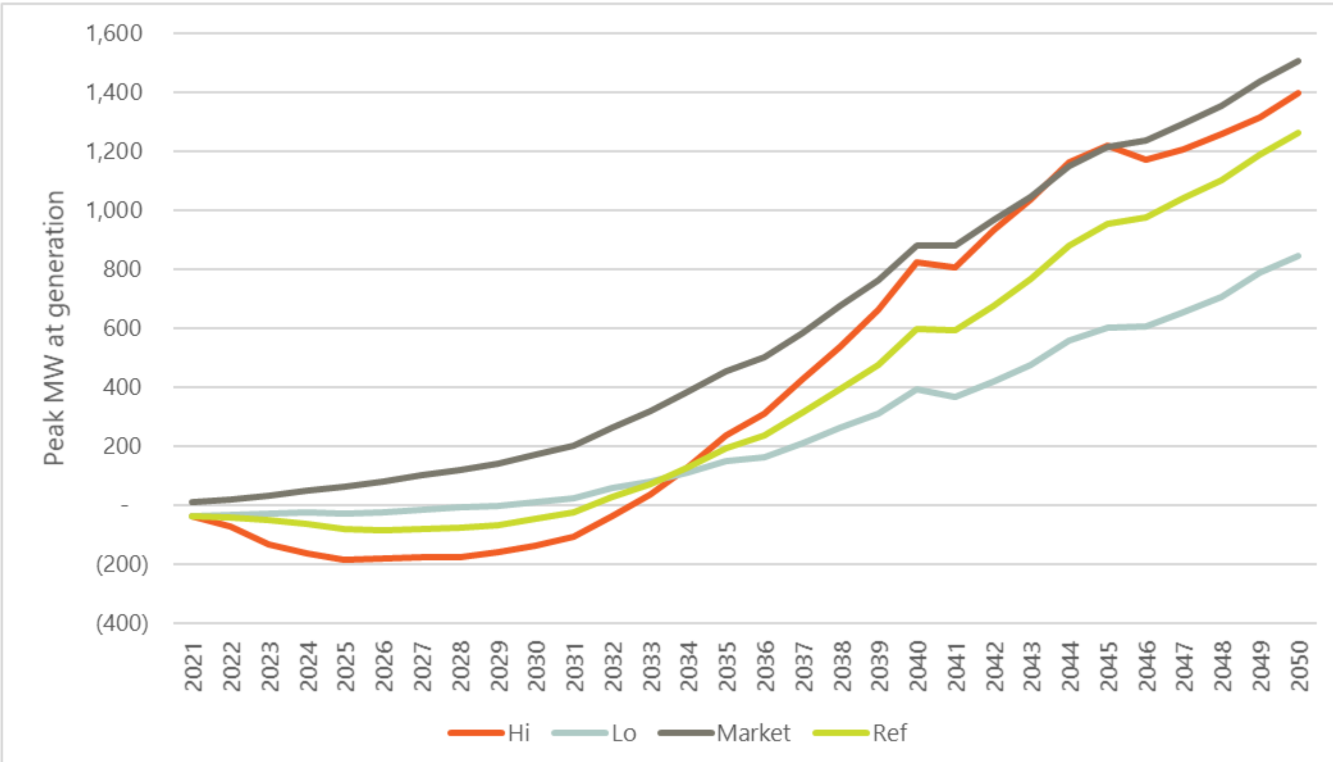
Figure 1-1. Aggregate Energy Impacts by Adoption Scenario



Even after accounting for increased solar adoption, transportation electrification (and to a much lesser extent, naturally occurring building electrification) is set to increase load by over 1,000 AMW in year 2050 in our reference case scenario. The market scenario in Figure 1-1 provides an idea of what we expect to see absent programmatic activity. In outer years, we see the impact of PGE's transportation electrification programs on the adoption of electric vehicles and greater utilization of charging infrastructure (we do not model building electrification programs in this analysis).

This increase in load points to the need for flexible resources to manage peaks and mitigate upgrade costs across PGE's system. We see the critical role that flexible loads play clearly when looking at peak impacts. The figure below shows the average, net demand impacts under each scenario, where peak is defined as the average over times of event dispatch in both summer and winter[2].

Figure 1-2. Aggregate Peak Impacts by Adoption Scenario



Here we see that PGE's continued development of its flexible load portfolio leads to a net decrease in peak loads, even accounting for transportation electrification. However, in outer years, the impact of electrification overtakes flexible load adoption. However, when comparing the reference to the market case we see that these programs continue to play an important role in mitigating these peak impacts.

Because in the market scenario there are no flexible loads or dynamic rates, we see changes in peak load are driven almost entirely by electrification[3], leading to steady and eventually large long-term increases. In the programmatic scenarios, these programs and rates help to reduce peak load to such an extent that in the early years of the planning period their effect is greater than total additions from electrification. However, as transportation electrification becomes near-universal in the out-years, there becomes a net positive impact on peak load. Because programs encourage both flexible loads and transportation electrification, the high scenarios

[2] This analysis is merely meant to be indicative and is not a replacement for a full ELCC analysis through the IRP.

[3] There is some reduction in peak load from behind-the-meter solar, but not that storage here is un-managed, so is only used for backup.

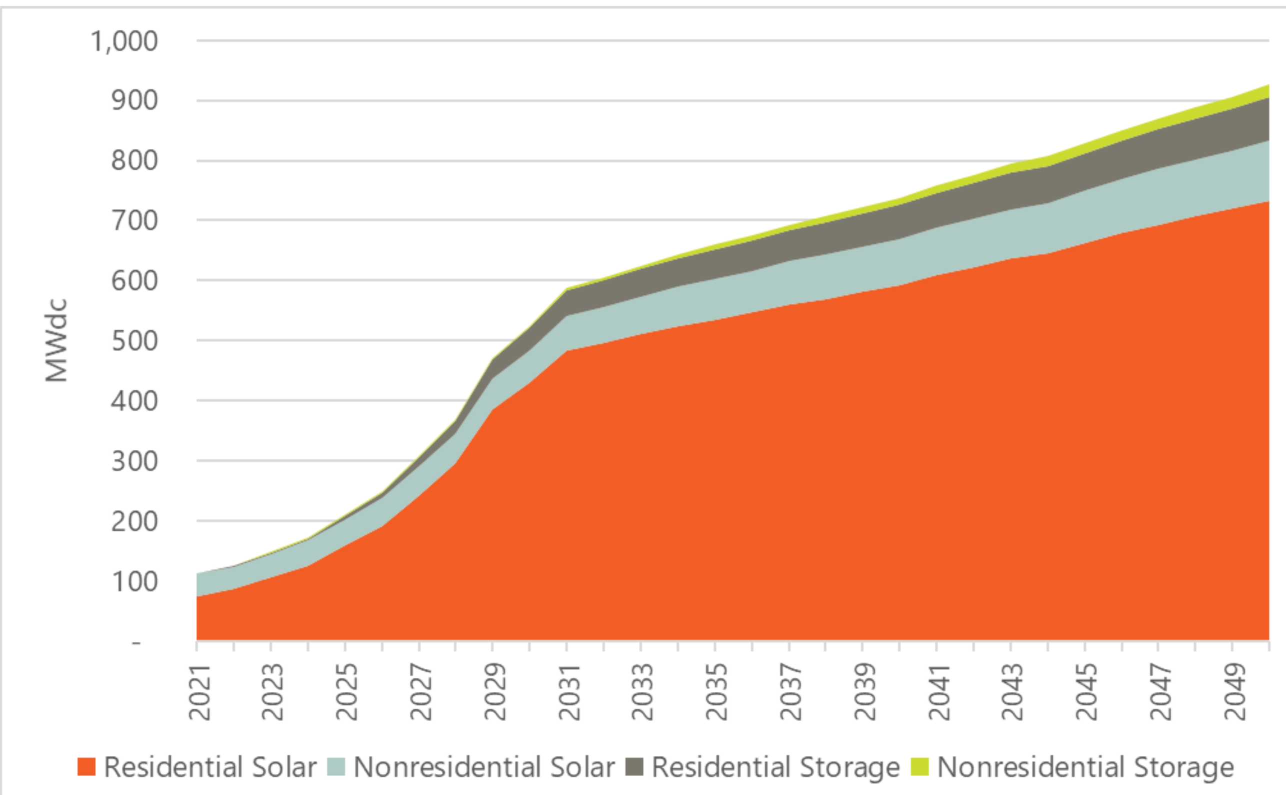
shows both greater negative impacts in the early years and high positive impacts in the later years of the planning period.

We explore each set of technologies and their expected adoption and impacts under different scenarios in greater detail below.

1.2.1 Solar and Storage

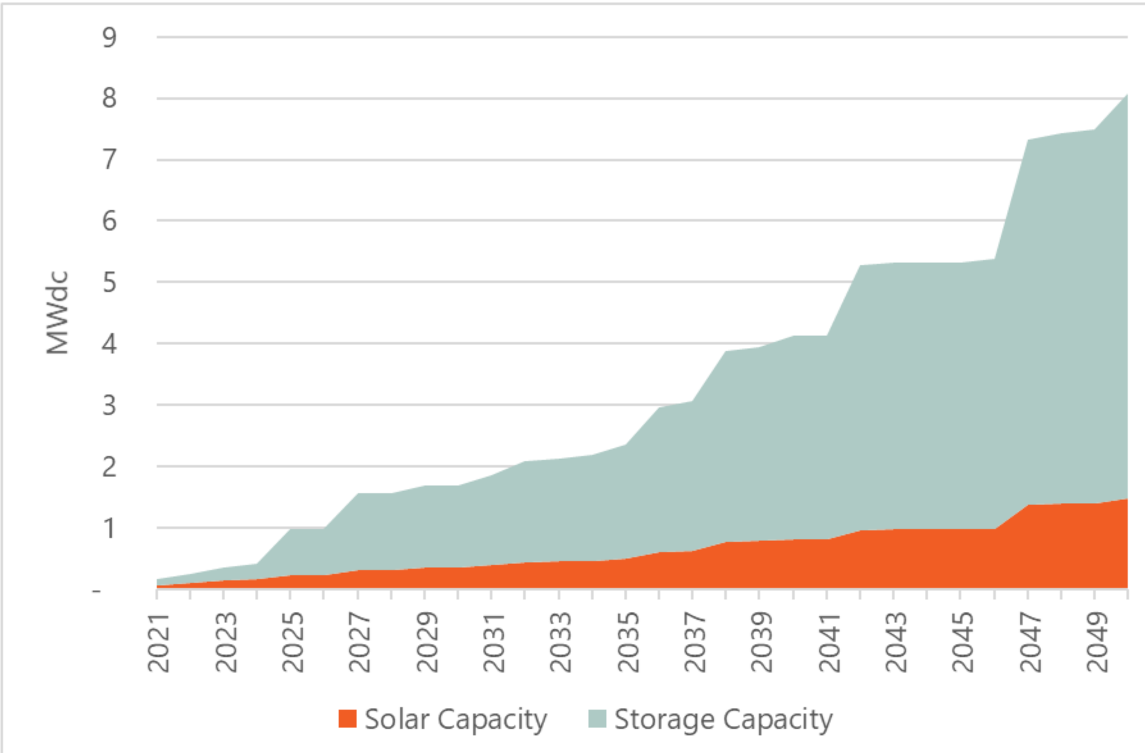
Despite a very large technical potential for both solar and storage, we expect approximately 926 MWdc of combined nameplate solar and storage across residential and commercial applications. Based on our analysis of the forecasts from NREL's DGEN model, we expect a large increase in residential solar in the later years, driven by declining costs of solar installations. We expect, as is the case in PGE's service area today, that residential will dominate the behind the meter solar market in PGE's service area. We forecast a small, but growing market for storage, with approximately 72 MW in residential and another 21 MW in nonresidential, largely driven by expected increases in solar attachment rates.

Figure 1-3. Projected Solar + Storage Adoption (MWdc, Reference Case)



We expect relatively modest microgrid adoption on average, though this is highly uncertain due to the bespoke design and needs of each project and increasing requirements for resiliency in the face of extreme weather events.

Figure 1-4. Projected Microgrid Adoption (Reference Case)



1.2.2 Transportation Electrification

We forecast much higher levels of adoption for electric vehicles than in the previous IRP study, consistent with industry consensus around pending market transformation, particularly in the light duty segment. By 2027, we expect 141,000 electric light duty vehicles on the road, dominated by the residential sector, and 2,100 medium and heavy duty EVs. By 2050, we expect nearly 80% of the vehicle market to be electric in all weight classes, with 1.4 million light duty vehicles (LDV) and 33,000 medium (MDV) and heavy-duty vehicles (HDV).

Figure 1-5. LDV Adoption by Adoption Scenario

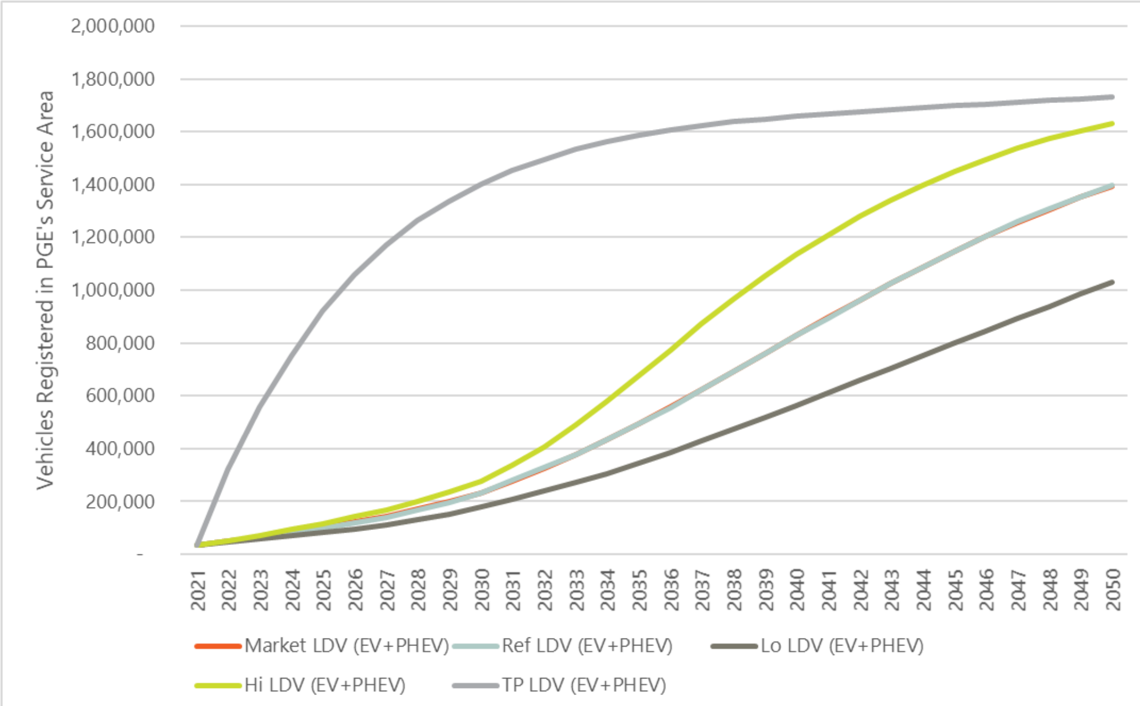
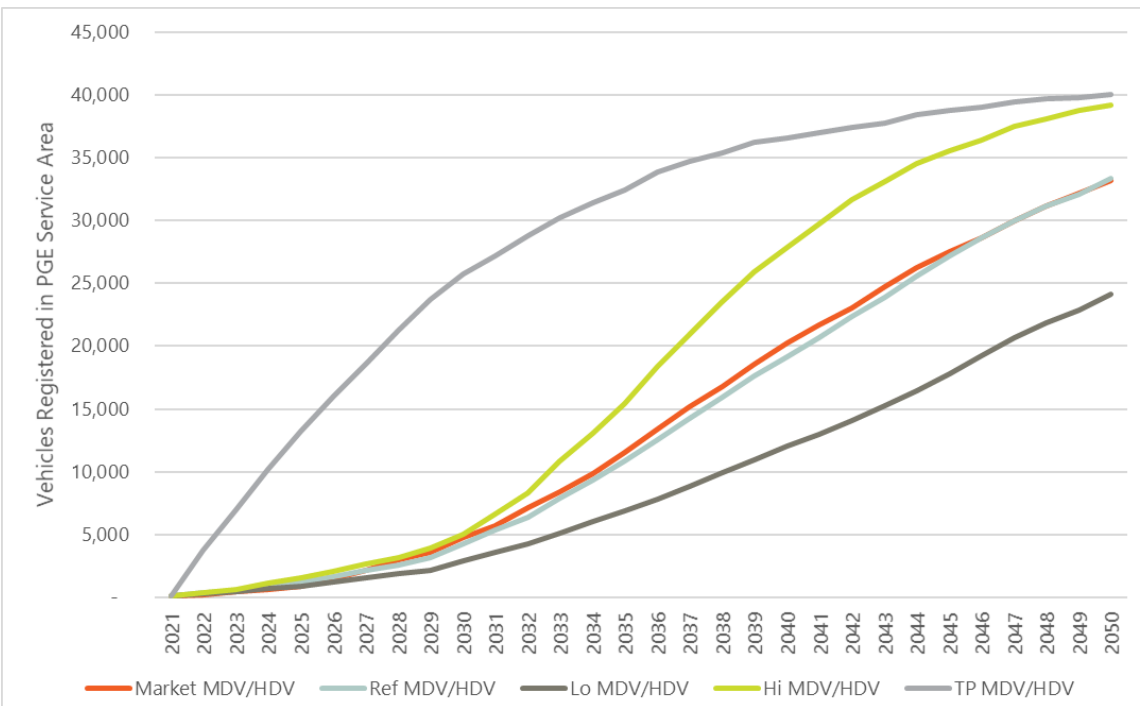


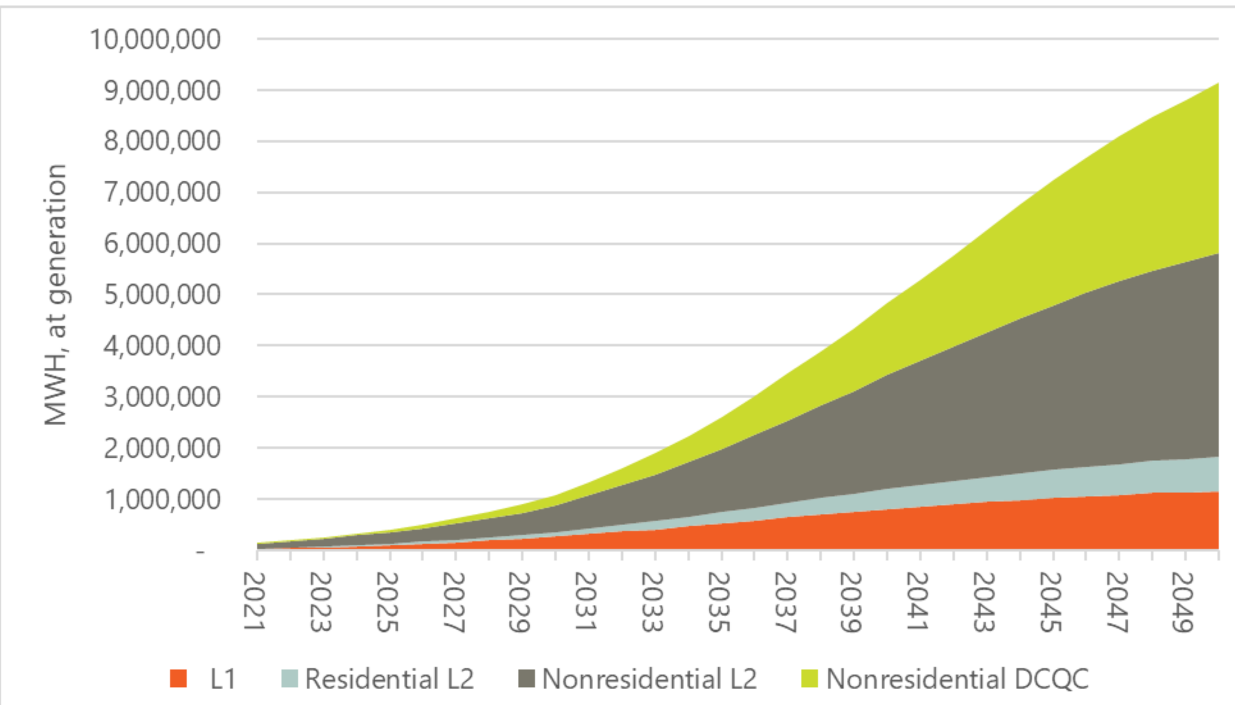
Figure 1-6. MDV Adoption by Adoption Scenario



By 2050, we forecast an increase in annual consumption of 9.1 million MWH (at generation) to serve electric vehicle charging. Of that, nearly 80% will come from charging not dedicated to a single residence. Our forecast explicitly accounts for constraints to home charging due to lack of panel ampacity and/or dedicated off street parking, thus we find that only a fraction of residential customers at the high expected levels of adoption can charge with personal EVSEs. Often, forecasts in the industry have relied on historical charging patterns as a guide to future behavior. However, this extrapolation of early adopters' charging patterns while neglecting to account for existing building stock can underestimate the needs for publicly available charging infrastructure in the long term. Our analysis assumes that sites will only install L2 charging if they have available panel ampacity and personal off-street parking, which leaves many residential sites without charging. Further research on streamlining panel/service upgrades and providing charging solutions for residents with only on-street parking could help to expand potential for home charging. There remains, regardless, a tremendous need in the long term for shared charging solutions.

The figure below shows this increased consumption, broken out by high level category. Nonresidential L2 charging — which includes multifamily, workplace, public, and fleet — becomes the dominant segment in the long run due to the need for charging beyond the home.

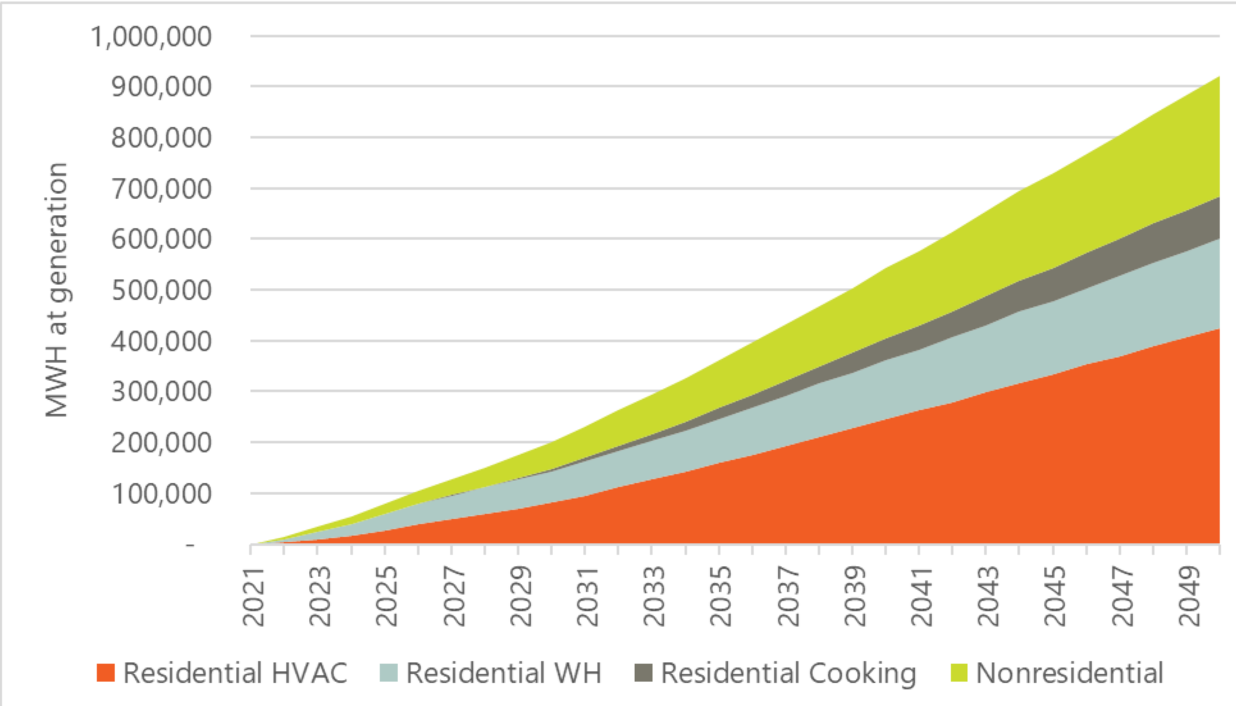
Figure 1-7. Projected Transportation Electrification Consumption (Reference Case)



1.2.3 Building Electrification

We expect only modest adoption of building electrification measures, largely concentrated in the residential sector. Though our AdopDER model can do so, this study does not simulate the impacts of local building codes (current or future) on the adoption of building electrification measures. Still, we project load growth from building electrification from new construction trends, where there is a small increase in the adoption of heat pumps to meet energy efficiency requirements. However, compared to transportation, these impacts are quite low.

Figure 1-8. Building Electrification Consumption (Reference Case)

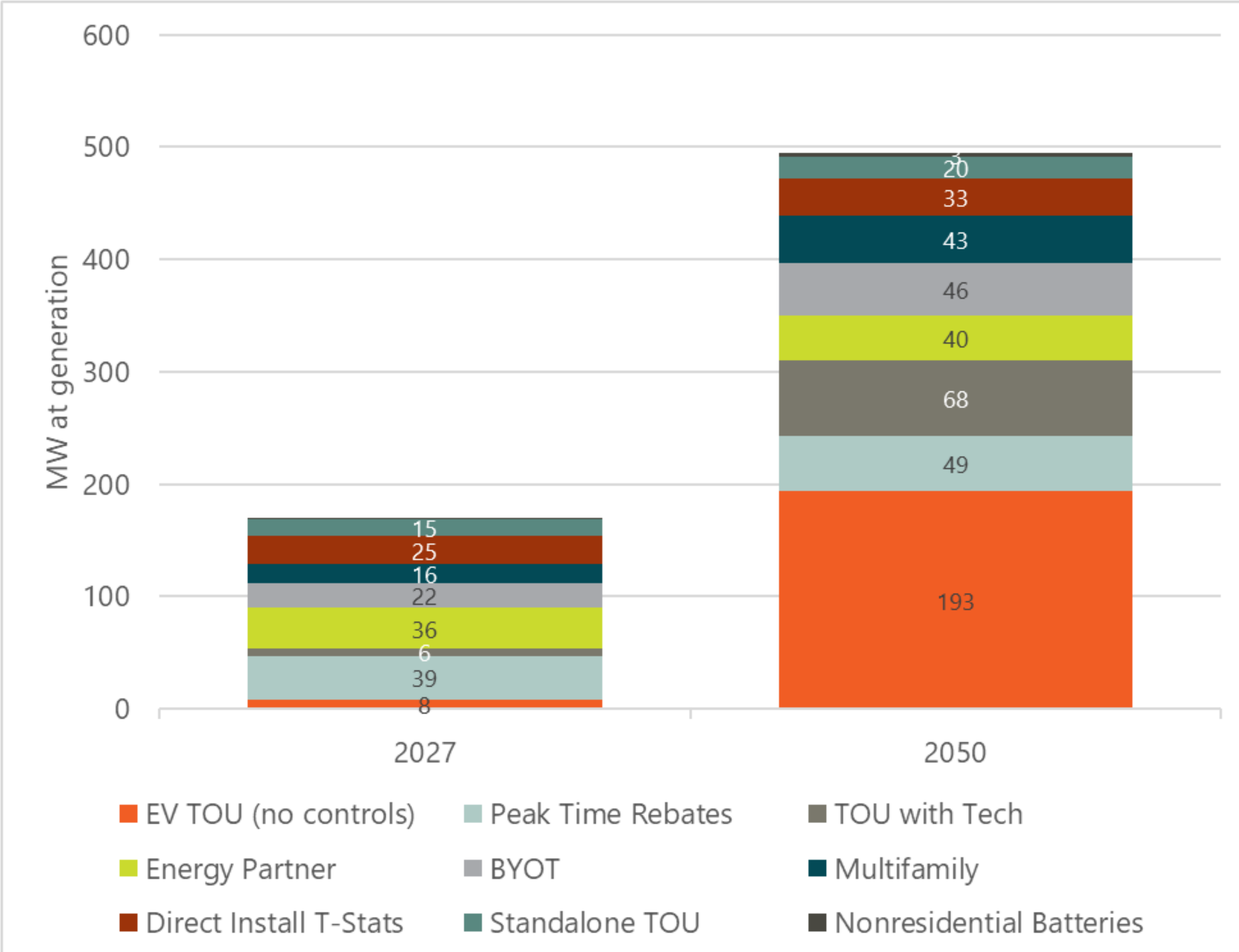


1.2.4 Demand Response

In aggregate, we expect approximately 169 MW of economic achievable demand response (including behind-the-meter storage enrolled in a program) by 2027. We expect PGE's portfolio to be dominated by peak time rebates, Energy Partner, and the thermostat programs in the near term (as it is today). By 2050, we expect 495 MW of summer DR, dominated by EV TOU due to near-universal adoption of light duty electric vehicles in the residential sector.

Additionally, tech-enabled TOU becomes a bigger portion of the portfolio. In this study, we considered TOU programs specifically targeted at customers with smart thermostats, storage, connected water heaters, or smart EVSE equipment. These options assume that customers purchase the enabling equipment on their own and self-select into a TOU option that offers automated routines for managing against that rate.

Figure 1-9. Summer Economic Achievable Demand Response (Reference Case)



As in previous studies, we expect slightly lower demand response in the winter season due to lower levels of electric heating relative to cooling in both residential and commercial. In 2027, we expect 134 MW of winter demand response, comprised of a mix of multifamily, thermostats, and the Energy Partner program (as shown in the Flex 1.0 evaluation, PTR and TOU rates have lower per-unit impacts in winter). In 2050, we forecast 344 MW of demand response. As in summer, EV TOU dominates due to its low level of seasonality, high impacts on peak, and high level of adoption.

Figure 1-10. Winter Economic Achievable Demand Response (Reference Case)

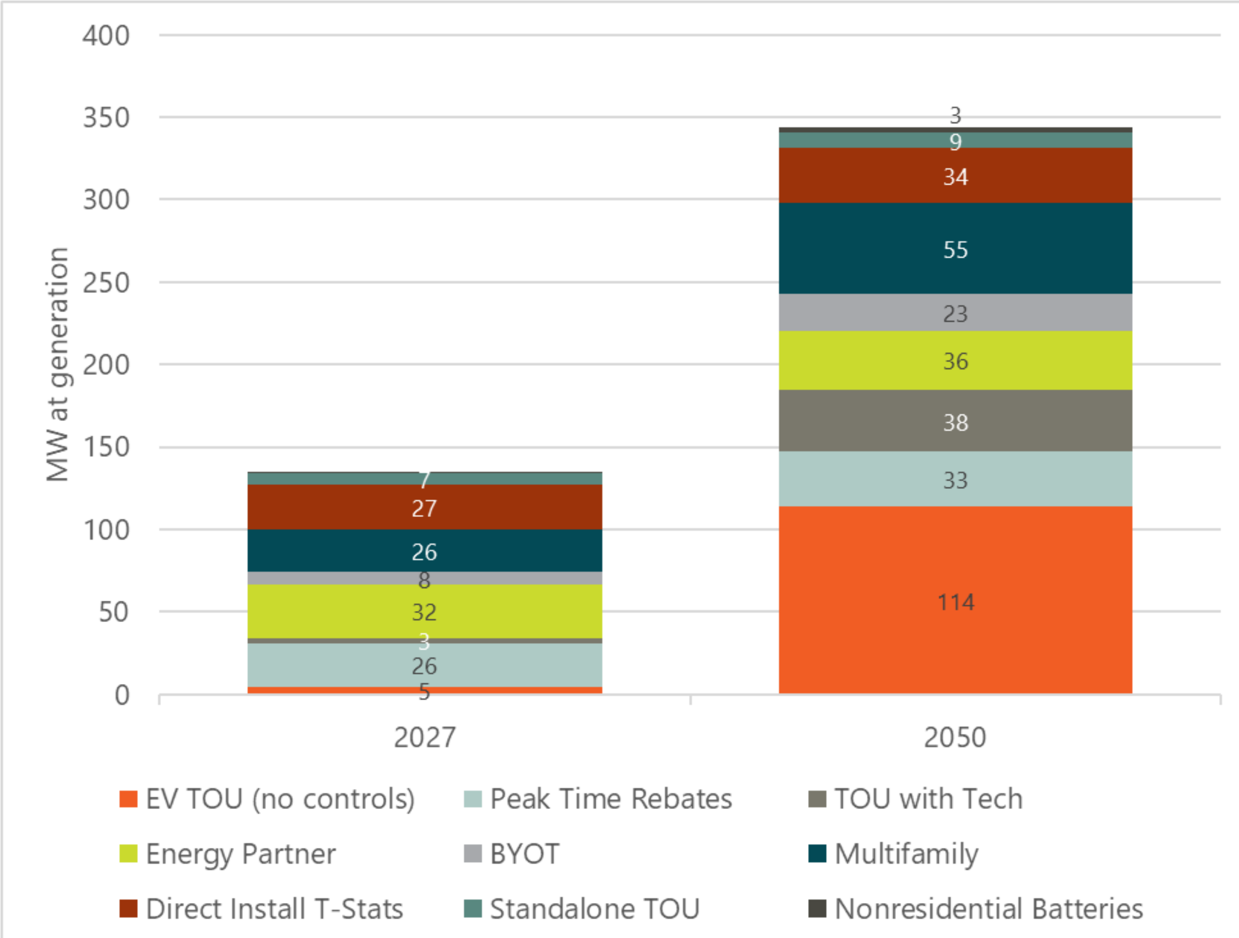


Table 1-1 provides a breakdown of expected MW impacts across different scenarios for both economic and achievable potential. In most scenarios, most of the demand response is economic in terms of total MW. Those measures that are not cost-effective remain relatively low in adoption regardless, even out to 2050. The range of potential impacts is broad, reflecting the still high level of uncertainty around adoption of these measures, with ranges in the +/- 50% range.

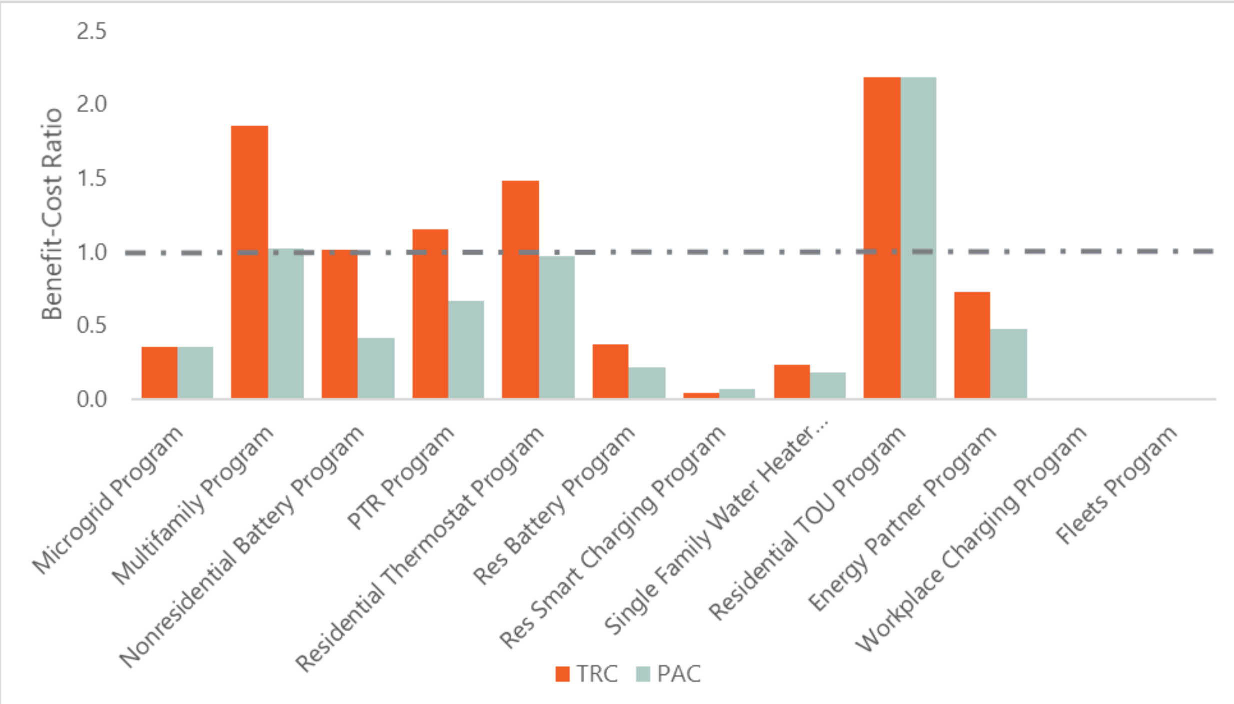
Table 1-1. Demand Response Results (MW at generation) for 2027 and 2050 by Season and Scenario

Adoption Scenario	Season	2027		2050	
		All Achievable	Economic Achievable	All Achievable	Economic Achievable
Reference	**Summer**	**207**	**169**	**598**	**495**
	Winter	**162**	**134**	**452**	**344**
Low	Summer	133	117	399	327
	Winter	100	91	310	235
High	Summer	298	261	912	735
	Winter	240	204	703	506

1.2.5 Cost-Effectiveness

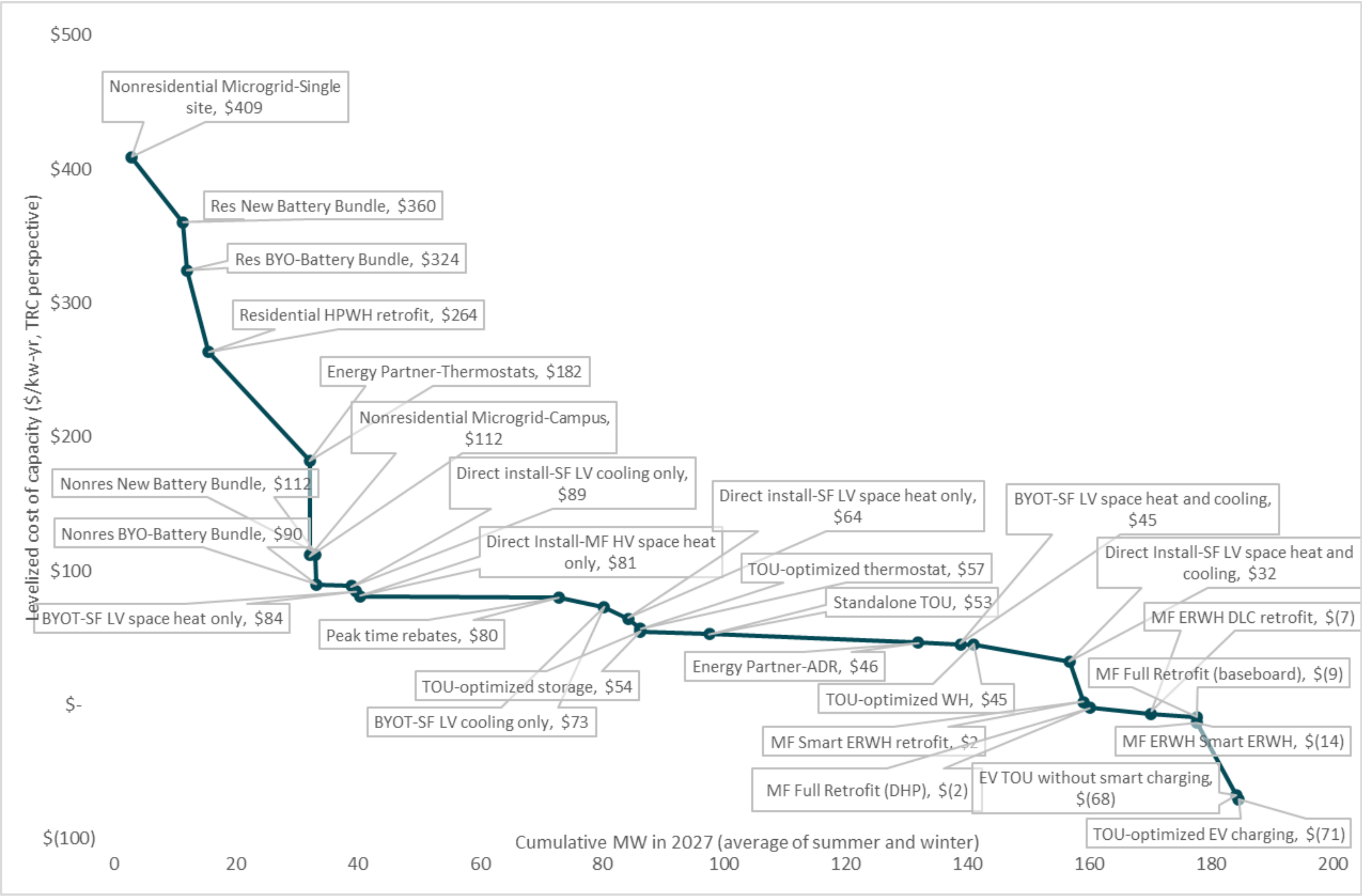
While AdopDER screens cost-effectiveness at the measure bundle level, we also calculate economics at the program level. Here we see that PGE's residential programs, particularly those that use price signals, are the most cost-effective. While the largest measure today for PGE's Energy Partner program (Schedule 26) is cost-effective, our inclusion of other measures such as agriculture, cold storage, and smart thermostats drags down program cost effectiveness. Interestingly, nonresidential storage appears to be marginally cost-effective due to its high availability and ELCC.

Figure 1-11. Cost-Effectiveness by Program



Because we model economics and impacts down to the site and annual level, we are able to develop supply curves for capacity resources at this level. Figure 1-12 shows levelized cost of capacity plotted against average 2027 peak MW impacts (average of summer and winter). Given the ability of some measures to provide services beyond generation capacity (such as energy, flexibility, and transmission capacity), we find that there are several measures that in fact have net levelized costs below zero. Interestingly, we see an inflection point in the supply curve to at approximately $100/kw-yr (roughly PGE's avoided cost of capacity), above which there are a handful of measures with very high costs and relatively low near term potential.

Figure 1-12. Supply Curve of Demand Response Resources



1.3 Conclusions

The tools developed and results generated from this analysis provide a foundation for PGE to build upon as it embarks on its efforts to create an integrated planning framework across Distribution System, Flexible Loads, Electrification, and Integrated Resource Planning. We find that PGE has a wide array of resources at their disposal as they seek to create value for their customers on the distribution grid.

We see several trends interacting in our forecast:

- Dramatically increasing adoption of residential solar is expected to increase needs on the distribution system and encourage adoption of storage;

- Electrification of transportation will create unprecedented impacts on the energy system and present growing opportunities for flexible loads;
- Flexible loads are becoming increasingly cost-effective and there are new opportunities to integrate them with new DERs;
- DERs of all sorts create new constraints on the built infrastructure: an integrated approach to their deployment will be critical.

1.3.1 Actionable Insights

We see several ways in which the results of this study can be used to inform future work by PGE planning and programs staff.

1 | We find that there are likely 169 MW of summer and 134 MW of winter economic and achievable demand response in PGE's service area by 2027, made up largely of programs they are already well into piloting. Continued focus on streamlining and scaling these programs will be critical to achieving these goals.

2 | Time of use rates, particularly when paired with increasingly prevalent enabling technology, show tremendous promise to manage peak demands, especially as transportation electrification becomes more prevalent. Further demonstration of how these rates might be deployed more rapidly could help to accelerate progress toward their goals.

3 | Storage programs appear to be within the grasp of cost-effectiveness and program incentives will be critical to stimulating this market in Oregon. PGE should explore new opportunities to find cost savings in program delivery and/or capture new value streams to further improve economics.

4 | While we did not explicitly model a service area-wide program in the scope of this study, our analysis of smart water heater adoption and controls shows that there is a rapidly growing opportunity for taking a market transformation approach to water heaters. We find that PGE's multifamily water heater program is already cost-effective and expect a program utilizing CTA-2045 more broadly would be as well.

1.3.2 Areas for Further Research

While the research here provides a robust foundation for understanding future DER adoption, we see a few areas where further research might be warranted.

1 | We modeled panel constraints statistically in our analysis and their impact on home charging, building electrification, solar, and storage could be significant. We recommend further and possibly primary research on the existing panel configurations in PGE's service territory and possible solutions to overcome these challenges more cost-effectively.

2 | Our analysis took a relatively simple approach to DER dispatch, calling the fleet of dispatchable assets in aggregate based on a forecasted LOLP. A more integrated optimization of the fleet as a single Virtual Power Plant may more accurately reflect the full co-optimized value of these assets.

3 | Our analysis shows that different segments of the population have lower adoption rates simply due to differences in the built infrastructure, existing equipment in place, and programs available to them. As we move toward locational analysis, the bottom-up approach that we use in this study could also be used to better understand the equity impacts of DER adoption today and under different portfolios of interventions.

4 | Building electrification measures show large potential in the commercial HVAC space, as analyzed in this study. A deeper investigation of these emerging technologies and potentially, industrial loads may be useful in allowing PGE to understand where greater carbon impacts may be possible.

1.3.3 Next Steps

1 | The Cadeo team will work with PGE to develop locational forecasts based on this work to further advance their Distribution System Planning efforts;

2 | We have already begun the process of transferring code base, results, and inputs to PGE internal analysts to ensure that they can replicate and advance this work; and

3 | Results from this study will serve as an input to PGE's 2021 Integrated Resource Plan.

Table of Contents

Section 2 Glossary

This section contains a glossary of acronyms and other terms that we use throughout this report:

aMW: Average megawatt (8760 megawatts of energy)

AEU: Avoided Energy Use

ASHP: Air-Source Heat Pump

BE: Building Electrification

BEV: Battery Electric Vehicle

BTM: Behind-the-Meter

BYOT: Bring Your Own Thermostat

CBSA: Commercial Building Stock Assessment

CDF: Cumulative Distribution Function

DCQC: Direct Current Quick Charger

DER: Distributed Energy Resource

DGEN: Distributed Generation Market Demand

DHP: Ductless Heat Pump

DLC: Direct Load Control

DOAS: Dedicated Outdoor Air System

DR: Demand Response

DSP: Distribution System Planning

ERWH: Electric Resistance Water Heater

EVSE: Electric Vehicle Supply Equipment

FLP: Flexible Load Plan

HDV: Heavy Duty Vehicle

HPWH: Heat Pump Water Heater

ICE: Internal Combustion Engine

IRP: Integrated Resource Plan

LDV: Light Duty Vehicle

LOLP: Loss of Load Probability

MDV: Medium Duty Vehicle

NREL: National Renewable Energy Laboratory

PAC: Program Administrator Cost

PDF: Probability Distribution Function

PHEV: Plug-in Hybrid Electric Vehicle

PTR: Peak Time Rebate

PV: Photovoltaic

RASS: Residential Appliance Saturation Survey

RBSA: Residential Building Stock Assessment

RTF: Regional Technical Forum

RTU: Rooftop Unit

T&D: Transmission and Distribution

TE: Transportation Electrification

TMY3: Typical Meteorological Year, version 3

TOU: Time of Use

TRC: Total Resource Cost

UMP: Uniform Methods Project

VIN: Vehicle Identification Numbers

VRF: Variable Refrigerant Flow Heat Pump

ZEV: Zero-Emission Vehicles

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[4] For a review of the AdopDER system see Chapter X section X of this report.

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- **Scalable granularity**: While there is often a debate between bottom-up and top-down approaches, there is almost always a mix of the two based on the appropriateness of the model and the availability of data. Where more granular data is available and needs warrant, AdopDER can model down to the individual site level. However, where that is not available, it augments missing data stochastically, simulating missing fields or applying average values, as necessary.
- **Agent-based approach**: AdopDER is natively agent-based, meaning that it starts with the individual site as the unit of analysis and models its feasibility and adoption decisions over time, considering outside system-level factors such as weather, rates, costs, and product availability. This is critical for an integrated view of DER adoption as many resources compete or complement each other for limited customer spending, available site ampacity, or program participation opportunities.
- **Explicit, time-variant modeling of feasibility**: AdopDER uses a stock turnover approach to update site-level characteristics over time, which in turn updates the site-level feasibility for each technology over time. The dynamic nature of feasibility in AdopDER leads to findings that would be missed in a study that holds current trends static. For instance, forecasts for Level 2 home charging often assume that current trends hold through the forecast period. However, when looking at high levels of EV adoption that the Cadeo team expects in later years, it becomes apparent that a large portion of the residential population cannot install this charging due to lack of available parking and/or panel ampacity.
- **Differentiation of technologies and programs**: The model explicitly models the hierarchy that exists between measures, programs, and specific bundles of measures delivered through a program. For instance, smart thermostats can be adopted either in the market or through a program, but the latter has a timeline and specific set of criteria around it. By decoupling program delivery from specific measures, AdopDER allows PGE to model specific program portfolios and see how that changes adoption in the market and between different program offerings.
- **Integration of industry-leading tools**: Because AdopDER is built on an open framework, we can readily incorporate other open tools into the model framework. For instance, for this study, we incorporated NREL's REOpt Lite, PVWatts, DGen, and EVI-Pro Lite tools into AdopDER to provide a robust set of adoption forecasts for solar, storage, microgrid, and EV charging measures.

A critical element of this work is the flexibility it provides PGE to respond to changing conditions. As system planning relies increasingly on the distribution system and communities, while technology and regulation are rapidly evolving, it is critical that utilities can rapidly update their models with new information. In creating an open codebase upon which PGE can develop new tools, we have enabled PGE and its communities to capitalize on new opportunities more rapidly for shared benefits on the distribution system.

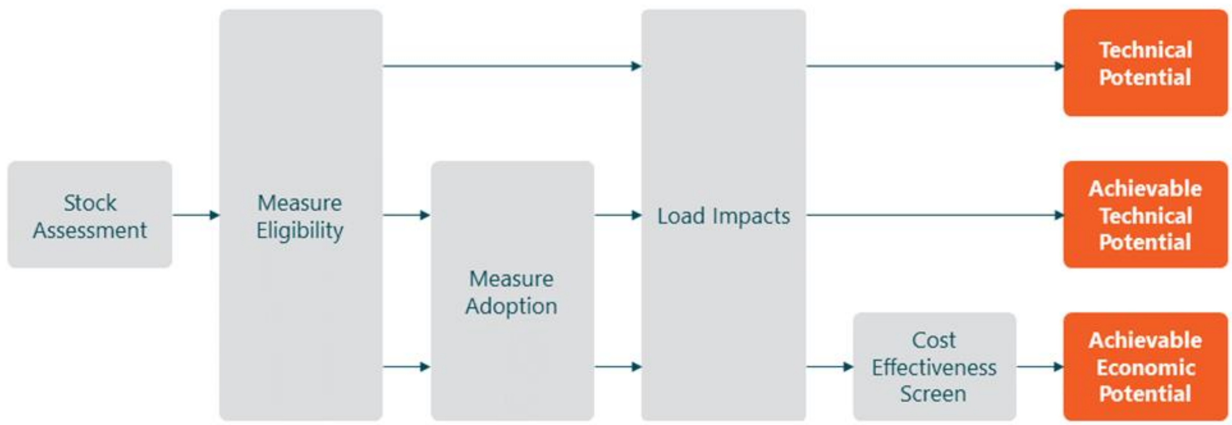
Section 4 Methodology

This section outlines our approach to modeling the adoption and impacts of DERs, flexible loads, and electrification for PGE.

4.1 Potentials Modeling Process

Figure 4-1 illustrates our approach to estimating technical, achievable technical, and achievable economic potential in PGE's service territory. We define these three types of DER potential as follows:

Figure 4-1. High Level Diagram of Potentials Estimation Step



Technical Potential assumes all customers adopt every DER measure their premise is eligible for, regardless of cost. As such, technical potential represents a theoretical upper bound rather than a practical upper bound. In some cases, where there are competing measures, we assume the customer adopts the technology with the most advanced DER (i.e., we assign a heat pump water heater instead of a smart electric resistance water heater, or smart L2 EVSE instead of L1 EVSE).

Mathematically, we express technical potential at any given hour *t* as follows, where Eligibility is a binary variable for measure eligibility at a given site and load impact is the kW impact of that measure, per unit size for a given site.

Equation 1. Technical Potential Formula

$$Technical\ Potential_t = \sum_{site\ s} \sum_{measure\ m} Eligibility_{smt} * Measure\ Size_{sm} * Load\ Impact_{smt}$$

Achievable Technical Potential is the portion of technical potential that is available after accounting for market barriers (i.e., technology costs, customer awareness) and programmatic constraints (i.e., incentives, program budgets). We express achievable technical potential mathematically in Equation 2, which adds a term to Equation 1 to account for measure adoption.

Equation 2. Achievable Technical Potential Formula

$$Achievable\ Technical\ Potential_t = \sum_{site\ s} \sum_{measure\ m} Eligibility_{smt} * Adoption\ Probability_{smt} * Measure\ Size_{sm} * Load\ Impact_{smt}$$

Achievable Economic Potential is the subset of achievable technical potential that is economically cost-effective relative to other supply-side resources. In this study, we evaluated cost-effectiveness for programmatic measures with a TRC test using a methodology that follows guardrails established by PGE's flexible load plan. We express achievable economic potential mathematically in Equation 3, which adds a term to Equation 2 to account the cost effectiveness of each measure.

Equation 3. Achievable Economic Potential Formula

$$Achievable\ Economic\ Potential_t = \sum_{site\ s} \sum_{measure\ m} Eligibility_{smt} * Adoption\ Probability_{smt} * Measure\ Size_{sm} * Load\ Impact_{smt} * Cost\ Effective_m$$

Our estimates of these DER potentials for PGE follow a process with six discrete steps, as follows. Each step is elaborated in the following sections.

- **Stock Assessment.** Use PGE-specific and other data sources to determine site-level characteristics that influence DER measure eligibility and/or measure adoption.
- **Measure Eligibility.** Apply criteria to determine which sites are eligible for each measure.
- **Measure Adoption.** Determine how, when, and which eligible sites adopt each measure.
- **Load Impacts.** For each adopter determine the hourly load impacts of each DER measure and aggregate to a system level.
- **Economic Screening.** Determine, at a system level, which programs of DER measures are cost-effective based on a set of cost and benefit assumptions.
- **Adoption and Load Scenarios.** Determine, at a system level, how adoption and load impacts vary under certain conditions.

4.2 Stock Assessment

Our DER potentials estimation in AdopDER begins with a comprehensive stock assessment. The purpose of the stock assessment is to create a time-variant set of site characteristics that we use to inform DER measure eligibility, adoption, and load impacts over the study period between years 2020 and 2050.

In this section, we present a description of each of the four steps in our stock assessment:

- Sampling
- Site-Level Characteristics
- Stock Turnover
- New Construction

4.2.1 Sampling

At the core of our stock assessment is a sample of PGE premises. Our modeling approach utilizes a ten percent sample of residential, and small commercial and industrial premises, along with a census of large commercial and industrial premises (Table 4-1). The dynamic way in which we forecast measure eligibility and measure adoption requires knowledge of characteristics at individual premises, rather than system-level averages.

Many premises in PGE service territories have multiple associated service points. If a premise in our sample has multiple service points, we include information for all service points in our assessment. Additionally, we have excluded direct access customers and customers in a street lighting revenue class from our sample.

Table 4-1. Customer Sampling Summary

Customer Segment	Revenue Classes	Sampling Rate
Residential	7	10%
Small C&I	32, 47	10%
Large C&I	38, 49, 83, 85, 89, 90	100%

Note: We excluded rate codes that are not eligible for DER measures: lighting (schedules 15, 91, 92, and 95) and direct access customers.

4.2.2 Site Level Characteristics

After developing our sample, we leveraged numerous data sources listed in Table 4-2 to develop a rich set of characteristics for each premise that we used to represent its state during the first year of our study (2020). In addition to listing sources, Table 4-2 also provides a high-level description of the characteristics that we acquired from each source. Appendix E lists each characteristic in detail.

Table 4-2. Stock Assessment Data Sources

Source	Description	Characteristics
PGE Residential Appliance Saturation Survey	Survey of end-use equipment for PGE residential customers, conducted Q2-Q3 2020.	Residential water heater types, heating systems, cooling system, EVSE type (L1,

Source	Description	Characteristics
		L2), hot tub, pool pump, smart thermostat type
PGE Customer Care & Billing Database (CC&B)	PGE customer information.	Residential and non-residential building type, billed kWh and kW, revenue class, service point and premise IDs
PGE Outside Data Subscriptions (ODS)	Data from Acxiom and InfoUSA, associated with PGE service points.	Residential and non-residential demographic and firmographic attributes, residential building size and cooling systems
PGE Active Generator File	Current file of solar and storage installations in PGE territory.	Current residential and non-residential solar and storage adopters, nameplate kW
PGE GIS Data	Geolocation of PGE service points.	Input to Project Sunroof
PGE DMV Data	Vehicle Identification Numbers (VIN)[6] for all vehicles registered associated with PGE service points – residential and non-residential.	Residential and non-residential vehicle stock assessment (age, weight class, and fuel type)
NEEA Commercial Building Stock Assessment[7]	Pacific Northwest regional study that characterizes energy-consuming equipment within commercial buildings, conducted in 2019.	Use to impute non-residential measure eligibility criteria where no other sources available: heating system, cooling systems, hydronic systems, on-site parking,
NEEA Residential Building Stock Assessment[8]	Pacific Northwest regional study that characterizes energy-consuming equipment within residential dwelling units (single-family homes, manufactured homes, and multifamily buildings), conducted in 2016	Use to impute residential measure eligibility criteria where no other sources available: existence of parking, breaker size, clothes washer, dryer, water heater location
Project Sunroof (Google)[9]	Publicly available website that estimates building-level rooftop solar potential	Residential and non-residential PV panel nameplate kW, panel tilt, and panel orientation
NREL Alternative Fuels Data Center[10]	Publicly available website that houses a database of public charging infrastructure.	Non-residential EVSE (L1, L2, and DCQC)

[6] For this study, the Cadeo team uses the first 8 digits of VIN to determine the make, model, weight rating, and fuel type for each vehicle. The team did not use the full 17-digit VIN to preserve customer anonymity.
[7] NEEA CBSA available at https://neea.org/data/residential-building-stock-assessment
[8] NEEA RBSA II available at https://neea.org/data/residential-building-stock-assessment
[9] Project Sunroof available at https://www.google.com/get/sunroof
[10] NREL Alternative Fuel Data Center available at https://afdc.energy.gov/

Source	Description	Characteristics
NREL ReOPT[11]	Publicly available website with an API that estimates the economic viability of microgrid installations.	Microgrid size and loadshapes.

In some cases, we have data for all or nearly all customer sites while other characteristics (i.e., residential water heating equipment) have incomplete coverage. Regardless, where site-level data is not available, we use aggregate statistics to predict that field stochastically. This allows us to generate a full population of sites using the best available data and leaves open the possibility to update with more site-specific data in future iterations.

Some characteristics listed in Table 4-2, such as building type or availability of parking, are time invariant; we hold the value of those constant throughout the study period (i.e., building type = Single Family). Other characteristics, such as heating system and vehicle type, are time variant which means that the value of those characteristics is subject to change during the study period; we describe this approach in Section 4.2.3 of this document.

Finally, there are some characteristics that we derive, as no primary or secondary data is available. The two characteristics to which this applies most critically for this study are maximum solar nameplate capacity (residential and non-residential) and available panel space (residential only). We discuss these fields in more detail below.

4.2.2.1 Maximum Solar Nameplate Capacity

We define maximum solar nameplate capacity as the most solar generation that can be hosted on a given rooftop that achieves a solar resource fraction greater than 75% (considered best practice for solar installations and a requirement for Energy Trust incentives). While these data can be purchased from proprietary sources, we opted instead to derive these amounts using data sources that are publicly available to increase transparency and preserve our ability to update our assumptions in the future at no cost.

We calculate solar technical potential for each site as follows:

- We first extract the total square footage available for panels, recommended nameplate kW at an assumed $500 monthly electricity bill, and the panel square footage associated with the recommended nameplate kW from Google's Project Sunroof.[12]
- Next, we calculate the technically feasible nameplate kW and bill savings for the site, based on the ratio of total, available square footage to Project Sunroof's recommended square footage.

[11] NREL ReOPT calculator available at https://reopt.nrel.gov/tool

[12] Project Sunroof recommends nameplate kW subject to a user-entered billing amount, which cannot exceed $500 month.

- Finally, we scale down the technically feasible nameplate kW by the ratio of the site's average electricity bill (from PGE CC&B) to bill savings from above. We apply this scaling factor because bill savings from the technically feasible nameplate kW may exceed that site's average, actual electricity bill and PGE's solar tariffs do not permit net export to grid from solar resources.
- Project Sunroof does not return a result for all sites; for missing sites, we impute nameplate kW based on census tract averages.

4.2.2.2 Available Panel Space

For residential sites, we modeled available panel space using a heuristic model using RBSA II data on panel ampacity and configuration. While actual panel loading calculations are specific to the mix of end uses and their nameplate ratings, we simplified this calculation by assuming that, on average, a residential panel could bear up to the number of available poles allotted to it. While a specific site may be able to host more (using split breakers) or less (due to high amperage end uses), this method allows for a straight-forward approximation of available panel ampacity using available data sources.

First, we assigned a panel size to each site. Examining panel sizes and configurations in RBSA II, we found that most residential electrical panels were either 100, 200, or 400A, and largely varied only by building type (surprisingly, building size was not very predictive of panel size). Rounding the RBSA sites to the nearest of these three sizes and binning by breaker vs non-breaker (i.e., fuse boxes), we arrived at distribution shown in Table 4-3 below. Based on engineering judgment and a review of products currently available, we assumed that a 100A panel has 20 poles, a 200A panel has 30 poles, and a 400A panel has 40 poles.

Table 4-3. Residential Electrical Panel Distribution

Building Type	100 A, w/ Breaker	200 A, w/ Breaker	400 A, w/Breaker	No Breaker
SF	13.2%	84.6%	0.6%	1.5%
MF	86.9%	11.2%	0.0%	1.9%
MH	7.4%	91.9%	0.2%	0.5%

Further, we assume that a site needs one 15-20A (single pole) per 100 sq ft for small end uses such as lights, plugs, and most kitchen appliances. We then allocate two poles for each 30+A (220V) circuit required for large end uses, including:

- Electric furnace (or Heat Pump with auxiliary heat)
- AC/heat pump compressor
- Hot tub
- Sauna
- Pool pump

- Electric water heater
- Baseboard heater
- Solar
- Storage
- L2 EV charger
- Clothes washer and dryer
- Electric range

Using simulated data on panel size configuration and estimated end-use/measure adoption for each site, we calculate the number of available poles and divide by two to determine the potential number of 220V breakers that could be added. We then use this field to determine eligibility for measures that require a dedicated 220V breaker (such as Level 2 EVSEs). For the purposes of this analysis, we assumed that sites would not upgrade their panel to accommodate measure adoption.

4.2.3 Stock Turnover

We use a stock turnover model to dynamically change the time-variant site characteristics. Our model, illustrated by Figure 4-2, includes a stochastic element to turnover where, for each premise, time-variant characteristic, and year, AdopDER does the following:

- Use a probability[13] distribution to calculate retirement probability p_{sct} for premise s, characteristic c, and year t.
- Generate random number x_{sct1}
- Retire premise s, characteristic c if $x_{sct1} \leq p_{sct}$
- If premise s, characteristic c retires, generate another random number x_{sct2}, use it to probabilistically select replacement from alternatives.
- Increment year from t to t+1

Figure 4-2. Stock Turnover Illustration

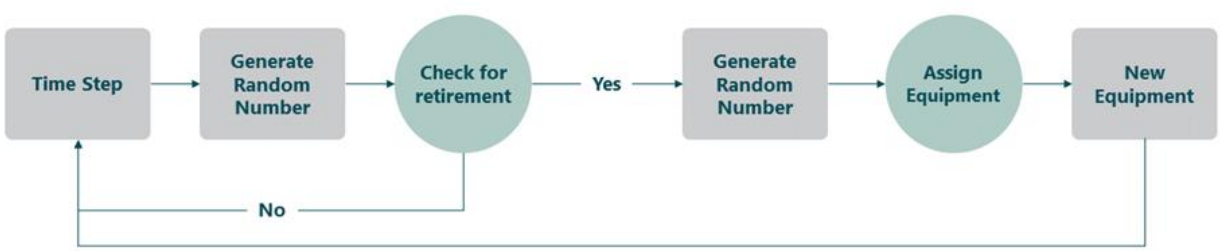


Table 4-4 lists the time-variant characteristics in our analysis for both residential and non-residential premises. Generally, these characteristics are related to vehicles and systems that are

[13] The Cadeo team uses a Weibull distribution for measure lives. The Weibull is a probability distribution allow for failure rates to vary over time and is commonly used to simulate the failure time in a product's lifespan.

impacted by building electrification. For each characteristic, we replace retired equipment with an alternative based on a set of conditional probabilities.

Table 4-4. Time-Variant Site Characteristics

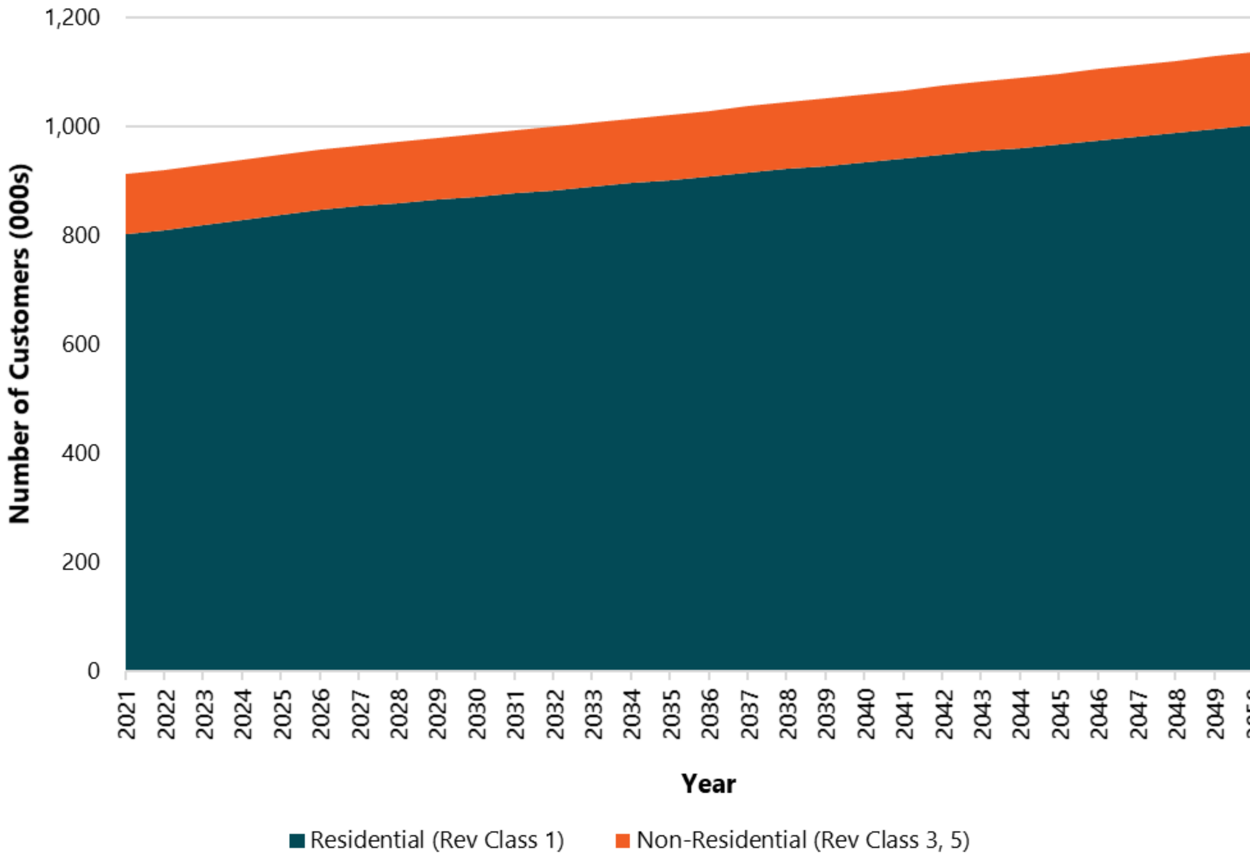
Characteristic	Alternatives	Conditional Probability Sources
LDV	ICE, BEV, PHEV	Brattle LDV forecast
MDV, HDV	ICE, BEV, PHEV	Brattle MDV/HDV forecast
Residential Water Heat	ERWH, Smart ERWH, HPWH, Non-Electric	Energy Trust ramp rates (ERWH to HPWH), Cadeo Analysis (ERWH to Smart ERWH), NREL Electrification Futures (Fuel Conversion)
Residential Space Heat (Non-Ducted)	Resistance Heat, DHP, Non-Electric	Energy Trust ramp rates (DHP), NREL Electrification Futures (Fuel Conversion)
Residential Space Heat (Ducted)	Electric Furnace, ASHP, Non-Electric Furnace	Energy Trust ramp rates (ASHP), NREL Electrification Futures (Fuel Conversion)
Residential Cooking Equipment	Electric Cooktop, Induction Cooktop, Non-Electric	Cadeo analysis (Electric to Induction), NREL Electrification Futures (Fuel Conversion)
Rooftop	New Rooftop	N/A
Non-Residential Space Heat (Ducted)	RTU, VRF, Other Electric, Non-Electric	Energy Trust ramp rates (RTU to VRF), NREL Electrification Futures (Fuel Conversion)
Non-Residential Hydronic System	Standard hydronic, Centralized hydronic	Energy Trust ramp rates (standard to centralized hydronic), NREL Electrification Futures (Fuel Conversion)

4.2.4 New Construction

The sample described above characterizes PGE's customer base in the first year of the study. We add premises so our total number of sites in any given year aligns with a customer forecast provided by PGE (Figure 4-3).[14]

[14] PGE customer forecast is at revenue class level; we use historic data to allocate to rate schedules.

Figure 4-3. PGE Customer Forecast



However, we cannot simply look up characteristics for sites that get added to our forecast in future years with existing data sources. Thus, we use the following process to simulate new sites for years 2021 through 2050:

1. Determine the number of new sites to create for the specific year based on PGE customer forecast.
2. Create a unique identifier for each new site.
3. Set the site vintage (year of construction) equal to the specific year.
4. Randomly select an existing site that is less than 10 years old, apply that existing site's characteristics to the new site.

4.3 Measure Eligibility

In this study, we examine the load impacts of the 44 DER measures, each with its own eligibility criteria determined by some combination of site characteristics and the adoption of other DER measures. We describe the eligibility criteria in the following four categories:

- Building Electrification (8 measures)
- Demand Response (16 measures)

- Solar and Storage (6 measures)
- Transportation Electrification (14 measures)

This section introduces the eligibility criteria for each measure; subsequent sections describe the processes by which we estimate adoption (with and without program activity) and load impacts.

4.3.1 Building Electrification

We included eight building electrification measures in this study, listed in Table 4-5. As building electrification measures, many of these have end-of-life equipment (i.e., heating system or water heating system) in their eligibility criteria. We also assume that residential customers have constraints on panel size and have included the availability of a breaker as eligibility criteria.

Table 4-5. DER Measure Eligibility - Building Electrification

Measure	Eligibility Criteria	Measure Size	Programmatic Measure
Ductless Heat Pump	Residential, non-ducted heat, SF or MF homes, has available breaker	Total conditioned space of building	No
Ducted Heat Pump	Residential, ducted heat, SF or MF homes, has available breaker	Total conditioned space of building	No
Central Variable Refrigerant Flow (VRF) Heat Pump	Schedule 83, 85, or 89, has end-of-life RTU or is new construction	Total conditioned space of building	No
Dedicated Outdoor Air System (DOAS) and High Efficiency Heat Pump	Schedule 83, 85, or 89, has end-of-life RTU or is new construction	Total conditioned space of building	No
Smart Electric Water Heater	Residential, end-of-life water heater, has available breaker	Number of water heating tanks	No
Heat Pump Water Heater	Residential, New construction or end-of-life water heater, has available breaker	Number of water heating tanks	No
Centralized Hydronic (Water and Space Heat)	Non-residential, Schedule 83/85/89, New construction, or end-of-life boiler	Total conditioned space of building	No
Residential Induction Cooking	Residential, has end-of-life cooking or new construction	N/A	No

4.3.2 Demand Response

We included sixteen demand response measures in this study, listed in Table 4-6. As demand response measures, these typically require some sort of enabling technology and are deployed in a program managed by PGE. Many of these enabling technologies are other measures included in our study. For instance, the residential low voltage thermostat controls measure requires a low voltage thermostat.

Table 4-6. DER Measure Eligibility – Demand Response

Measure	Eligibility Criteria	Measure Size	Programmatic Measure
Residential High Voltage Smart Thermostat	Residential, has electric non-ducted HVAC system.	If building sqft > 1000 then 3 else if building sqft >500 then 2 else 1	Yes
Residential High Voltage Smart Thermostat Controls	Residential, has high voltage smart thermostat	N/A	Yes
Residential Low Voltage Smart Thermostat	Residential, has ducted HVAC system	Generate random number between 0 and 1. If random number > .2 then 1, else 2.	No
Residential Low Voltage Smart Thermostat Controls	Residential, has low voltage smart thermostat	N/A	Yes
Time-of-Use	Residential	N/A	Yes
Electric Vehicle TOU	Residential, has LDV EVSE	N/A	Yes
Peak-Time Rebates	Residential	N/A	Yes
Residential DHP controls	Residential, has DHP	N/A	Yes
ERWH Smart Controls	Residential, has smart ERWH	N/A	Yes
ERWH Retrofit Switch	Residential, has ERWH	N/A	Yes
HPWH Smart Controls	Residential, has smart HPWH	N/A	Yes
Commercial Low Voltage Smart Thermostat	Has ducted HVAC, Schedule 32 or 83	if conditioned space <2000, 1 else if 15000 > conditioned space>2000, 4 else if conditioned space>= 15000, 10	No
Commercial Low Voltage Smart Thermostat Controls	Has smart thermostat, Schedule 32 or 83	if conditioned space <2000, 1 else if 15000 > conditioned space>2000, 4 else if conditioned space>= 15000, 10	Yes
Cold Thermal Storage	Non-Residential, has campus, has chiller	if peak kW is missing then set peak kW = 50, else size = peak kW*.50	No

Measure	Eligibility Criteria	Measure Size	Programmatic Measure
Irrigation DLC	Schedule 49	N/A	Yes
Large C&I Curtailable tariff	Has curtailable load (HVAC, pumping, refrigeration, industrial process) and Peak Load >50 kW	if peak kW is missing then set peak kW = 50; else if Grocery then 0.252* peak KW; else if Large Office then 0.320* peak KW; else if Wastewater/water utilities then 0.05*peak KW; else if industrial then 0.15 * peak KW.	Yes

4.3.3 Solar and Storage

We included six solar and storage measures in this study, listed in Table 4-7. In addition to standalone storage and standalone solar, this category of measure includes microgrids – a resilience measure that has critical facilities (e.g., hospital, law enforcement, fire station, emergency operation center, public school, or water treatment facility) as eligibility criteria.

Table 4-7. DER Measure Eligibility – Solar and Storage

Measure	Eligibility Criteria	Measure Size	Programmatic Measure
Solar PV	Residential or Non-Residential, Roof ≤ 15 years old, owns property, solar potential from Project Sunroof > 0	Project Sunroof kW	No
Behind-the-Meter (BTM) Energy Storage	Residential SF or MH homeowner, or Non-Residential	Residential & commercial with peak load < 50kW: 5 kW Commercial, with peak load ≥50kW: 50 kW	No
BTM Energy Storage Controls	Has Storage	size of storage unit * (1 - reserve capacity). Reserve capacity = 20%	Yes
Single-Site Microgrid (solar, storage, and genset)	Critical facility, single site, owns property, no solar, no solar + storage	ReOpt Solar Size	Yes

Measure	Eligibility Criteria	Measure Size	Programmatic Measure
Campus Microgrid (solar, storage, and genset)	Critical facility, campus, owns property, no solar, no solar + storage, all sites belong to same customer	ReOpt Solar Size	Yes
Single and Campus Microgrid Controls	Has single site or campus microgrid	ReOpt Storage Size	Yes

4.3.4 Transportation Electrification

We included fourteen transportation electrification measures in this study, listed in Table 4-8. These measures include both vehicles and various configurations of EVSE. We treat vehicles only as enabling technologies in our analysis – a premise is only eligible for EVSE if it has a battery electric or plug-in hybrid electric vehicle.[15] In addition to vehicles and EVSE, the transportation electrification measures include three direct load control measures, which require a smart (internet-enabled, connected) EVSE for eligibility.

[15] We introduce additional public charging as a program in subsequent steps or our analysis, these public chargers do not require the premise to have associated vehicles.

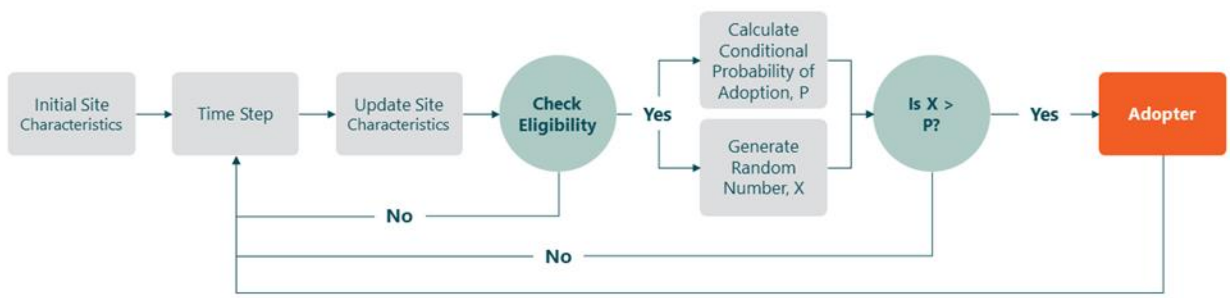
Table 4-8. DER Measure Eligibility – Transportation Electrification

Measure	Eligibility Criteria	Measure Size	Programmatic Measure
Residential L1 EVSE	Residential, has LDV or MDV EV	N/A	No
Non-Residential L1 EVSE	Non-Residential, has LDV/MDV EV fleet	max (0, number of EVs (of any class) - number of Public/Non-residential DCQC EVSE - Public/Non-residential DCQC EVSE)	No
Residential L2 EVSE	Residential, has LDV/MDV EV, has spare 220V breaker, has parking	min(round(number of EVs/2), number of available 220V circuits)	No
Smart Residential L2 EVSE	Residential, has LDV/MDV EV, has spare 220V breaker, has parking	min(round(number of EVs/2), number of available 220V circuits)	No
Non-residential/Public L2 EVSE	Non-residential, has parking, has fleet EV or is public site	if no fleet, poisson(4) if fleet, round(number of EVs/2)*14	No
Smart non-residential/Public L2 EVSE	Non-residential, has parking, has fleet EV or is public site	if no fleet, poisson(4) if fleet, round(number of EVs/2)*14	No
Public/Non-residential DCQC EVSE	Non-residential, has parking, has fleet EV or is public site	if fleet, round (number of medium and/or heavy duty EVs/4)* DCQC Nameplate Ratings If public, 4* DCQC Nameplate Ratings	No
Battery Electric Vehicle (BEV)	Has ICE LDV or end-of-life Electric LDV (personal or fleet)	number of EOL vehicles	No
Plug-in Hybrid Electric Vehicle (PHEV)	Has ICE LDV or end-of-life Electric LDV (personal or fleet)	number of EOL vehicles	No
Electric Medium-Duty Vehicle (MDV)	Has ICE MDV or end-of-life Electric MDV (personal or fleet)	number of EOL vehicles	No
Electric Heavy-Duty Vehicle (HDV)	Has ICE HDV or end-of-life Electric HDV	number of EOL vehicles	No
Residential L2 EVSE DLC	Residential, has Smart L2 EVSE	N/A	Yes
Non-residential L2 EVSE DLC	Non-Residential, has Smart L2 EVSE	size of Smart non-residential/Public L2 EVSE	Yes
Non-residential DCQC EVSE DLC	Non-Residential, has DCQC EVSE	size of Public/Non-residential DCQC EVSE	Yes

4.4 Measure Adoption

After determining eligibility for each DER measure at each site, AdopDER then applies a set of conditional probabilities that simulate measure adoption. Fundamentally, each site adopts each measure probabilistically using a framework like that shown in Figure 4-4.

Figure 4-4. Measure Adoption Framework



The approach by which we determine the probability of adoption, conditioned on eligibility, varies by measure. We separate measure adoption into two categories:

- **Programmatic adoption** simulates measure adoption through PGE programs, mapping each measure to a bundle delivered through a given program(s) with its own parameters around timing and eligibility.
- **Market adoption** simulates naturally occurring measure adoption for building electrification, transportation electrification, solar, and storage measures in absence of program incentives (though there are interactions in some cases between programs and the market due to competing/complementary measures).

4.4.1 Programmatic Adoption

For programmatic adoption, we bundle measures described above into programs. Table 4-9 (Residential) and Table 4-10 (Non-Residential) list each program that we considered in our analysis and describes how we bundled DER measures within each program. Table 4-9 and Table 4-10 also indicate which programs PGE is currently running. We have supplemented the portfolio's current programs with other programs of interest to PGE for this analysis.

Table 4-9. Residential Programs

Program Name	Measure Bundle Name	Measure Bundle Description	Current PGE Program Offering
Residential Opt-in PTR	Peak time rebates	Peak time rebates measure adopted in isolation	Yes
Residential Storage	Res BYO-Battery Bundle	Storage controls for customers that already have storage	Yes

Program Name	Measure Bundle Name	Measure Bundle Description	Current PGE Program Offering
	New Battery Bundle	Storage and controls for customers that do not already have storage	Yes
Single Family Smart Charging	Standalone L2 EVSE	Residential L2 EVSE installed in a SF residence without DR	Yes
	L2 EVSE + DR	Residential L2 EVSE installed in a SF residence with DR enrollment	Yes
Multifamily Demand Response	MF ERWH DLC retrofit	Retrofit switch added to basic electric resistance water heater for DR	Yes
	MF ERWH Smart ERWH	Installation of new smart ERWH, with DR enrollment	Yes
	MF Full Retrofit (baseboard)	Full retrofit of MF premise with baseboard heat and ERWH. Adds switch and smart thermostat and enrolls in DR.	No
	MF Full Retrofit (DHP)	Full retrofit of MF premise with DHP and ERWH. Adds switch and DHP controls and enrolls in DR.	No
	MF ERWH DLC retrofit	Controls added to smart electric resistance water heater for DR.	No
Residential Smart Thermostat	BYOT-SF LV Space Heat Only	BYOT for customers with a low voltage thermostat and electric heat w/o CAC	Yes
	BYOT-SF LV Cooling Only	BYOT for customers with a low voltage thermostat and CAC w/o electric heat	Yes
	BYOT-SF LV Space Heat and Cooling	BYOT for customers with a low voltage thermostat, electric heat w/ CAC	Yes
	Direct install-SF LV space heat only	Direct install thermostat DR for customers with electric heat w/o CAC	Yes
	Direct install-SF LV cooling only	Direct install thermostat DR for customers with CAC, no electric heat	Yes
	Direct Install-SF LV space heat and cooling	Direct install thermostat DR for customers with CAC and electric heat	Yes
	Direct Install-MF HV space heat only	Direct install thermostat DR for customers with baseboard electric heat	No
Residential Smart Water Heating	Residential HPWH retrofit	BYO program for customers with existing HPWH	No
	Residential HPWH direct install	Direct install HPWH with DR enrollment	No
Residential Opt-in TOU	Standalone TOU	Time-of-use without device optimization	Yes
	TOU-optimized thermostat	Time-of-use with thermostat optimization	No

Program Name	Measure Bundle Name	Measure Bundle Description	Current PGE Program Offering
	TOU-optimized storage	Time-of-use with storage optimization	No
	TOU-optimized WH	Time-of-use with water heater optimization	No
	TOU-optimized EV charging	EV specific time-of-use rate with optimized charging[16]	No
	EV TOU without smart charging	EV specific time-of-use rate without optimized charging	No

Table 4-10. Non-Residential Programs

Program Name	Measure Bundle Name	Measure Bundle Description	Current PGE Program Offering
Nonresidential Storage	Nonres BYO-Battery Bundle	Storage controls for customers that already have storage	No
	New Battery Bundle	Storage and controls for customers that do not already have storage	No
Energy Partner	Thermostats	Smart thermostat DR for small-medium commercial customers that don't have an existing building management system	Yes
	ADR	Standard option for Energy Partner using either manual process or integrated controls through a gateway. Typical end uses: HVAC, industrial process, refrigeration, pumping	Yes
	Agriculture	Energy Partner option for irrigation customers, utilizing communicating controls to throttle pumping loads	No
	Cold Thermal storage	Energy Partner option for cold thermal storage	No
Nonresidential Microgrid	Microgrid-Single site	Single site microgrid	Demonstration
	Microgrid-Campus	Campus microgrid	Demonstration
Nonresidential Smart Charging	Workplace L2 - No DR	Workplace EV charging installed without DR	Yes
	Workplace L2 - with DR	Workplace EV charging installed with DR enabled	No

[16] We include a device-enabled option for EVs as well as a rate-only option. These differ in that all EV owners can participate in the rate-only option, while only customers with smart EVSEs can participate in the device-enabled option. It should also be noted that these don't consider potential impacts on distribution peaks that might occur due to simultaneous scheduling of EV loads to system peaks.

Program Name	Measure Bundle Name	Measure Bundle Description	Current PGE Program Offering
	Public L2	Public L2 charging installed at a nonresidential site with utility assistance	Yes
	Public DCQC	Public DCQC charging installed at a nonresidential site with utility assistance	No
Nonresidential Fleet[17]	Nonresidential Fleet Smart Charging	L2 EV charging installed with DR enabled for servicing fleets	No
	Fleet DCQC	DCQC EV charging installed with DR enabled for servicing fleets	No

Each program consists of one or more bundles. Each bundle is a set of one or more DER measures. The eligibility criteria for our programs are compound - they may include both the criteria of the measures that the program includes and some other criteria specific to the program itself (for more details see Appendix F - Measure and Program Eligibility).

We primarily bundle measures into programs to assess cost-effectiveness, for which we describe our approach in section 4.6. We also use a specific approach for programmatic measure adoption[18] in our model: a bass diffusion function[19] (see Equation 4). In Equation 4, the probability of program adoption at year t is a function of two parameters: M, which represents the maximum adoption rate, and T, which represents the number of years to arrive at 99% of maximum adoption rate.

Equation 4. Bass Cumulative Distribution Function

$$Cumulative\ Probabilty(t)\ \approx M * \frac{1 - Exp\left(-14 * \frac{0.5}{T} * t\right)}{1 + 13 * Exp\left(-14 * \frac{0.5}{T} * t\right)}$$

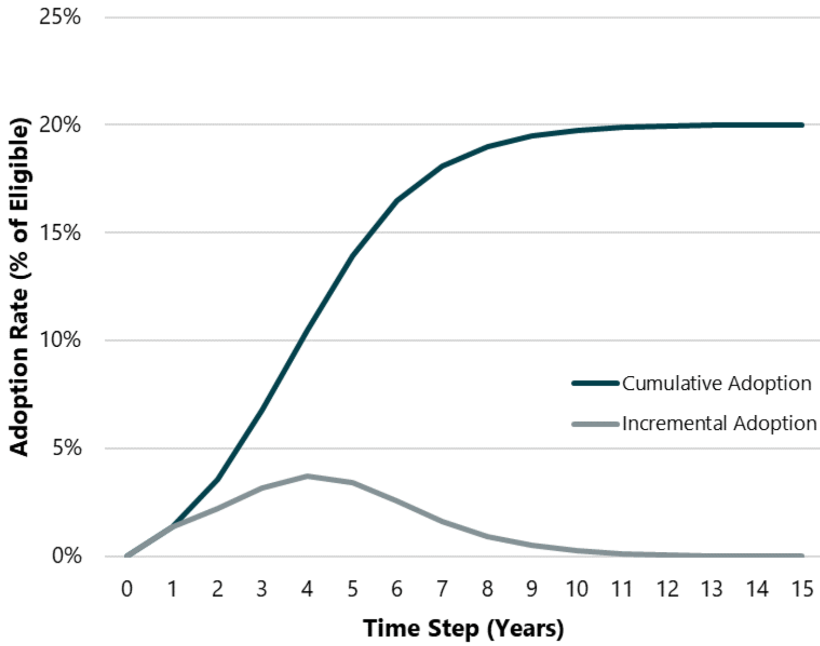
Figure 4-5 shows an illustration of annual adoption probabilities for a hypothetical program with parameter M = 20% and T = 10 years.

[17] As of the time when this document was written, OPUC had approved PGE's fleet pilot tariff, effective July 1, 2021.

[18] The new battery bundles do not use bass diffusion framework. See market adoption section below for further discussion.

[19] We use an alternate parameterization of bass model (https://en.wikipedia.org/wiki/Bass_diffusion_model) that fixes the traditional innovation and imitation parameters (*p* and *q*) at typical values where *q* = 13**p* based on a lit review of the relationship of p and q for new consumer products.

Figure 4-5. Example of Bass Diffusion Curve (M=20%, T=10)



Many of PGE's existing programs are early in their lifetime and may have elements of pilot programs that do not necessarily represent long-term design. As such, the Cadeo team used a three-step process to estimate the M and T parameters for each program by balancing past PGE program activity with the performance of other, similar programs.

- Estimate empirical M and T parameters by using historic PGE program participation data.
- Conduct a literature review to find the M and T parameters from similar programs.
- Average the empirical and literature review to determine the final M and T parameters, which we list in Appendix C – Adoption Curves.

Equation 4 above is a cumulative distribution function (CDF) and thus represents total adoption as a percentage of eligible population. We used the CDF for programs that include lost opportunity measures (i.e., a DER measure replaces end-of-life equipment or is installed concurrent with a lost opportunity measure). Programs that include discretionary, retrofit measures (i.e., the DER measure could be adopted at any time, such as demand response program participation) use the probability distribution function (PDF) of the bass curve shown in Equation 4. To obtain the PDF in year *t*, we simply take the difference of the CDF between year *t* and year *t-1* (Equation 5).

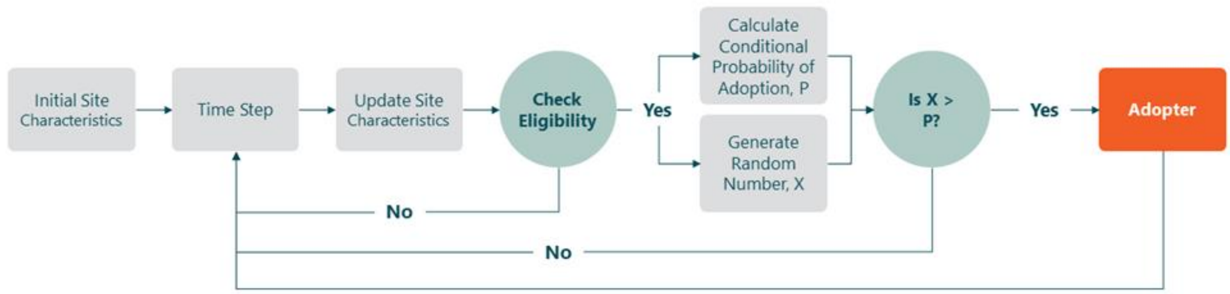
Equation 5. Bass Probability Distribution Function

$$Probabilty(t) \approx M * \left(\frac{1 - Exp\left(-14 * \frac{0.5}{T} * t\right)}{1 + 13 * Exp\left(-14 * \frac{0.5}{T} * t\right)} - \frac{1 - Exp\left(-14 * \frac{0.5}{T} * (t-1)\right)}{1 + 13 * Exp\left(-14 * \frac{0.5}{T} * (t-1)\right)} \right)$$

4.4.2 Market Adoption

We model the naturally occurring (market) adoption for three families of DER measure: solar and storage, transportation electrification, and building electrification[20]. Each family uses a different approach; we describe these approaches in this section using the framework that we show in Figure 4-6 below.

Figure 4-6. Measure Adoption Framework



4.4.2.1 Solar and Storage

We leverage multiple sources to inform our adoption estimate for the non-programmatic solar and storage measures in our study.

Initial Site Characteristics

We use PGE's "active generators" file, a listing of existing solar and storage installations to identify the sites in our sample that have existing installations (i.e., have already adopted the measures) as of October 2020.

Eligibility Criteria

For sites that do not already have installed solar and/or storage, we determine the site's eligibility and nameplate size per the criteria described in Table 4-11 below. Thus, our estimate of solar and storage technical potential includes all sites that meet the eligibility criteria and with an installation size listed in Table 4-11.

Table 4-11. DER Measure Eligibility – Solar and Storage

Measure	Eligibility Criteria	Measure Size
Solar PV	Residential or Non-Residential, Roof ≤ 10 years old, owns property, solar potential from Project Sunroof > 0, has available breaker	Project Sunroof kW, scaled such that annual generation = annual consumption
Behind-the-Meter (BTM) Energy Storage	Residential SF or MH homeowner, or Non-Residential. Residential must have available breaker.	Residential & non-res with peak load < 50kW: 5 kW Non-res, with peak load ≥ 50kW: 50 kW

[20] We also modeled market adoption of smart thermostats, which for our purposes are categorized as a demand response measure.

We keep a running tally of breaker availability for residential sites, which changes over time as sites adopt other DER measures. This is one of our eligibility criteria for residential solar and storage.

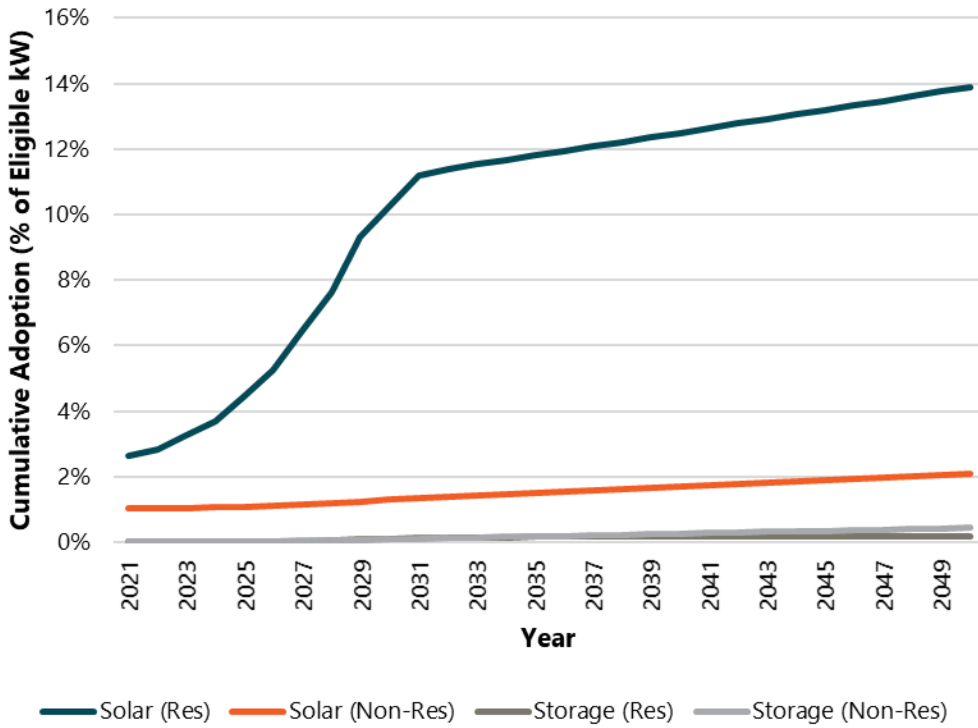
Probability of Adoption

We use NREL's DGEN, an open-source, agent-based simulation model that NREL has developed to estimate solar and storage adoption,[21] to determine the solar and storage adoption probabilities for PGE as follows:

- **Run DGEN model.** The DGEN model's inputs are extensive and include solar and storage cost technology forecasts from NREL, assumptions for utility rates, consumption, sizing, and geospatial information for each agent (i.e., a site) in its simulation model. For our DER potentials analysis, we used NREL's agent file for the state of Oregon and did not modify any of NREL's open-source data in our DGEN runs to characterize market adoption for solar and storage.
- **Extract DGEN model results.** The DGEN model produces a bi-annual forecast that indicates which agents have adopted solar and storage measures. We transformed this result set into a data set that contains the probability that an eligible site adopts solar and the probability that an eligible site adopts storage. Figure 4-7 shows the reference case adoption probabilities for solar and storage.

[21] See https://www.nrel.gov/analysis/dgen/ for DGEN documentation, and https://github.com/NREL/dgen to access the open-source DGEN model.

Figure 4-7 Solar and Storage Adoption Rates from DGEN Model



- **Apply Probabilities to PGE sites.** We use the annual probabilities from the DGEN analysis to simulate which eligible sites in our model adopt solar and storage over time. This simulation produces our achievable technical potential estimate for solar and storage.

4.4.2.2 Transportation Electrification-Vehicles

Our approach for modeling adoption of electric vehicles blends a top-down statistical forecast of electric vehicles developed by the Brattle Group for PGE's service territory with a bottom-up accounting of the vehicle stock associated with each PGE premise.

Initial Site Characteristics

Our approach to characterizing the vehicle stock began with a dataset that contained VIN information for all vehicles (light, medium, and heavy duty) registered in a ZIP code served by PGE. We conducted an analysis of this VIN information and determined that PGE had mapped approximately 80% of these vehicles to sites. For our potentials estimate, we grossed up the vehicle counts across the service territory to account for the missing 20%. Additionally, we use PGE's RASS and NREL's AFDC database to inform our estimate of EVSE equipment in the first year of the study.

Eligibility Criteria

We apply the stock turnover approach described above to the known PGE vehicle stock, which changes site-level eligibility for EVSE over time. In addition to conditioning EVSE adoption on the presence of an EV, we have two other criteria for residential EVSE adoption.

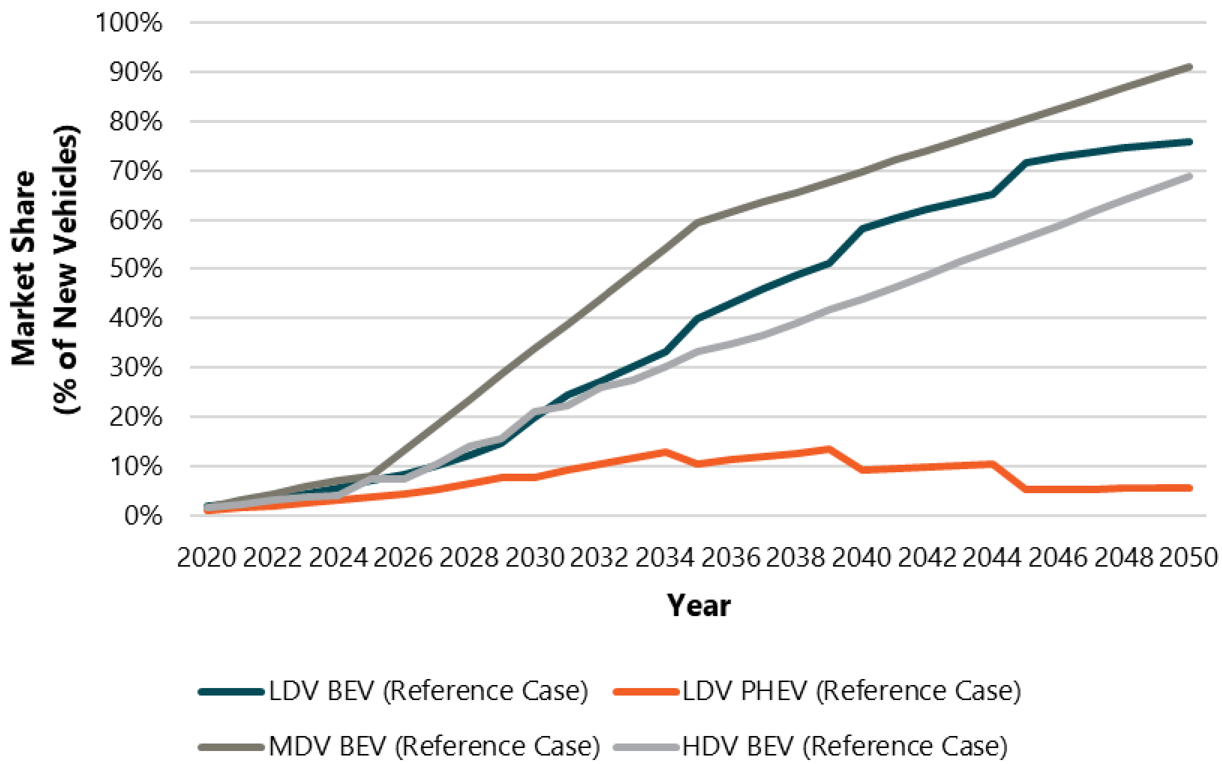
- **Has available parking.** This is the most restrictive criteria for residential EVSE adoption; our analysis of NEEA's 2016 residential building stock assessment found that approximately 40 percent of single-family homes do not have appropriate parking for an L2 EVSE.
- **Have an available breaker.** We keep a running tally of breaker availability for residential sites, which changes over time as sites adopt other DER measures and is one of our eligibility criteria for residential level 2 EVSE measures.

Probability of Adoption

Over time, we simulate the adoption of electric vehicles upon turnover by using the electric LDV market shares from two sources. For light duty vehicles, we use the results of Brattle's econometric model trained on historical results from all 50 states and calibrated to PGE's service territory. For MDV and HDV market shares, we use the results from a Delphi panel of experts in the sector to generate likely scenarios based on different expected conditions. We provide a detailed account of these approaches in Appendix A: Electric Vehicle Adoption Estimation Methodology.

After calibrating these modeled results to the vehicle stock assessment data, we derive the following probabilities (Figure 4-8) that we use as AdopDER input.

Figure 4-8. Electric Vehicle Market Share from Brattle Econometric Forecast



4.4.2.3 Transportation Electrification-Charging Infrastructure

Once we estimate the number of electric vehicles that we expect to be adopted, we then estimate the required charging infrastructure at each charging level and use case.

Initial Site Characteristics

There are three levels of charging infrastructure in our model: Level 1, Level 2, and DCQC. We further break these down in to private (home or fleet) and public. In AdopDER, public charging is simply any charging not associated with a vehicle registered to the customer site. In this sense, we consider multifamily charging and non-fleet workplace charging to be public.

We identify the presence of public charging using a combination of PGE's customer data and NREL's AFDC database. We estimate existing home charging stochastically for sites with EVs based on survey data provided by PGE.

Eligibility Criteria

For private charging, we determined eligibility based on an assumed ratio of vehicles to plugs, and in the case of residential, available panel ampacity and parking onsite. Given the short historical record on the relationship between increasing EV penetration, EV charger utilization, and infrastructure adoption, we chose to hold this relationship constant through the analysis period. Over time, there may a move toward adopting multiple chargers at a single residence but currently the data suggests that it is exceedingly rare. We determined eligibility hierarchically based on charge rate (i.e., if a customer site already had Level 2 charging for all EVs on site, then it was ineligible for Level 1 charging).

Table 4-12. Private EV Charging Eligibility

Measure	Eligibility Criteria	Measure Size
All Level 1	Residential or Non-Residential, has EVs not addressed by other onsite charging, has driveway or garage	Number of plugs
Residential Level 2 (smart and standard)	Residential, has EV, has spare 220V breaker, has driveway or garage	Number of plugs: minimum of number of EVs/2, number of available 220V breakers available
Nonresidential Level 2 (smart and standard)	Nonresidential, has EVs not served by DCQC	Rated capacity multiplied by number of plugs (number of EVs/2)
DCQC	Nonresidential, has MDV/HDV	Rated capacity multiplied by number of plugs (number of MHDVs/4)

To account for all vehicles that could not charge onsite, and some amount of public charging expected from all vehicles, AdopDER generates new public charging sites to meet total energy demand by electric vehicles. These are new sites, and thus do not have specific eligibility criteria.

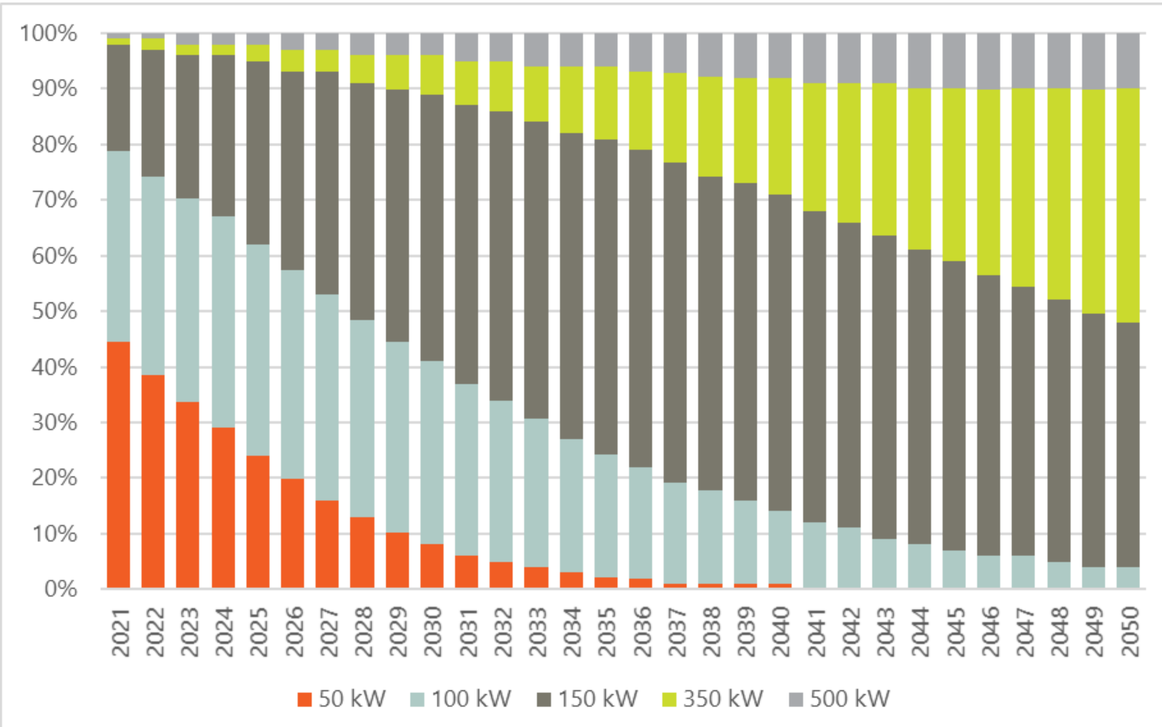
Adoption Probability

After generating a vehicle forecast for each vehicle weight class, we use NREL's EVI-Pro Lite tool to determine the required total charging energy for all vehicles and across segments. EVI-Pro Lite relies on historical charging behavior and as such assumes that a much higher proportion of charging takes place at home for residential customers than is feasible in the general population (in 2050, we estimate there will be approximately 1.3 million residential EVs under the reference scenario but only 150,000 customers can feasibly install Level 2 charging at home). Where feasible, we first model adoption probability based on the anticipated splits from EVI-Pro Lite. Where a higher charger rate is not feasible, but a lower charge rate is, we model adoption of the lower charge rate. We then calculate the remaining unmet energy for vehicles.

To meet that remaining energy, AdopDER generates new public charging sites that contain a mix of Level 2 and DCQC. We scale the number of sites generated to match aggregate consumption of "missing" charging sites. We do this assuming a ratio of 8:1 for L2 to DCQC chargers (consistent with EVI-Pro assumptions). Given the typical consumption of residential EV owners, we generate 8 L2s and 1 DCQC charger for every 36 residential EVs without access to home charging. We group chargers into sites by fours, with four 7kW L2s and four DCQC's sized by their expected nameplate capacity per charging site.

We developed our nameplate charging speed forecast by pegging relative near-term growth rate differentials between charging rate categories and projecting them forward in the planning period[22]. When AdopDER generates a new DCQC charging measure, it randomly selects a nameplate rating for the charger with probabilities based on the projected market shares (see Figure 4-9).

Figure 4-9. Nameplate DCQC Forecast (% of Chargers by kW)



4.4.2.4 Building Electrification

Our approach to modeling building electrification is complex because these measures are also energy efficiency measures that overlap with Energy Trust's energy efficiency potential study. As we describe below, we take steps to avoid double counting the load impacts of building electrification in PGEs IRP while still preserving the ability to use building electrification as eligibility criteria for other DER measures.

Initial Site Characteristics

We leverage multiple data sources (PGE's RASS, PGE's ODS, NEEA CBSA) to impute the type and fuel for heating, cooling, water heating, and cooking equipment at each residential site and the type and fuel of HVAC systems at each non-residential site for the start year of our study.

[22] For this analysis, we extrapolated trends found in NREL's most recent EV infrastructure market report: Electric Vehicle Charging Infrastructure Trends from the Alternative Fueling Station Locator: First Quarter 2020 (nrel.gov)

Eligibility Criteria

We apply the stock turnover approach that we describe above to the heating, cooling, water heating, and cooking equipment at each site, which changes site-level eligibility over time. We also keep a running tally of breaker availability for residential sites, which changes over time as sites adopt other DER measures and is one of our eligibility criteria for building electrification measures.

Adoption Probability

We segment the PGE customer base into three groups and apply a different adoption probability to each group.

- **Electric-to-Electric Upgrades.** We use the ramp rates (the rate at which customers adopt energy-efficiency measures over time) in Energy Trust's energy-efficiency potential study for PGE as adoption probabilities for the segment of customers that begin with an inefficient, electric technology. The adoption probability represents the site's probability of converting to an efficient, electric technology (i.e., convert from electric resistance water heat to a heat pump water heaters). Though we do not assign load impacts for inefficient electric to efficient electric conversions to avoid double counting savings from the Energy Trust energy-efficiency potential study, we still track adoption for this segment, because their measure adoption is part of the eligibility criteria for other measures (i.e., heat pump water heater is a requirement for the HPWH Smart Controls DR measure).
- **New construction.** Like the electric-to-electric upgrade segment, we use Energy Trust's energy efficiency measure ramp rates as adoption probabilities for this segment, in both residential and non-residential markets.
- **Fuel Switching.** Building electrification measures can also be adopted under fuel switching - that is, a customer could switch from a gas-fired furnace to air source heat pump or from a gas-fired water heater to a heat pump water heater. Population data is very scare on the incidence rate of fuel switching to electric equipment; therefore we use NREL's Electrification Futures study to derive our fuel switching assumptions. Our load impacts, which we describe in the next section of this document, include the load growth associated with fuel switching. Figure 4-10 and Figure 4-11 show the Electrification Futures study fuel conversion probabilities that we use in this study.

Figure 4-10. Electrification Futures Fuel Conversion Rates (Reference Case)

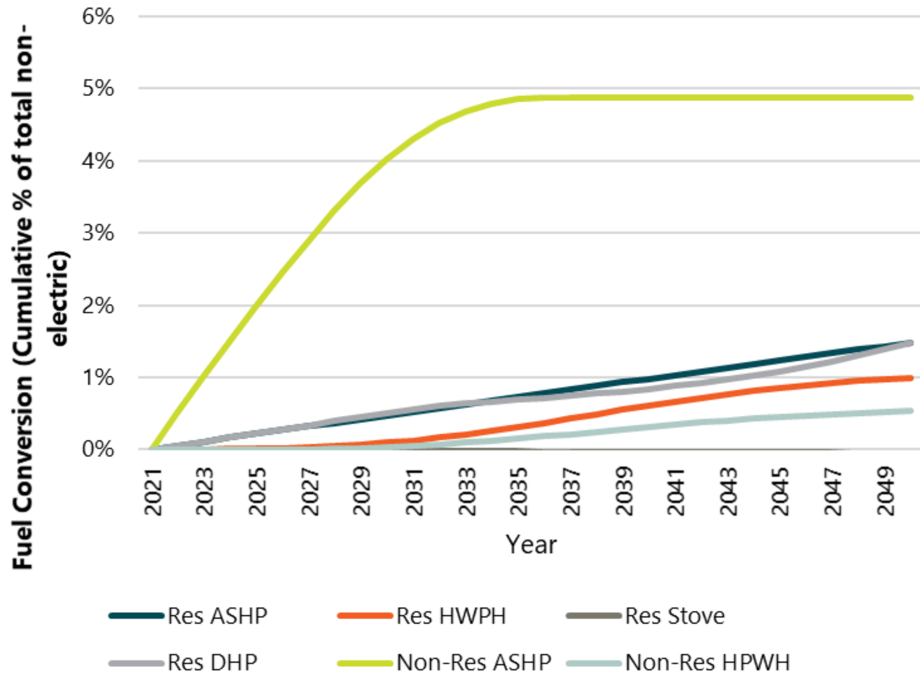
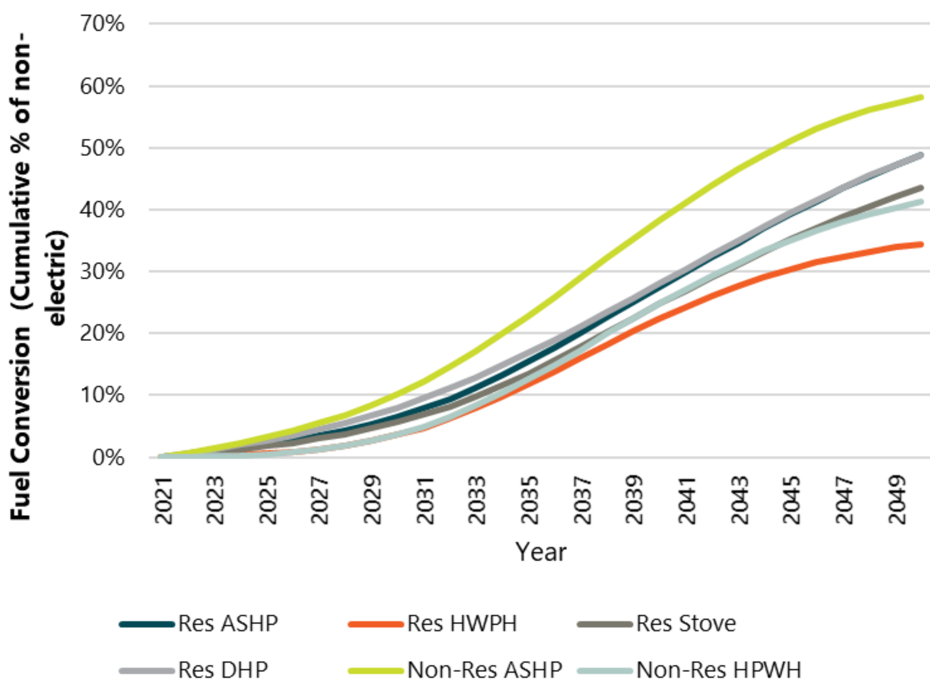


Figure 4-11. Electrification **Futures Fuel Conversion Rates (High Case)**



4.5 Load Impacts

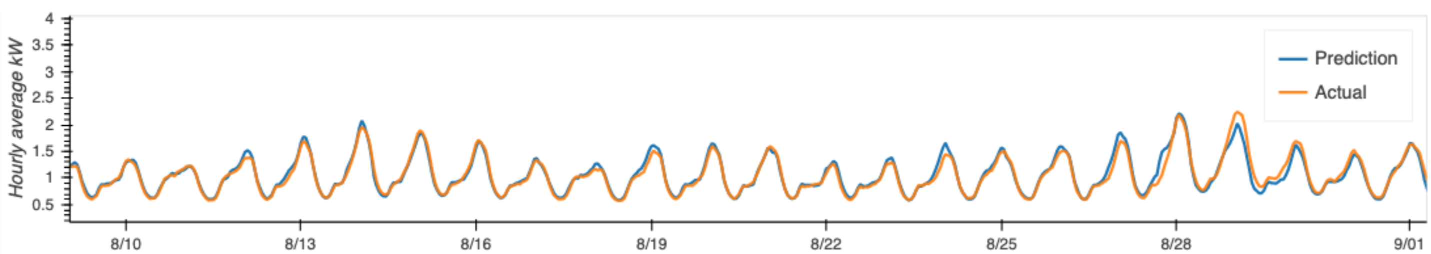
Once the stock assessment model has estimated which customers will adopt which measures in which years, we determine system-level load impacts. We estimate these impacts by combining baseline loadshapes for all customers with passive (year-round) and dispatch (event-based) measure shapes. AdopDER then forecasts these aggregate shapes for all years and scenarios and calculates impacts in the following steps:

- Forecast gross loadshapes across the study period;
- Calculate passive measure shapes for all years;
- Calculate likely event dispatch periods;
- Calculate event-based impacts; and
- Aggregate the customer-level hourly impact for each forecast year and summarize by the many reporting dimensions.

4.5.1 Develop Baseline Loadshapes

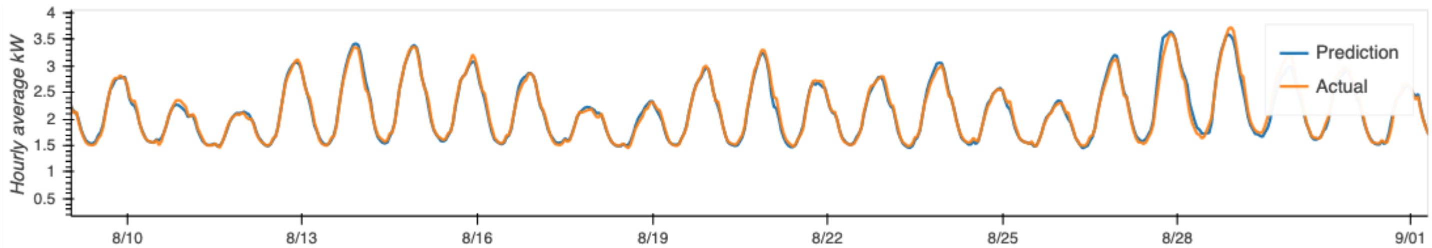
First, we model typical-year baseline loadshapes for each sector using a time-of-week and outdoor temperature model. Our key assumption for this analysis is that each customer has the average loadshape for the customer's sector (rate code and revenue class).[23] We derived these average loadshapes by starting with 2019 sector averages provided by PGE as the baseline year. We then used CalTRACK[24] standard methods to model each sector against month, hour-of-week, occupancy, and outdoor air temperature. The figures below compare actual 2019 sector-level energy trends versus the CalTRACK models' estimated energy, given 2019 weather data.

Figure 4-12. Average kW Per Residential Customer, 2019



[23] This assumption is appropriate for system-level estimates of DER potential, which are the scope of this study; we will revise this approach to use a more individualized loadshape during Phase 2 the study.
[24] CalTRACK is a set of methods for estimating avoided energy use (AEU), related to the implementation of one or more energy efficiency measures, such as an energy efficiency retrofit or a consumer behavior modification. It uses an approach that follows ASHRAE Guideline 14, IPMVP Option C, and the Uniform Methods Project (UMP), and uses segmented regression models to estimate whole-building energy consumption.

Figure 4-13. Average kW Per Non-Residential Customer (Rate Class 32-3), 2019



We then ran the sector-level CalTRACK models against the Portland TMY3 (NREL's Typical Meteorological Year) data to create a typical year's loadshape, not biased by the 2019 weather. While the same TMY3 weather data is used to model every year from 2022 to 2050, each year uses the actual calendar days, which means that TMY3 extremes do not always fall on the same day of the week.

Finally, we scale each sector's baseline loadshape to match PGE's monthly load growth forecast, so that the sector's per-customer TMY3 monthly energy use is equal to the load forecast, while preserving the hourly dynamics of the CalTRACK-model.

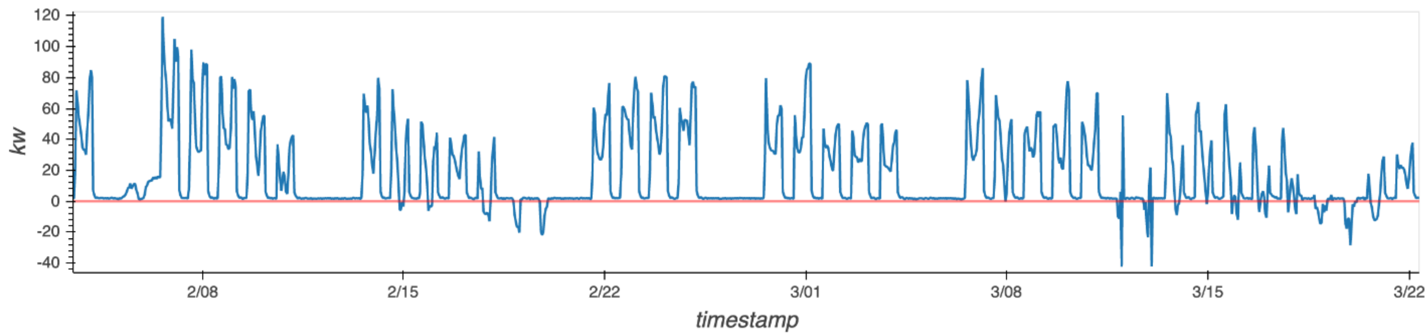
4.5.2 Define Measure Impact Loadshapes

We create hourly loadshapes for each measure from the most appropriate data source available for the measure type. Each family of measures (building electrification, demand response, solar and storage, and transportation electrification) requires a different approach to loadshape development; we describe each category at a high level in the subsections below.

4.5.2.1 Building Electrification

Building electrification measures are passive, though their adoption can in some cases lead to changes in the shape of demand response measures. For nearly all measures, we modeled 8,760-hourly impacts for TMY3 using EnergyPlus and assumed baselines consistent with RTF assumptions. As an illustration, Figure 4-14 shows a portion of an 8,760-hourly impact loadshape for our Centralized Hydronic measure in a particular forecast year (2030), scaled by the number of non-residential customers that adopted this measure.

Figure 4-14. Central Hydronic Measure Shape for 2030



As discussed in Section 4.4, the building electrification measures are also energy efficiency measures. Thus, we only apply load impacts to fuel-switching adopters and new construction. As a result, the building electrification measures principally show load growth rather than savings relative to less-efficient electric end uses. However, our models net out any electric loads from the baseline fossil-fuel system such as pumps and fans as well as cooling savings, which can result in load reductions for some hours of the year.

For residential water heating, we used measured 8760 loadshapes taken from the RBSA I metering data.

4.5.2.2 Demand Response

We modeled the impacts of DR using program evaluation results and literature review. These measures can produce passive loadshapes from TOU rates, as well as event-driven loadshapes from dispatchable devices and PTR rates.

We define dispatchable loadshapes in terms of hourly impacts in pre-event, event, and post-event periods for each applicable month, day of week, time-of-day (AM or PM), and event duration (number of hours the event is called for). If the exact duration of a called event is not defined for a particular measure, we will use the loadshape with the closest duration for that month and day, but the event period will be truncated if needed (i.e., impacts for a 2 hour event would use the first 2 event hours of a 3 hour event loadshape if no 2 hour event loadshape was provided.) Non-dispatchable loadshapes can be defined with an explicit 8,760 loadshape (should be modeled for TMY3) or with a 24-hr loadshape for each month and day. Again, categories of month and day (e.g., summer weekdays) can be specified.

Table 4-13. Demand Response Loadshape Sources

Measure	Segments	Source
Residential high voltage Smart thermostat	TOU, non-TOU	BC Hydro Evaluation[25]

[25] https://www.aceee.org/files/proceedings/2016/data/papers/1_88.pdf

Measure	Segments	Source
Residential high voltage Smart thermostat controls	All	BC Hydro Evaluation
Residential low voltage smart thermostat	TOU, non-TOU	Cadmus PGE flex 1.0 pilot evaluation, Arcterus 2.0 database[26]
Residential low voltage smart thermostat Controls	Cooling only, Heating only, Heating and cooling, DI/BYOT	Cadmus DI Evaluation Reports Winter 2018, Summer 2019; Cadmus BYOT Evaluation Reports Winter 2019/2020, Summer 2020
Cold thermal storage	Cold Storage Thermal, Storage Chiller	Viking Cold Solutions case study[27], LBNL simulations[28]
Irrigation DLC	All	Engineering calculation
Large C&I ADR/curtailable tariff	Refrigeration, HVAC, Pumping, Industrial Process	Guidehouse 2020 Energy Partner Evaluation, NREL Paper on Water Facilities[29], RMI Demand Response Overview[30]
Electric Vehicle TOU	All	Research paper on CA/PGE EV-TOU response[31]
Peak-time Rebates	All	Cadmus Flex 2.0 Year One Evaluation
ERWH smart controls	All	BPA CTA-2045 Demonstration report[32]
ERWH retrofit switch	All	BPA CTA-2045 Demonstration report
Residential DHP controls	All	PGE Testbed work papers[33]
HPWH smart controls	All	BPA CTA-2045 Demonstration report

[26] https://www.cpuc.ca.gov/uploadedFiles/CPUC_Website/Content/Utilities_and_Industries/Energy/Energy_Programs/Electric_Rates/2017%20Arcturus%202%200%20(10-12-2017).pdf

[27] https://vikingcold.com/downloads/Viking-Cold-Case-Study_Ammonia-Warehouse+TES.pdf control_of_thermal_energy_storage_in_commercial_buildings_for_california_utility_tariffs_and_demand_response_lbnl-1003740.pdf (lbl.gov)

[28] https://simulationresearch.lbl.gov/sites/all/files/t_hong_-_electric_load_shape_benchmarking_for_small-_and_medium-sized_commercial_buildings.pdf

[29] Opportunities and Challenges for Water and Wastewater Industries to Provide Exchangeable Services (nrel.gov)

[30] https://www.swenergy.org/data/sites/1/media/documents/publications/documents/Demand_Response_White_Paper.pdf

[31] https://gib.people.uic.edu/Electric%20Cars%20and%20Charging.pdf

[32] https://www.bpa.gov/EE/Technology/demand-response/Documents/Demand%20Response%20-%20FINAL%20REPORT%20110918.pdf

[33] https://assets.ctfassets.net/416ywc1laqmd/6Ojz70LC2Vzb55noURmiCD/ed29676a4eb5df55c988e6e581bd12c8/PGE_Advice_No_20-23_Sch_13_Residential_Testbed_Pilot_OL_082520.pdf

Measure	Segments	Source
Commercial low voltage smart thermostat	None	No impact modeled, just an enabling measure
Commercial low voltage smart thermostat controls	ASHP/ER heat/cooling only, pre/post-1980 envelope	CLEAResult Measure Development Analysis
TOU	All	Cadmus PGE flex 1.0 pilot evaluation

4.5.2.3 Solar and Storage

For the solar measure, we modeled the 8,760-hourly impact of PV systems using NREL's PVWatts calculator, using separate loadshapes for both horizontal arrays and prototypical cardinal-direction oriented arrays (south, west, etc.), for which we assumed a tilt of 20 degrees. We modeled seasonal hourly impacts from battery storage measures based on available studies of how residential and commercial customers can achieve bill savings through load-shifting with battery storage systems.

We modeled battery impacts for customers on a TOU rate, so they discharge their entire capacity evenly across the high peak periods, then recharge during off-peak. However, we allowed batteries to recharge during the winter mid-peak period after discharging during the morning peak, since that would make economic sense for customers. We modeled commercial non-TOU customer batteries to operate during their likely bill peak periods and recharge overnight. We assumed a round-trip efficiency of 90% for all batteries.

Since microgrids act like the combination of PV and batteries when they are connected to the grid, we modeled them as the sum of those two measures. More complicated interactions between the PV and storage during times when they are islanded are ignored since that does not impact the grid during normal operations. Similarly, we do not model blackouts and any battery-recharging behavior that might follow them.

4.5.2.4 Transportation Electrification

While increased adoption of electric vehicles is the cause of transportation electrification load growth, the grid will experience that load via the chargers (EVSE). We started using modeled EV adoption and the seasonal weekday/weekend charging patterns at residential, public, and fleet EVSE using EVI Pro. We then augmented these shapes with primary data provide by PGE, including loadshapes from their Electric Avenue public charging sites and the Tri-met demonstration project.

For the direct load control (DLC) measures, we assumed that 50% of the load during DR event hours would be shifted to post-event hours, and that recharging would consume the same energy over the same duration as it would have during the event hours. Since the vehicles are not discharged and the event only delays their charging behavior, there are no round-trip energy penalties.

Table 4-14. Transportation Electrification Loadshape Sources

Measure	Segments	Source
All Level 1	Residential, Fleet	EVI-Pro Lite
Residential Level 2 (smart and standard)	TOU, Non-TOU	EVI-Pro Lite, IEEE Paper on EV TOU in PGE and PG&E[34]
Nonresidential Level 2 (smart and standard)	Fleet, Public	EVI-Pro Lite
DCQC	HDV Fleet, MDV Fleet, School Bus, Public	EVI-Pro Lite, PGE Electric Avenue data, Tri-Met Demonstration data, Engineering analysis
Smart Charging	L2, Fleet DCQC, Public DCQC	Engineering analysis

For DCQC measures, we normalize loadshapes to their nameplate capacity and dynamically model changes in capacity over time.

4.5.3 Define Demand Response Events

We estimate the load impacts for dispatchable measures over a schedule of simulated demand response events, over our study's time horizon (2020 through 2050). We established this schedule of events by analyzing the intersection of high loss-of-load probability hours and high demand days.

First, we looked at the top 5% of hours in the PGE loss of load probability (LOLP) dataset. Each hour in the top 5% was a weekday (no weekend days were within that threshold); these hours included evenings in August and both mornings and evenings in January and December. To allow the peak demand response impacts to coincide with the high LOLP hours, we timed our events start one hour before the peak LOLP. Table 4-16 shows our selected event start times and durations for each month where events could be called.

While these high LOLP hours indicate the likely timing and duration of demand response events, we did not assume that there would be a DR event called on every weekday August evening. To determine which day would have a DR event in January, August, and December of each modeled year, we

Table 4-15. High Loss of Load Probability Hours

Month	Hour Beginning	Loss of Load Probability
Jan	18	4.5%
Jan	19	4.4%
Dec	18	4.1%
Dec	16	4.0%
Jan	8	3.9%
Aug	20	3.7%
Dec	19	3.6%
Dec	8	3.6%
Jan	20	3.2%
Jan	7	3.0%
Jan	17	2.9%
Jan	9	2.8%
Aug	14	2.7%
Jan	16	2.7%

34 https://gib.people.uic.edu/Electric%20Cars%20and%20Charging.pdf

selected the day with the highest weekday peak in each of the forecast years. This allows the event day-of-month to change by year to match our estimated peak (sum of the population-scaled, sector-level loadshapes with TMY3 weather). In addition, the magnitude of the peak varies due to the coincidence of TMY3 weather and weekend days in different calendar years.

These high LOLP hours simulate both the timing and duration of five demand response events. To allow the peak demand response impacts to coincide with the high LOLP hours, we timed our events to start one hour before the peak LOLP. Table 4-16 shows our selected events and durations.

While these peak event hours are constant, the event day-of-month changes by year to match our estimated peak (sum of the population-scaled, sector-level loadshapes with TMY3 weather). In addition, the magnitude of the peak varies due to coincidence of TMY3 weather and weekend days in different calendar years.

Table 4-16. Weekday Event Timing

Month	Event Start Hour	Duration (Hours)
August	17	4
December	8	3
December	16	4
January	7	3
January	16	4

4.5.4 System Load Impacts

To calculate system level load impact, we apply all adopted measures to each customer (or group of customers who share the same set of relevant characteristics), and generate measure impact loadshapes specific to each customer as follows:

- For each customer in our sample and adopted measure, we apply the measure loadshape associated with that customer's individual attributes (revenue class, building type, roof orientation, etc.)
- Our measure impact loadshape definitions are expressed in terms of per-unit hourly impacts, and are scaled based on the attributes defined for each customer in each year:
    - Some measures are either absent or present, and simply have a size of 1.
    - Some measures can represent the number of installed measures (such as hot water tanks or thermostats) for that customer, and could have an integer size (i.e. 1, 2, 3, …).
    - Other measures are scaled with continuous factors that represent the physical characteristic that drives energy impacts, such as the DC rating of a PV array, the kWh capacity of a battery, or the conditioned floor area of a building.
- Some measures are scaled as a percentage of load; for these, we first calculate the baseline load using the sector loadshape plus all the non-dispatchable measure impacts that apply to that customer, then use the net loadshape and the 8,760 percent-of-load factors to calculate the hourly measure impact in kW.
- If the loadshape was calculated for a customer from a statistically sampled population (such as residential customers, which are sampled from 1% of the population), then the loadshape is multiplied by the weighting factor to get the full population impact.

We use these measure impact loadshapes to calculate 8,760-hourly impacts for each forecast year, using the actual calendar days and TMY3 weather data. For stipulated measures that are defined as 24-hr profiles, they are mapped to the actual calendar days for each forecast year. For dispatchable measures, we only trigger the impact loadshape according to the forecasted event hours from the DR event schedule for each year.

Once we calculate the 8,760 hourly measure impacts for all customers in all years, we can then aggregate (typically a sum, average, minimum or maximum) results as needed. For this report and the corresponding analysis for PGE's IRP, we group by various combinations of customer revenue class, time period (month, year, hour, DR event period, and NERC-defined on/off peak hour) measure, and program.

4.6 Economic Screening

Once we have technical achievable potential for all measures and programs, we screen these measures based using a TRC test. To the extent possible, we aligned our cost-effectiveness approach with principles outlined in PGE's Flexible Load Plan (FLP)[35]. This approach generally follows the approach used by the Energy Trust in its evaluation of energy efficiency measures, with some adjustments to account for the unique nature of flexible loads:

- Use an Effective Load Carrying Capacity (ELCC) adjustment to avoided capacity costs for each measure;
- Exclude some T&D avoided capacity costs;[36]
- Use Value of Lost Service to account for customer impacts of events;
- Exclude risk reduction and Regional Act Credits.

[35] UM 2141 Portland General Electric Company Flexible Load Plan available at https://edocs.puc.state.or.us/efdocs/HAS/um2141has132229.pdf

[36] We include transmission avoided cost in all scenarios, but include distribution costs only in the high DER adoption scenarios.

Additionally, the FLP calls for programs to be evaluated for cost-effectiveness only once they have exited the pilot phase, while Energy Trust has a more nuanced set of rules for cost-effectiveness exemptions that includes research needs, potential for market transformation, and programs focused on underserved communities. The FLP contains a table that compares cost-effectiveness parameters FLP and Energy Trust energy efficiency study. For context, we have copied this content from the FLP into Table 4-17.

Table 4-17. Comparison of Flex Load and Efficiency Cost-Effectiveness Parameters (from FLP)

Modeling Category	Flexible Load		Energy Efficiency	
	Value	*Source*	*Value*	*Source*
Capacity				
Value	$103	2019 IRP. 2020 $	$103	2019 IRP. 2020 $
ELCC	Varies	RECAP modeling	N/A	
Deficiency	NA		2021	2016 IRP Update
Line Loss Factors				
PGE transmission	NA		1.6%	PGE OATT
Distribution, primary, (industrial)	2.85%	Internal Loss Factor, 2015 GRC Line Loss Study	2.85%	Internal Loss Factor, 2015 GRC Line Loss Study
Distribution, secondary, average (commercial and residential)	4.74%	Internal Loss Factor, 2015 GRC Line Loss Study	4.74%	Internal Loss Factor, 2015 GRC Line Loss Study
Distribution, sub transmission	1.45%			Internal Loss Factor, 2015 GRC Line Loss Study
Distribution marginal to average line loss ratio	70%	Applied to applicable distribution line loss. RAP Marginal Line Loss Study 2011	varies	Power Council's marginal loss formula applied to a generic system load shape
BPA line factor	1.90%	Wholesale market purchase: 1 leg of BPA		
Transmission				
Deferral credit	NA		$9.38	Per kW-yr. 2019 GRC. 2019 $
Winter value			100%	
Summer value			0%	
Distribution				
Deferral credit	NA		$24.39	Per kW-yr. 2019 GRC Marginal Cost Study for sub transmission and substation. Shaped 12x24. 2019 $
Winter value			100%	
Summer value			0%	
Energy		Per MWh. Aurora on-peak forecast. Annual, monthly, or hourly		Per MWh. Aurora forecast, on and off-peak, monthly
Risk Reduction Value	NA		$3.00	Per MWh. 2016 IRP; not updated in 2016 IRP Update. Describes forward price exposure. 2016 $
RPS Compliance	NA		$0.00	Per MWh. In the 2016 IRP Update, no incremental cost of PNW wind net of capacity value and energy value
Regional Act Credit	NA		10%	1978 Power Act. Demand side can be 110% of cost of supply side proxy

Using the FLP cost-effectiveness approach as a starting point, we made adjustments and clarified details based on feedback from PGE program and planning staff, a review of best practices, and a desire to capture some impacts that are expected in the future but may not be realized in the near term.

Specifically, we:

- Add transmission capacity to all capacity impacts (split evenly between summer and winter);
- Add distribution capacity in the high adoption scenario;
- Incorporate flexible capacity value (based on the Blue Marble Analytics analysis in the 2019 IRP) for programs that respond to sub-hourly signals;
- Explicitly parameterized a pilot period (5 years) for all programs based on their start year and evaluated cost-effectiveness over a standard program period (10 years);
- Assume that revenue lost from time-of-use rates at scale is recovered through a recovery mechanism
- Do not value fuel savings benefits from electrification measures or environmental benefits not already captured within PGE's avoided cost of energy.

We calculate a set of program and measure costs based on a review of PGE's own cost-effectiveness workbooks used in regulatory filings, benchmark data from other utilities, and interviews with PGE program staff. In many cases, we used adjusted cost data from similar PGE programs that are already in the field to ground-truth to real-world experience in PGE's service area.

Table 4-18. Key Cost Effectiveness Assumptions

Variable	Value	Units	Source
Avoided cost of generation capacity	109.74	$/kW-yr	2021 IRP Update
Avoided cost of transmission capacity	9.57[37]	$/kW-yr	2020 Flexible Load Plan
Avoided cost of distribution capacity	24.39	$/kW-yr	2020 Flexible Load Plan
Incremental avoided cost of flexible capacity	25.4	$/kW-yr	Using a 2.7-hour battery value (via res storage, interpolated from 2019 IRP)
Distribution losses	4.74%		PGE staff
Distribution marginal-to-average line loss ratio	70%		PGE staff
BPA line factor	1.90%		PGE staff
Reserve margin requirement	15%		PGE staff
Real discount rate	4%		PGE staff
Inflation rate	2%		PGE staff
Pilot life	5	Years	Analytical assumption
Program life	10	Years	Analytical assumption

By default, AdopDER screens cost-effectiveness at the measure bundle level, as this is the smallest unit of program delivery. As a hypothetical example, a residential thermostat program could be cost-effective at the program level, but a direct install measure bundle (including a smart thermostat and the controls measures) for cooling-only/heating-only customers might not be while all other measures bundles are. In this case, the non-cost-effective bundles would be screened out and the remaining bundles would be added to economic potential.

We should note that, given the focus here on generating portfolios for the IRP, our cost-effectiveness screening was focused on the acquisition of resources programmatically for energy and capacity purposes. We did not include non-programmatic measures not currently offered or planned for PGE's program portfolio (such as residential solar or building electrification) and did not tailor our cost-effectiveness to pure transportation electrification measures such as charger rebate programs that do not include demand response. Where a measure had multiple impacts, such as smart thermostat direct install programs that include DR and EE, we only assessed the incremental costs and benefits of the DR portion of the intervention.

[37] We include distribution avoided costs only in the high DER scenarios.

4.7 Adoption and Load Scenarios

We use scenario analysis to place bounds on how achievable potential (both technical and economic) varies under different DER adoption rate and load forecast scenarios. Our analysis consists of eleven unique scenarios that we derive from a matrix of five adoption scenarios and three load scenarios (Table 4-19).

Table 4-19. DER Potentials Analysis Scenarios

		Load		
		Low	**Reference**	**Hi**
Adoption	**Low**	x	x	x
	Reference	x	x	x
	Hi	x	x	x
	Market Only		x	
	Technical Potential		x	

4.7.1 Adoption Scenarios

The number of factors that influence adoption in our analysis are plentiful, thus the number of scenarios that we would need to isolate each of their measure adoption and load impacts is impractically large. Given that our interest is in bounding the amount of achievable potential, we simplified this complexity into the five adoption scenarios that we describe below.

Reference Adoption. This scenario represents our "most likely" adoption scenario, which is generally an extension of past trends in technology prices and adoption trends. Table 4-20 describes the input parameters in detail.

Low Adoption. This scenario is a pessimistic adoption scenario, where we decrease program incentives, increase technology costs, and parameterize the bass curves as follows: long-term adoption rates are lower (decrease M parameter), and the curve takes more time to reach its maximum adoption rate (increase T parameter). In addition to creating a headwind for measure adoption, we also dampen the cost-effectiveness benefits for programs (see Table 4-20).

High Adoption. This scenario is an optimistic adoption scenario, where we boost measure adoption by increasing program incentives, decreasing technology costs, and parameterize the bass curve as follows: long-term adoption rates are higher (increase M parameter), and the curve takes less time to reach its maximum adoption rate (decrease T parameter). In addition to increasing measure adoption, we also increase the cost-effectiveness benefits for programs (see Table 4-20).

Table 4-20. Adoption Scenario Summary (Reference, Low, and High Scenarios)

Assumption	Reference Adoption	Low Adoption	High Adoption
Technology Costs			
Solar	NREL DGEN open-source data: pv_price_atb19_mid	NREL DGEN open-source data: pv_price_atb19_high	NREL DGEN open-source data: pv_price_atb19_low
Storage	NREL DGEN open-source data: batt_prices_FY20_mid	NREL DGEN open-source data: batt_prices_FY20_mid	NREL DGEN open-source data: batt_prices_FY20_low
Building Electrification			
Electric-to-Electric Upgrade	Energy Trust EE ramp rates	Energy Trust EE ramp rates	Energy Trust EE ramp rates
Fuel Conversion	NREL Electrification Futures: Reference case	NREL Electrification Futures: Reference case	NREL Electrification Futures: High case
EV Adoption Drivers			
LDV: Additional Total Incentive	$0	$0	$2,000
LDV: Additional Battery Price	0%	25%	-10%
LDV: Relative Fuel Price	0%	25%	-10%
LDV: Chargers in Range	On	Off	On
LDV: Vehicle Cost Decline	On	On	Exogenous impact of declining non-battery EV costs reduced by 50%
MDV: Adoption Rate	Expert Panel - most likely	Expert panel - lower bound	Expert panel - upper bound
Programmatic Adoption			
Bass Curve M parameter	Cadeo analysis of PGE and similar programs	50% lower than reference case	50% higher than reference case
Bass Curve T parameter	Cadeo analysis of PGE and similar programs	50% lower than reference case	50% higher than reference case
Cost Effectiveness			
Program Incentives	Cadeo analysis	25% lower than reference case	25% higher than reference case
Retail Rates	Current PGE residential, non-residential rates	TOU rate range 13% narrower than reference case	TOU rate range 13% wider than reference case
Distribution Avoided Cost	None	None	Include for all measures
Flexibility Avoided Cost	Include for DR/storage programs	None	Include for DR/storage programs

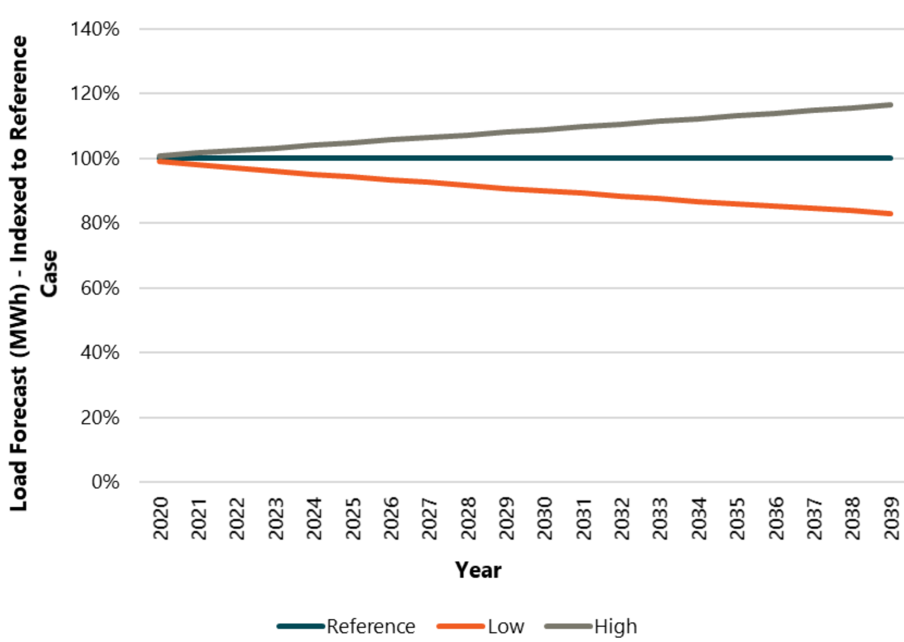
Technical Potential. This scenario aligns with the definition of technical potential described in section 4.1 in that our analysis forces all customers to adopt all measures their premise is eligible for. In the context of adoption, this means that we set the adoption probability to 100% for each measure. In some cases, measures compete for the same end-use, such as DCQC versus Level 2 EVSE for fleet charging, and smart ERWH versus HPWH in residential premises. In these cases, we select the measure with the highest DER potential, i.e., DCQC and HPWH in the example above.

Market-Only Scenario. This scenario is a special case of the reference case scenario in which we only analyze naturally occurring (non-programmatic) adoption of DER measures. As such, this scenario includes only building electrification measures, solar, storage, and transportation electrification measures. The load impacts from adoption in the market-only scenario represent zero-cost resources to PGE. Levelized costs and cost effectiveness ratios (e.g., TRC and PAC) for measures under the market scenario are not applicable since PGE does not have to expend any capital to acquire these resources. Consequently, for the purpose of PGE's integrated resource plan, these resources are a "must take" and often include load growth.

4.7.2 Load Scenarios

We used three load "need" scenarios provided by PGE in our scenario analysis: reference, low, and high. Figure 4-15 shows how these three forecasts relate to the reference case over time at a system level. In 2030, the high need forecast is approximately 9% higher than the reference case forecast, and the low need forecast is approximately 10% lower than the reference forecast. Individual sectors have different variances relative to their reference forecasts: residential has the largest variance (+/- 15% in 2030), while industrial has the smallest variance (+/- 5%).

Figure 4-15. Load Scenarios Relative to Reference Case



We calculate load impacts for the low and high scenarios at a sector level using the following four steps. These steps describe the low need forecast; the high need forecast follows an identical process.

1. For each sector, calculate the reference case loadshapes;
2. For each year within sector, determine the annual ratio of PGE's low need load forecast to its reference case load forecast;
3. Use the annual ratio from step 2 to scale the reference case forecast from step 1 to obtain the low case forecast; and
4. Apply load impacts.

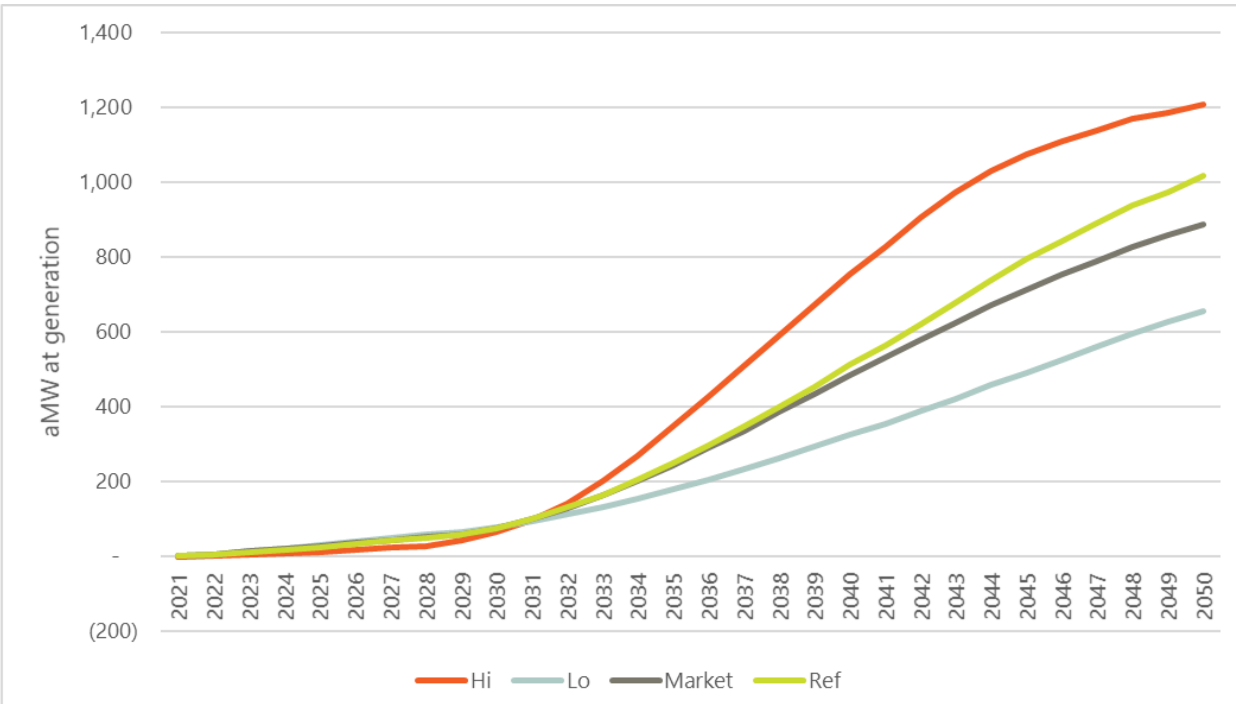
Section 5 Findings

5.1 Overall Impacts

This section describes the results of the Phase I potential analysis. These results will be used to inform PGE's subsequent IRP analysis.

In aggregate, under the confluence of solar, storage, transportation and building electrification, and flexible loads is set to have a dramatic impact on PGE's system and its customers. The graph below shows the expected energy impacts (in aMW at generation) through 2050 under the different adoption scenarios.

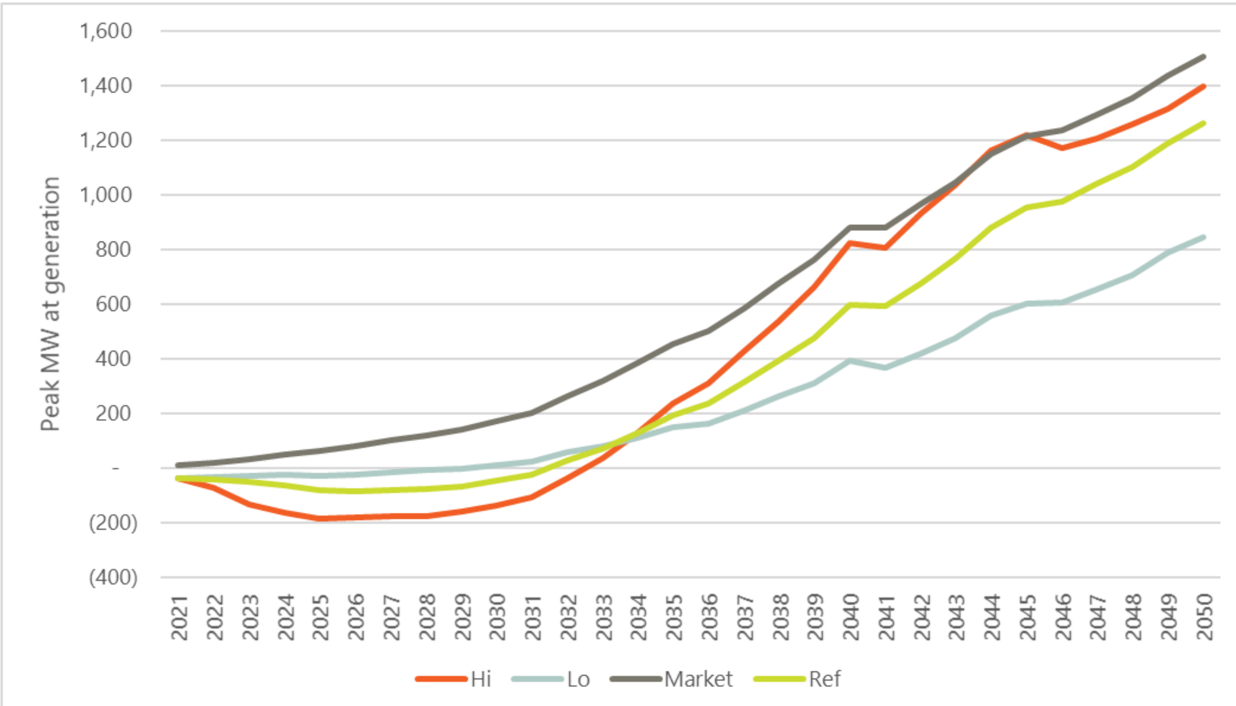
Figure 5-1. Aggregate Energy Impacts by Scenario



Even after accounting for increased solar adoption, transportation electrification (and to a much lesser extent, naturally occurring building electrification) is set to increase load by over 1,000 aMW in the reference case adoption scenario. The market scenario in Figure 5-1 provides an idea of what we expect to see absent programmatic activity. In outer years, we see the impact of PGE's transportation electrification programs on the adoption of electric vehicles and greater utilization of charging infrastructure (we do not model building electrification programs in this analysis).

This increase in load points to the need for flexible resource to manage peaks and mitigate upgrade costs across PGE's system. We see the critical role that flexible loads play clearly when looking at peak impacts. The figure below shows the average net demand impacts under each scenario, where peak is defined as the average over times of event dispatch in both summer and winter[38].

Figure 5-2. Aggregate Peak Impacts by Scenario



Here we see that PGE's continued development of its flexible load portfolio leads to a net decrease in peak loads in the early years of our study, even accounting for transportation electrification. However, in outer years, the impact of electrification overtakes flexible load adoption. When comparing the reference to the market case we see that these programs continue to play an important role in mitigating these peak impacts.

In the market scenario there are no flexible loads or dynamic rates; we see changes in peak load are driven almost entirely by electrification.[39] This leads to steady, and eventually large long-term increases. In the programmatic scenarios, these programs and rates help to reduce peak load to such an extent that in the early years of the planning period their effect is greater than total additions from electrification. However, as transportation electrification becomes near-universal in the out-years, there becomes a net positive impact on peak load. Because programs encourage both flexible loads and transportation electrification, the high scenarios shows both

[38] This analysis is merely meant to be indicative and is not a replacement for a full ELCC analysis through the IRP.

[39] There is some reduction in peak load from behind-the-meter solar, but not that storage here is un-managed, so is only used for backup.

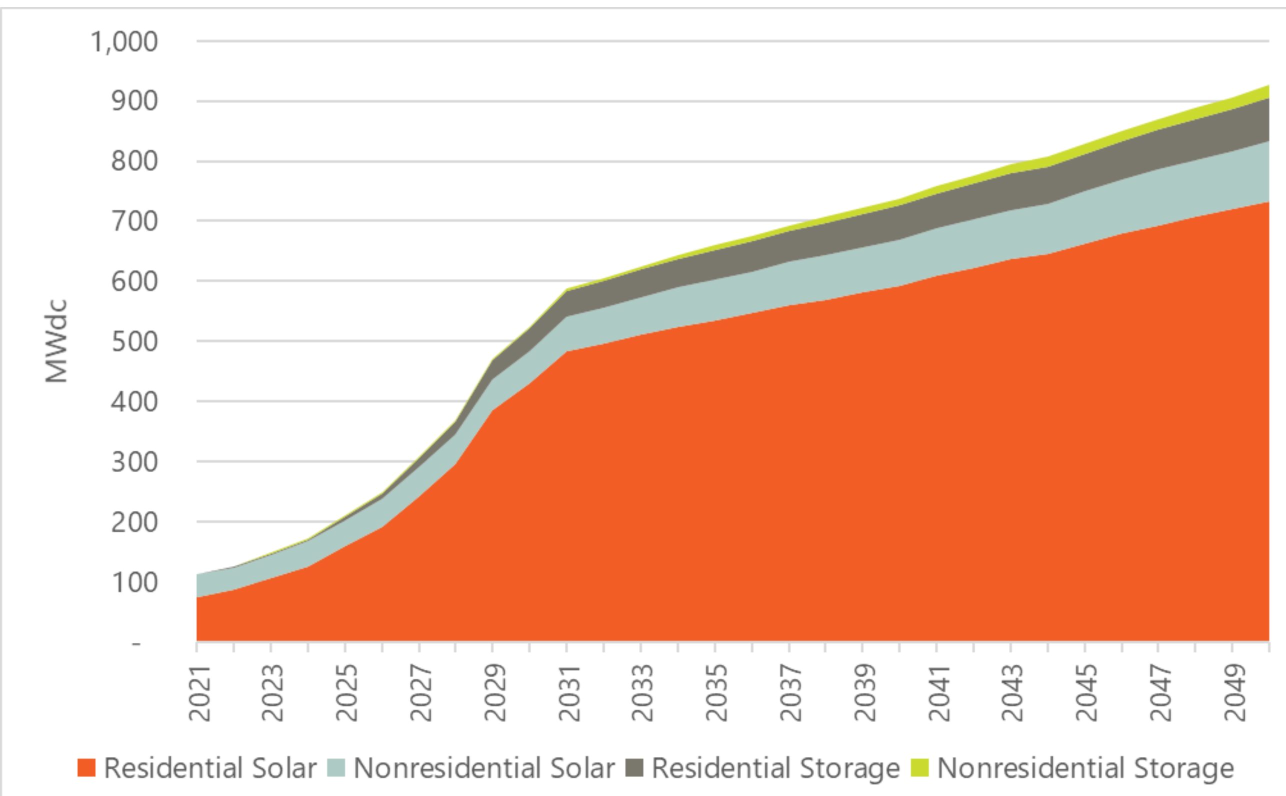
greater negative impacts in the early years and high positive impacts in the later years of the planning period.

We explore each set of technologies and their expected adoption and impacts under different scenarios in greater detail below.

5.2 Solar and Storage

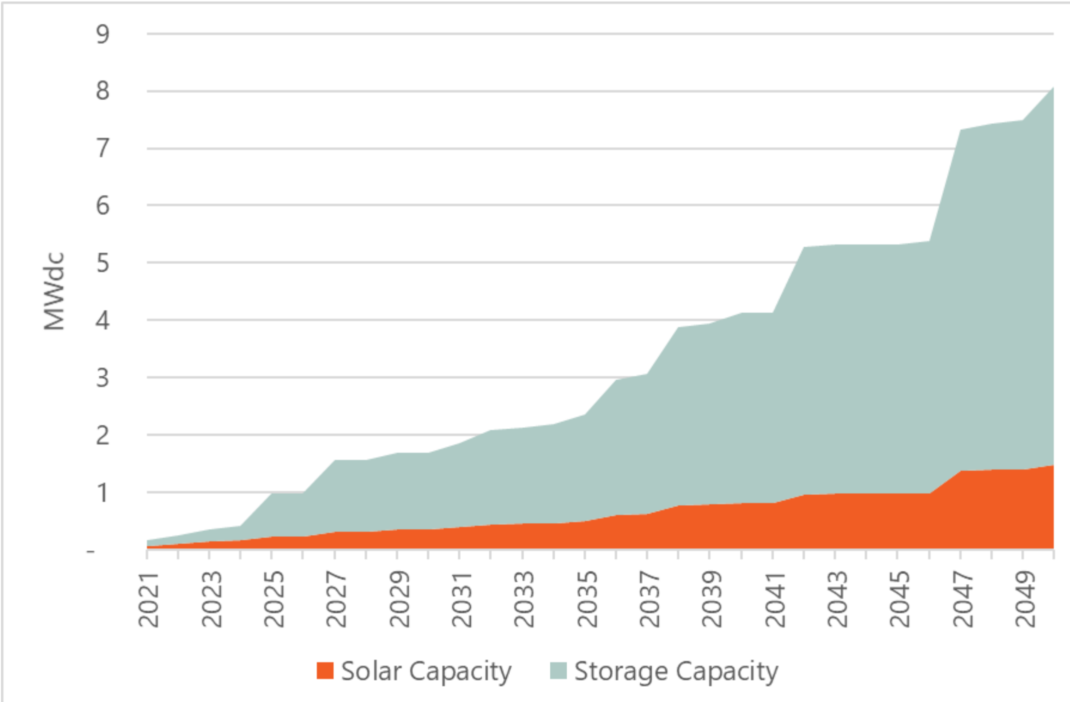
Despite a very large technical potential for both solar and storage, we expect approximately 926 MW of combined nameplate solar and storage across residential and commercial applications. As reflected in the forecasts from DGEN, we expect a large increase in residential solar in the later years, driven by declining costs of solar installations. We expect, as is the case in PGE's service area today, that residential will dominate the behind the meter solar market in PGE's service area. We forecast small, but growing market for storage, with approximately 72 MW in residential and another 21 MW in nonresidential, largely driven by expected increases in solar attachment rates.

Figure 5-3. Projected Solar + Storage Adoption (Reference Case)



We expect relatively modest microgrid adoption on average, though this is highly uncertain due to the bespoke design and needs of each project and increasing requirements for resiliency in the face of extreme weather events.

Figure 5-4. Projected Microgrid Adoption (Reference Case)



Technical potential for solar and storage is quite high, with gigawatts of nameplate capacity available. However, our analysis only accounts for building hosting capacity and does not account for distribution and transmissions constraints that would be expected at even a fraction of these adoption levels.

Figure 5-5. Technical Potential for Solar + Storage in 2050

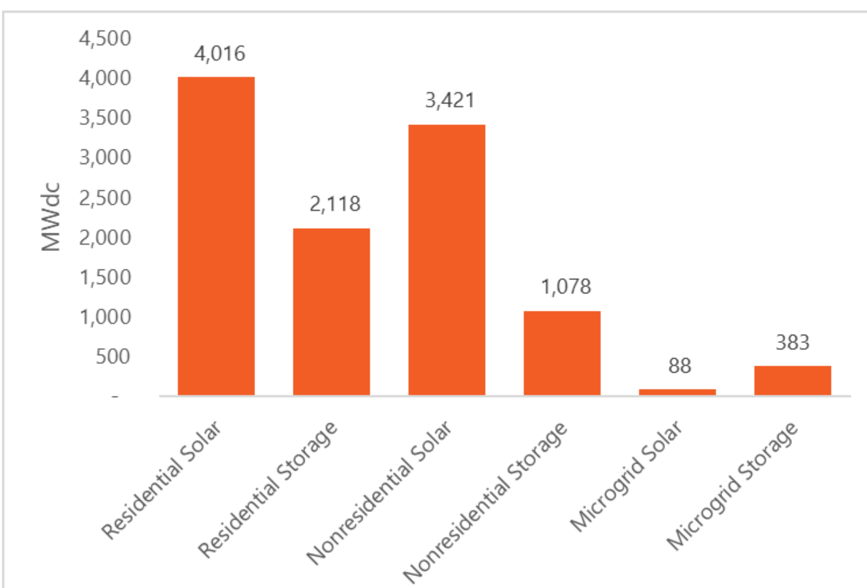
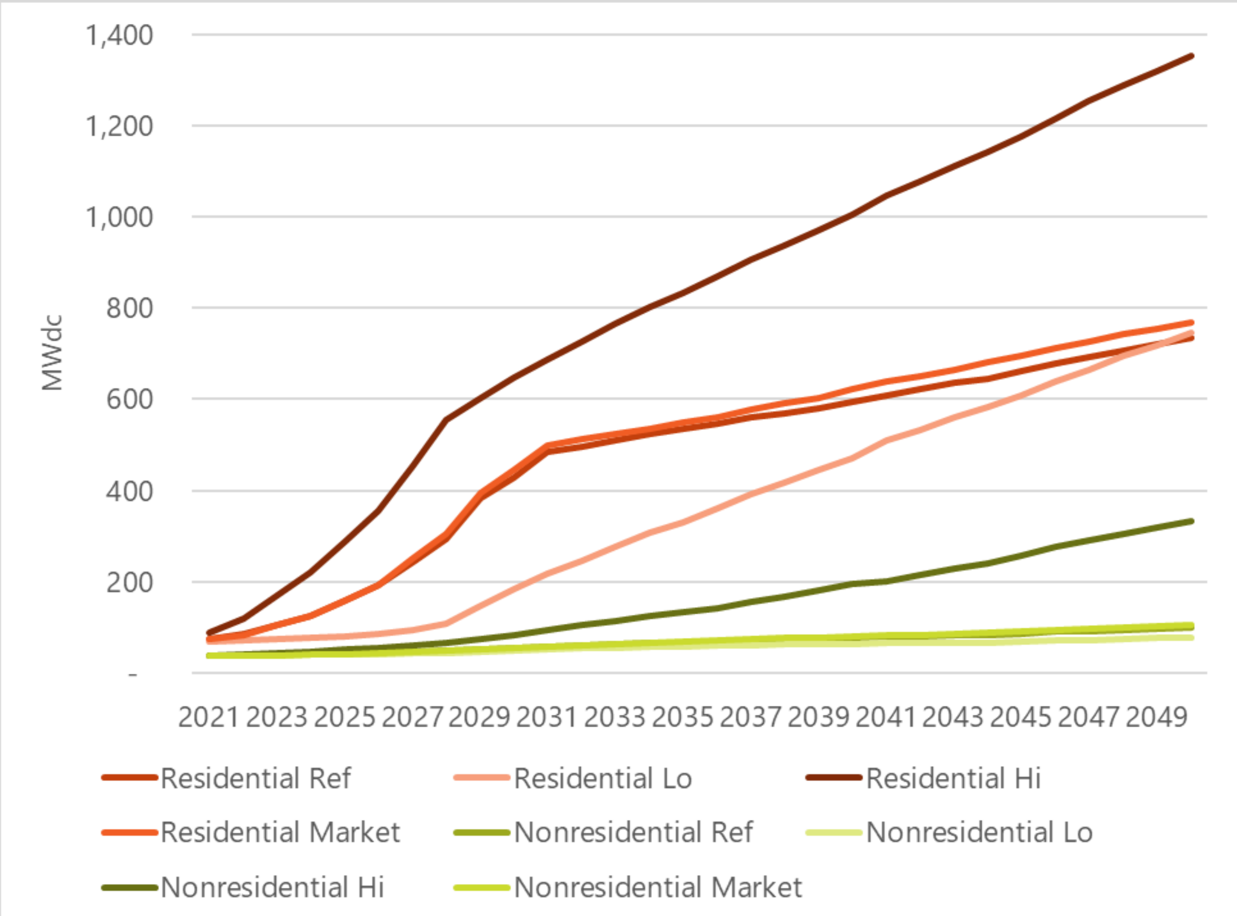


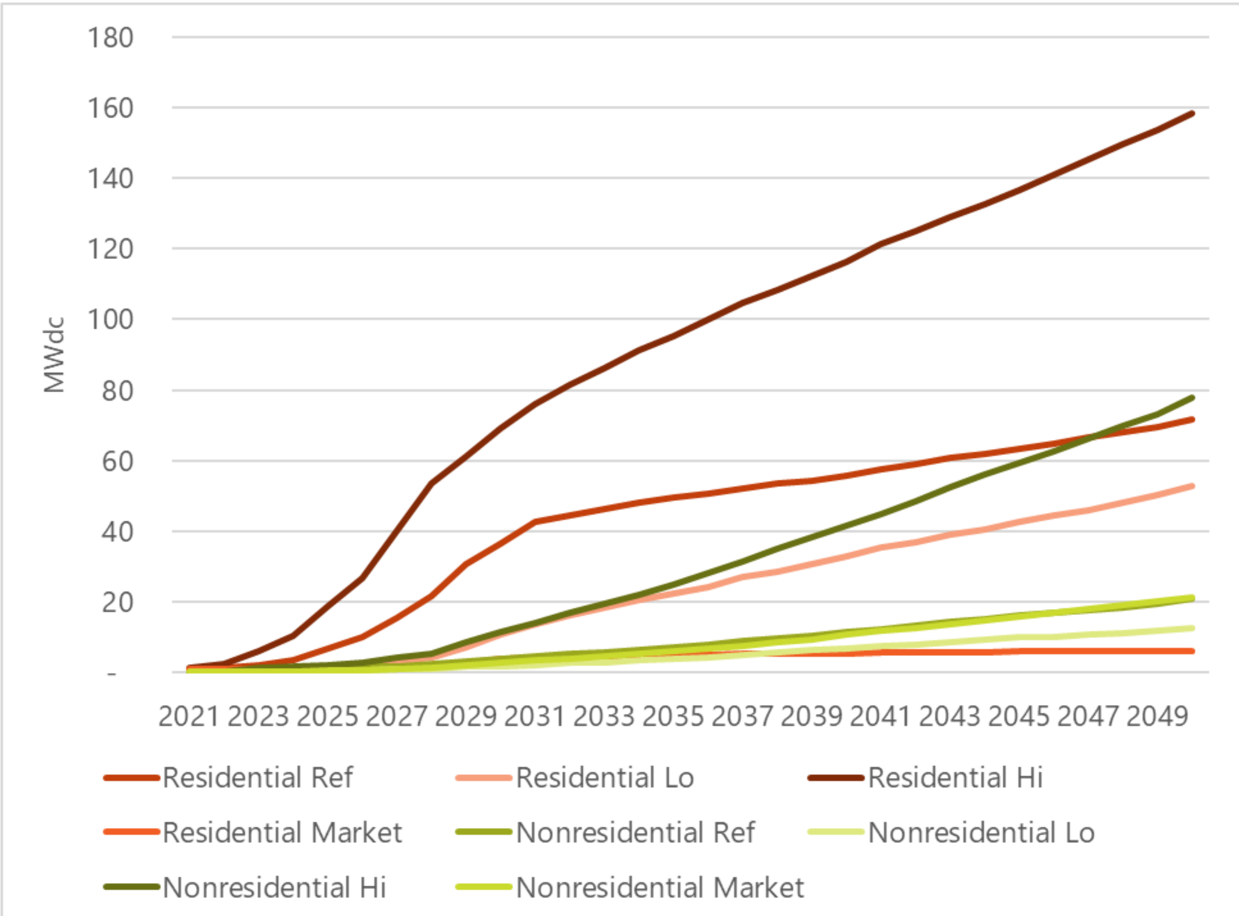
Figure 5-6 presents adoption under different modeled scenarios for solar. There is a small negative impact on solar adoption in the reference scenario relative to market due to the increased adoption of competing measures (largely L2 charging) that lowers the available panel hosting capacity on site.

Figure 5-6. Solar Adoption by Sector and Scenario



The figure below presents adoption under different modeled scenarios for storage. Here we see that residential storage adoption is largely driven by programmatic activity. This is consistent with what we have seen in more mature markets.

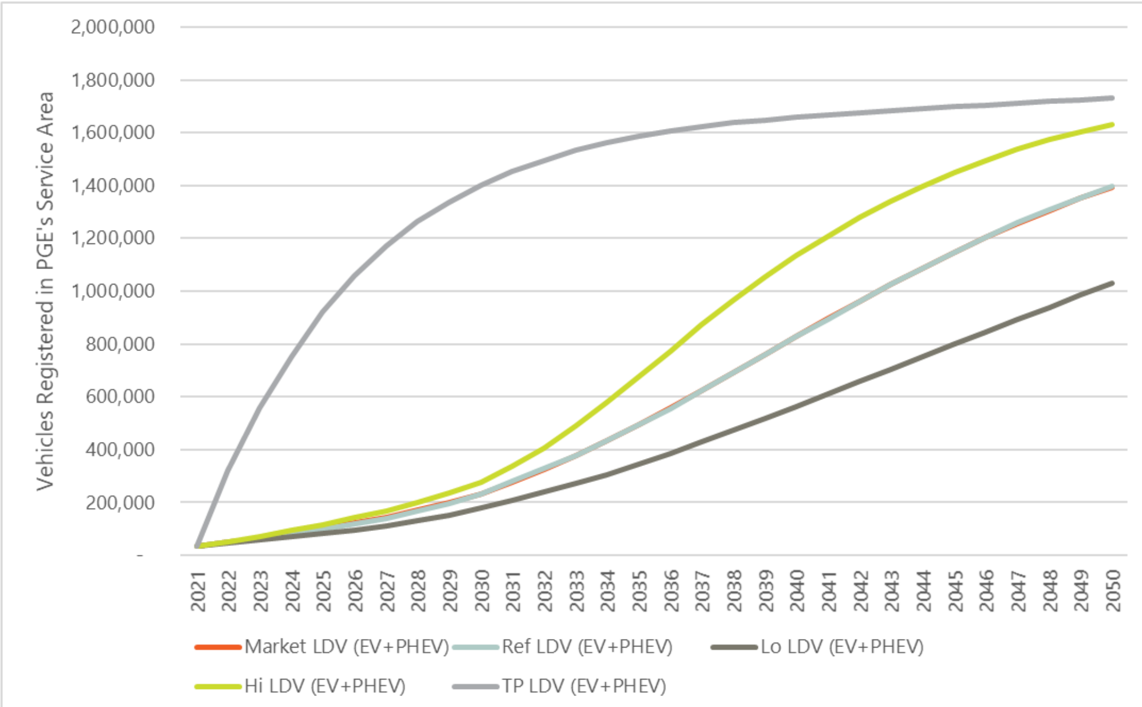
Figure 5-7. Storage Adoption by Sector and Scenario



5.3 Transportation Electrification

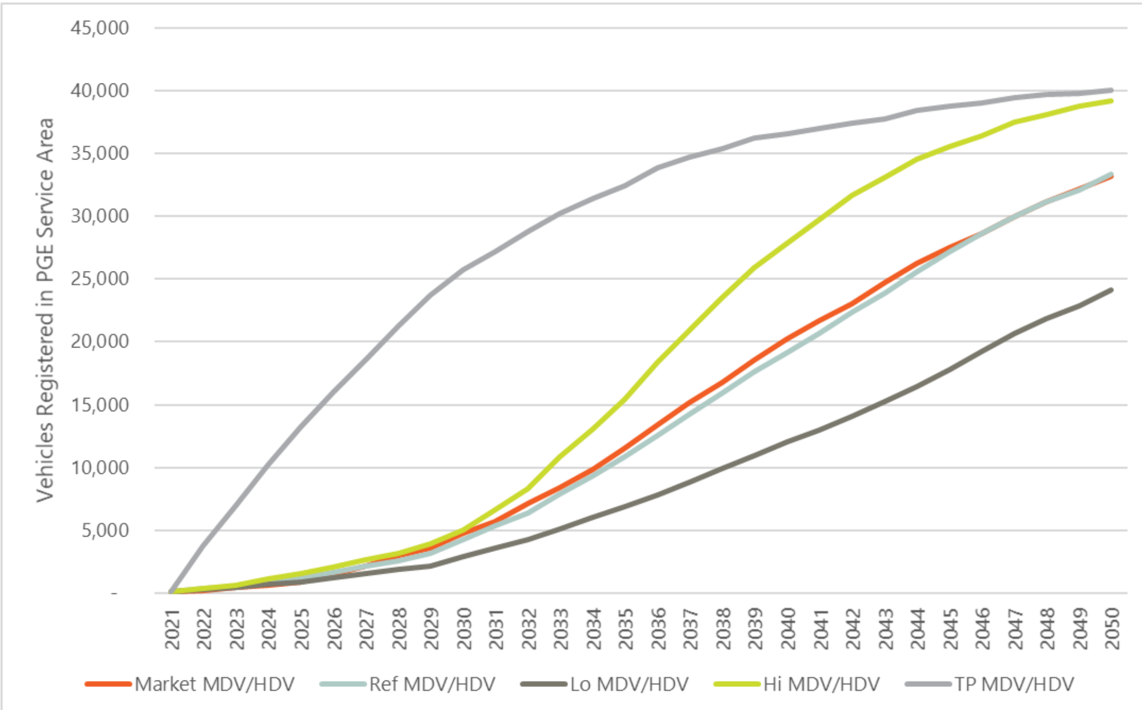
We forecast much higher levels of adoption for electric vehicles than in the previous IRP study, consistent with industry consensus around pending market transformation particularly in the light duty segment. By 2027, we expect 141,000 electric light duty vehicles on the road in 2027, dominated by the residential sector, and 2,100 medium and heavy duty EVs. By 2050, we expect nearly 80% of the vehicle market to be electric in all weight classes, with 1.4 million LDVs and 33,000 MHDVs.

Figure 5-8. LDV Adoption by Scenario



Note: In Figure 5-8, the reference case LDV curve and market case LDV curve overlap one another.

Figure 5-9. MDV Adoption by Scenario

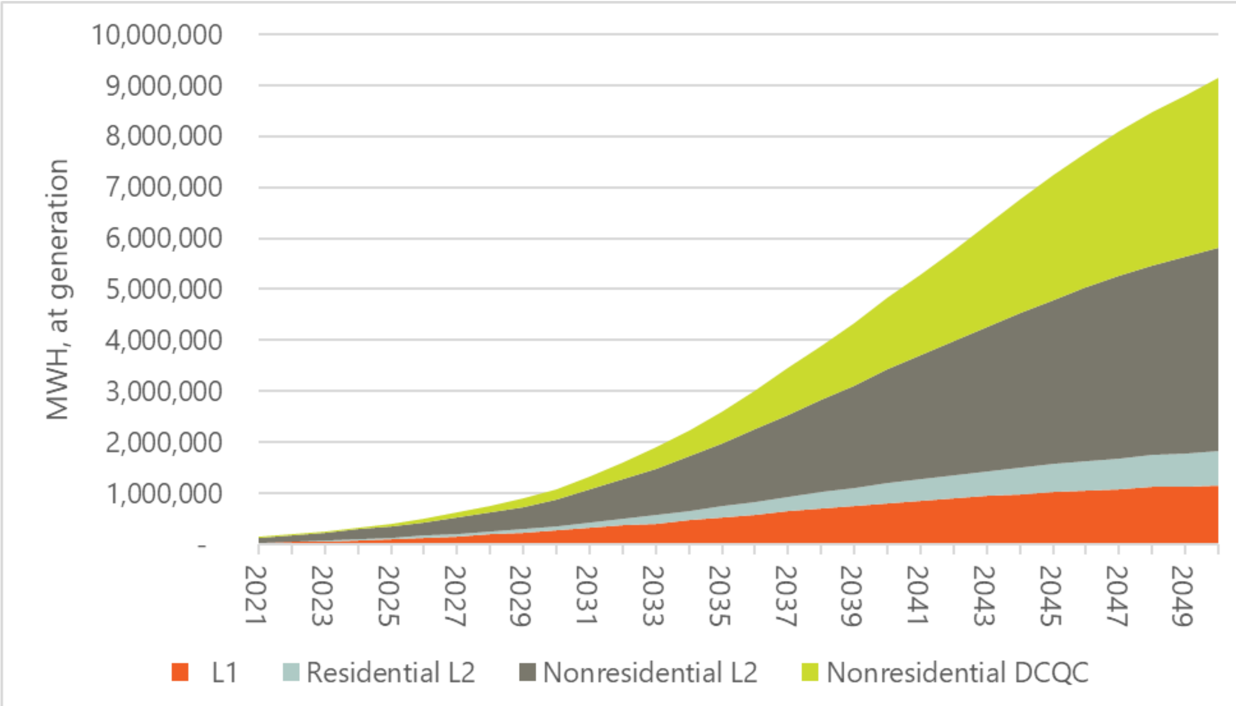


By 2050, we forecast an increase in annual consumption of 9.1 million MWH (at generation) to serve electric vehicle charging. Of that, nearly 80% will come from charging not dedicated to a single residence. Our forecast explicitly accounts for constraints to home charging due lack of panel ampacity and/or dedicated off street parking, thus we find that only a fraction of residential customers at the high expected levels of adoption can charge with personal EVSEs. Often, forecasts in the industry have relied on historical charging patterns as a guide to future behavior. However, this extrapolation of early adopters' charging patterns and neglecting to account for existing building stock can dangerously underestimate the needs for publicly available charging infrastructure in the long term.

This analysis assumes that sites will only install L2 charging when they have available panel ampacity and personal off-street parking, which leaves many residential sites without charging. Further research on streamlining panel/service upgrades and providing charging solutions for residents with only on-street parking could help to expand potential for home charging. There remains, regardless, a tremendous need in the long term for shared charging solutions.

The figure below shows this increased consumption, broken out by high level category. Nonresidential L2 charging - which includes multifamily, workplace, public, and fleet- becomes the dominant segment in the long run due to the need for charging beyond the home.

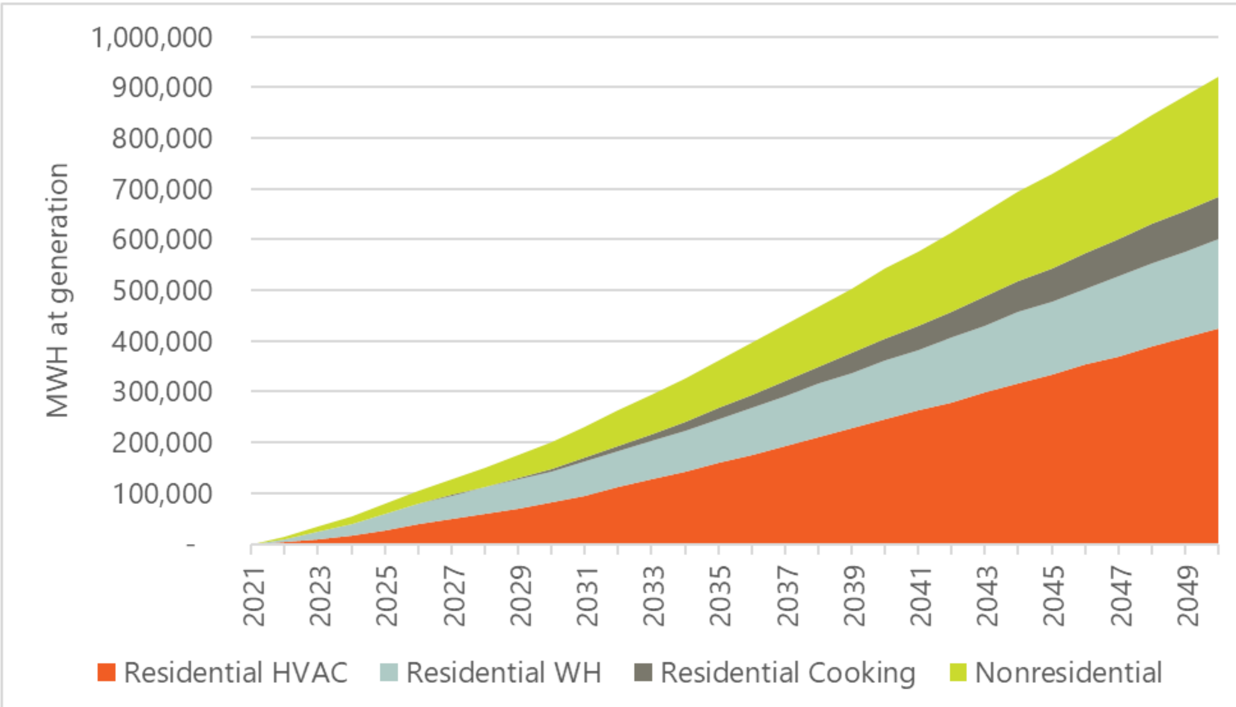
Figure 5-10. Projected Transportation Electrification Consumption (Reference Case)



5.4 Building Electrification

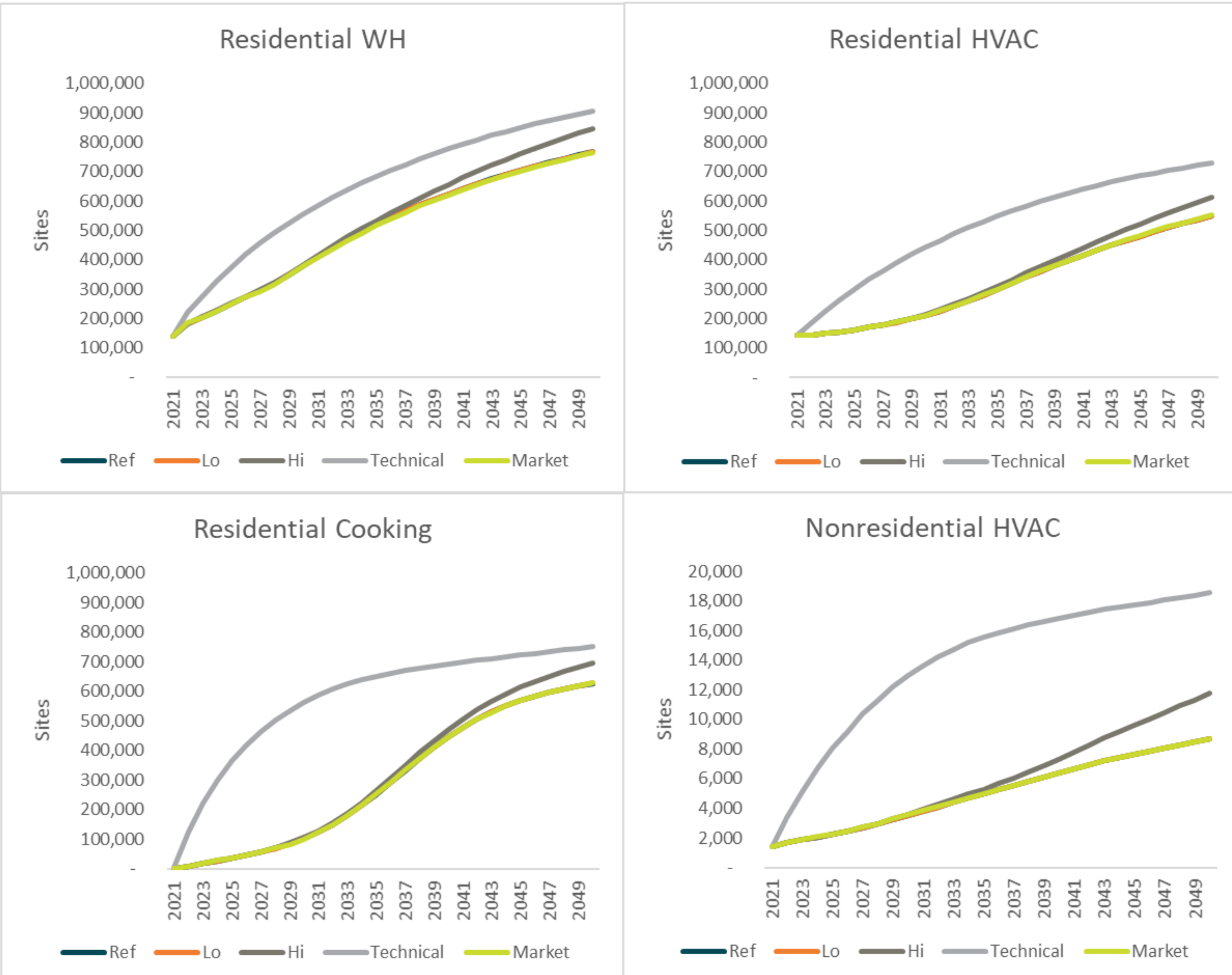
We expect only modest adoption of building electrification measures, largely concentrated in the residential sector. This is largely driven by new construction trends, where there is a small increase in the adoption of heat pumps to meet energy efficiency requirements. However, compared to transportation, these impacts are quite low.

Figure 5-11. Building Electrification Consumption (Reference Case)



The set of charts below outline the adoption of different end use technologies under each scenario. These charts include both efficiency upgrades and fuel conversions to provide a sense of the total addressable market for these technologies. For instance, while water heating and cooking present near term opportunities, they are expected to be nearly 80% transformed by 2050. Nonresidential HVAC, however, is expected to remain a larger opportunity for decarbonization.

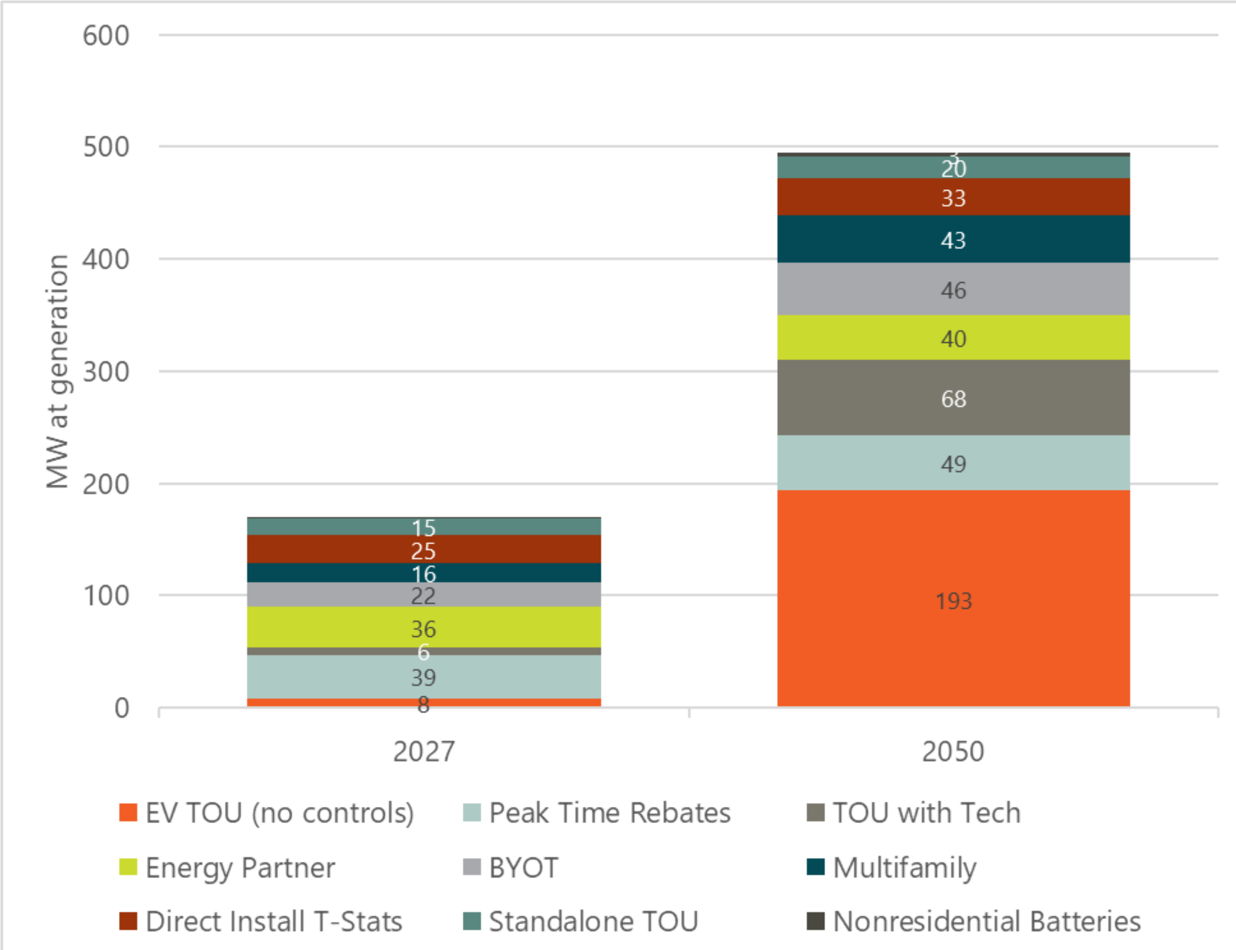
Figure 5-12. Building Electrification by End Use and Scenario (inclusive of electric-electric upgrades)



5.5 Demand Response

In aggregate, we expect approximately 169 MW of economic achievable demand response (including behind-the-meter storage enrolled in a program) in 2027. We expect PGE's portfolio to be dominated by peak time rebates, Energy Partner, and the thermostat programs in the near term (as it is today). By 2050, we expect 495 MW of summer DR, dominated by EV TOU due to near-universal adoption of light duty electric vehicles in the residential sector. Additionally, tech-enabled TOU becomes a bigger portion of the portfolio.

Figure 5-13. Summer Economic Achievable Demand Response (Reference Case)



As in previous studies, we expect slightly lower demand response in the winter season due to lower levels of electric heating relative to cooling in both residential and commercial. In 2027, we expect 134 MW of winter demand response, comprised of a mix of multifamily, thermostats, and the Energy Partner program (as shown in the Flex 1.0 evaluation, PTR and TOUs have lower per-unit impacts in winter). In 2050, we forecast 344 MW of demand response. As in summer, EV TOU dominates due to its low level of seasonality, high impacts on peak, and high level of adoption.

Figure 5-14. Winter Economic Achievable Demand Response (Reference Case)

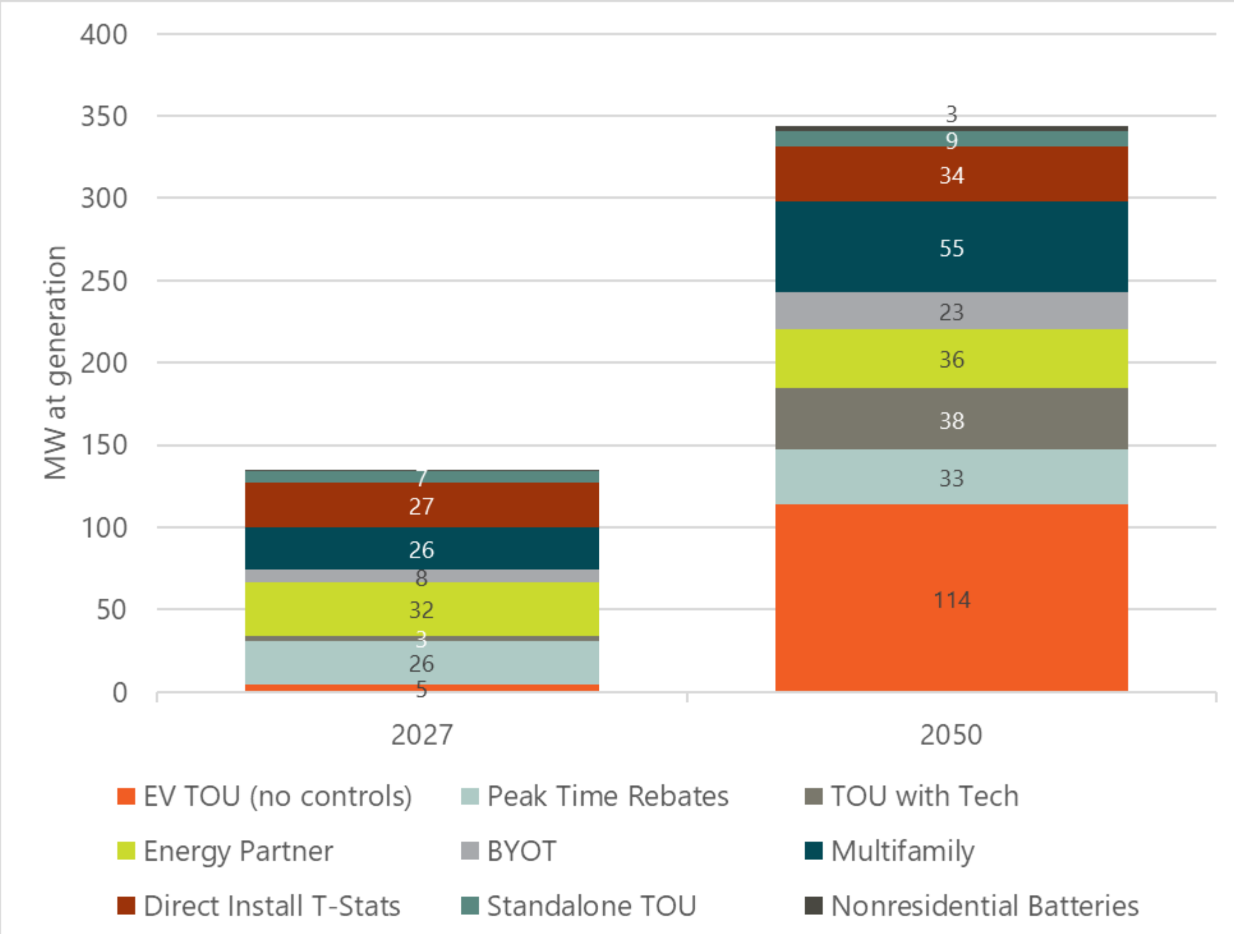


Table 5-1 provide a breakdown of expected MW impacts across different scenarios for both economic and achievable potential. In most scenarios, most of the demand response is economic in terms of total MW. Those measures that are not cost-effective remain relatively low in adoption regardless, even out to 2050. The range of potential impacts is broad, reflecting the still high level of uncertainty around adoption of these measures, with ranges of approximately +/- 50% relative to the reference case forecast.

Table 5-1. Demand Response Results (MW at generation) for 2027 and 2050 by Season and Scenario

Scenario	Season	2027		2050	
		All Achievable	Economic Achievable	All Achievable	Economic Achievable
Reference	**Summer**	**207**	**169**	**598**	**495**
	Winter	**162**	**134**	**452**	**344**
Low	Summer	133	117	399	327
	Winter	100	91	310	235
High	Summer	298	261	912	735
	Winter	240	204	703	506

As shown in the figures below, the load forecast has a very small impact on DR forecasts relative to the impact of adoption.

Figure 5-15. Summer Economic Achievable DR by Scenario

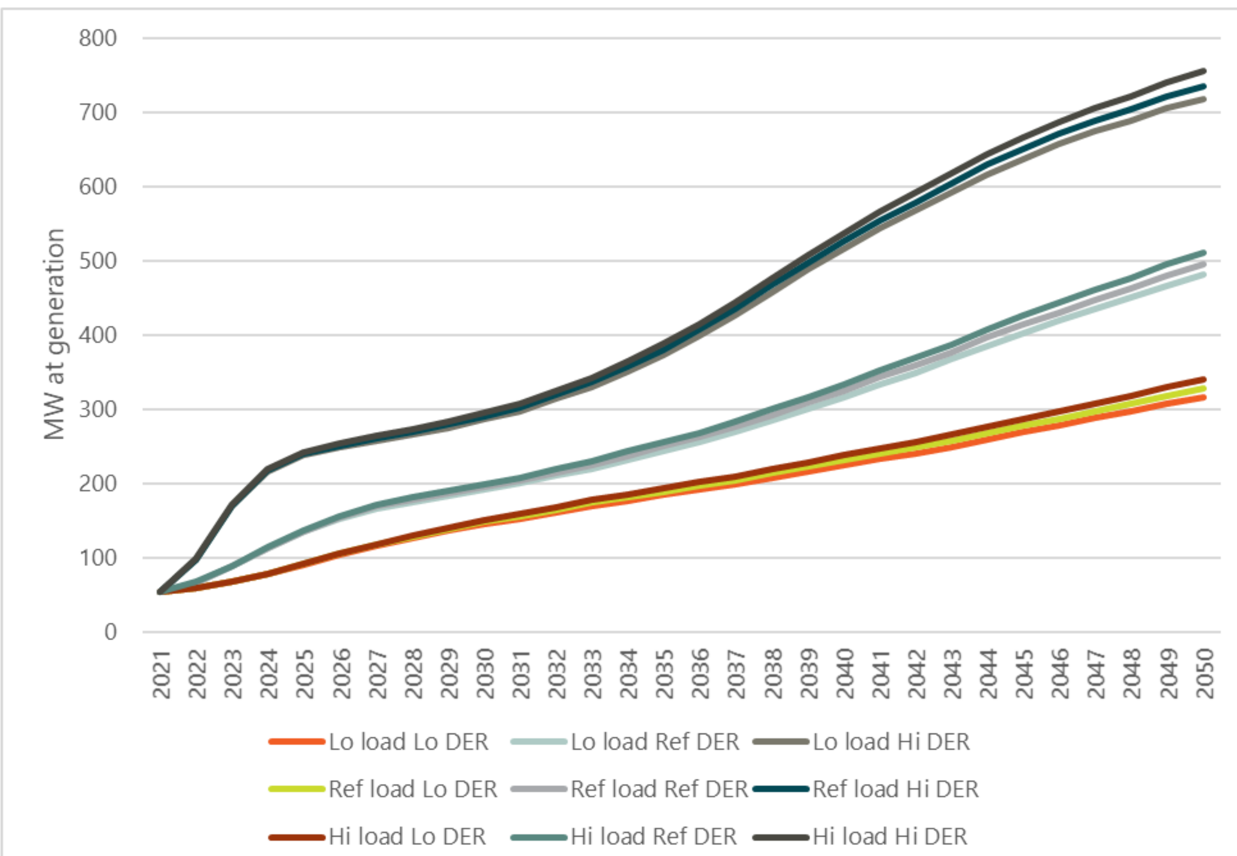
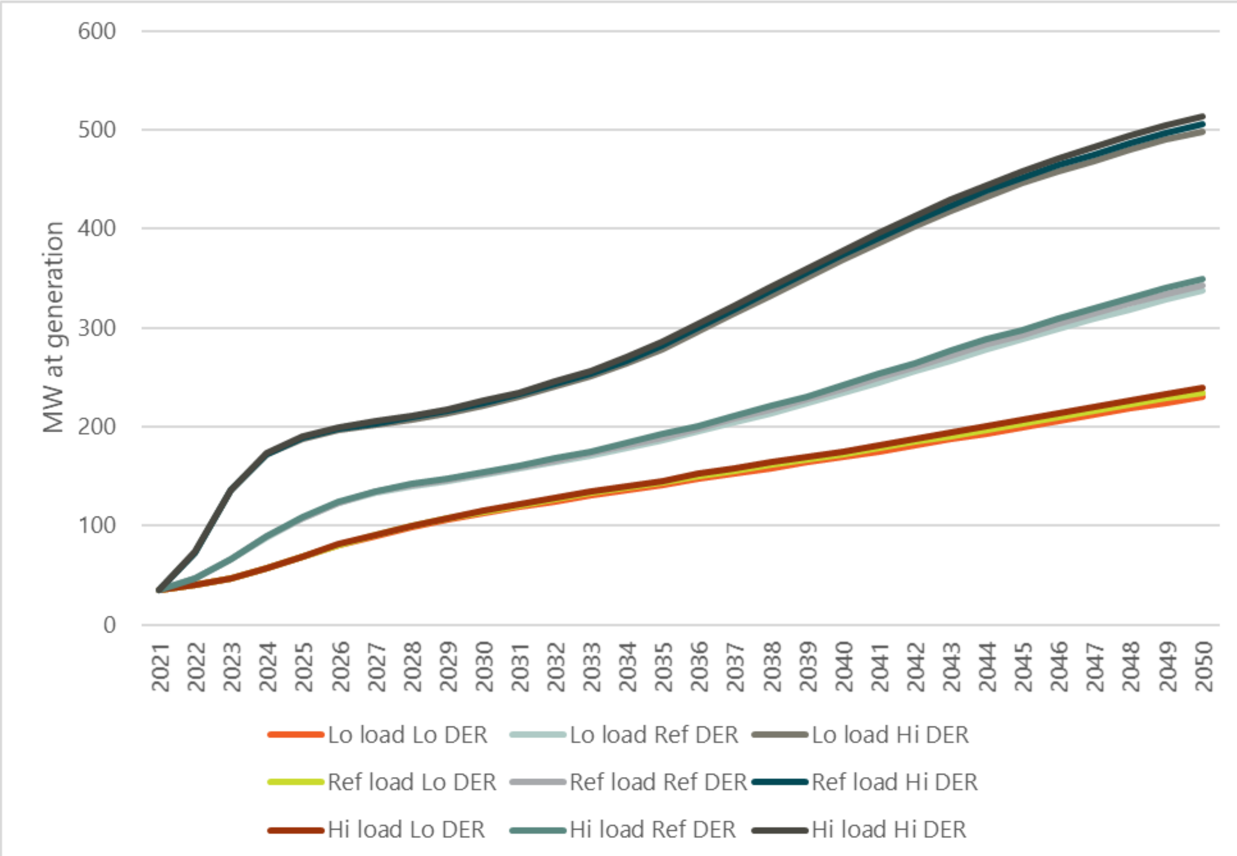


Figure 5-16. Winter Economic Achievable DR by Scenario



5.6 Cost-Effectiveness

While AdopDER screens cost-effectiveness at the measure bundle level, we also calculate economics at the program level for this study and present the findings from our analysis in this section. Though we applied a cost-effectiveness approach that we adapted from PGE's FLP, this study is independent of the FLP and its results may differ due to our selection of input values (see section 4.6 for more detail on this study's cost-effectiveness methodology)

Figure 5-17 shows the cost-effectiveness ratios that AdopDER calculated for each program in the study. PGE's residential programs, particularly those that use price signals, are the most cost-effective. While the largest measure today for the Energy Partner program, Schedule 26, is cost-effective, our inclusion of other measures such as agriculture, cold storage, and smart thermostats drags down program cost effectiveness.

Figure 5-17. Cost-Effectiveness by Program

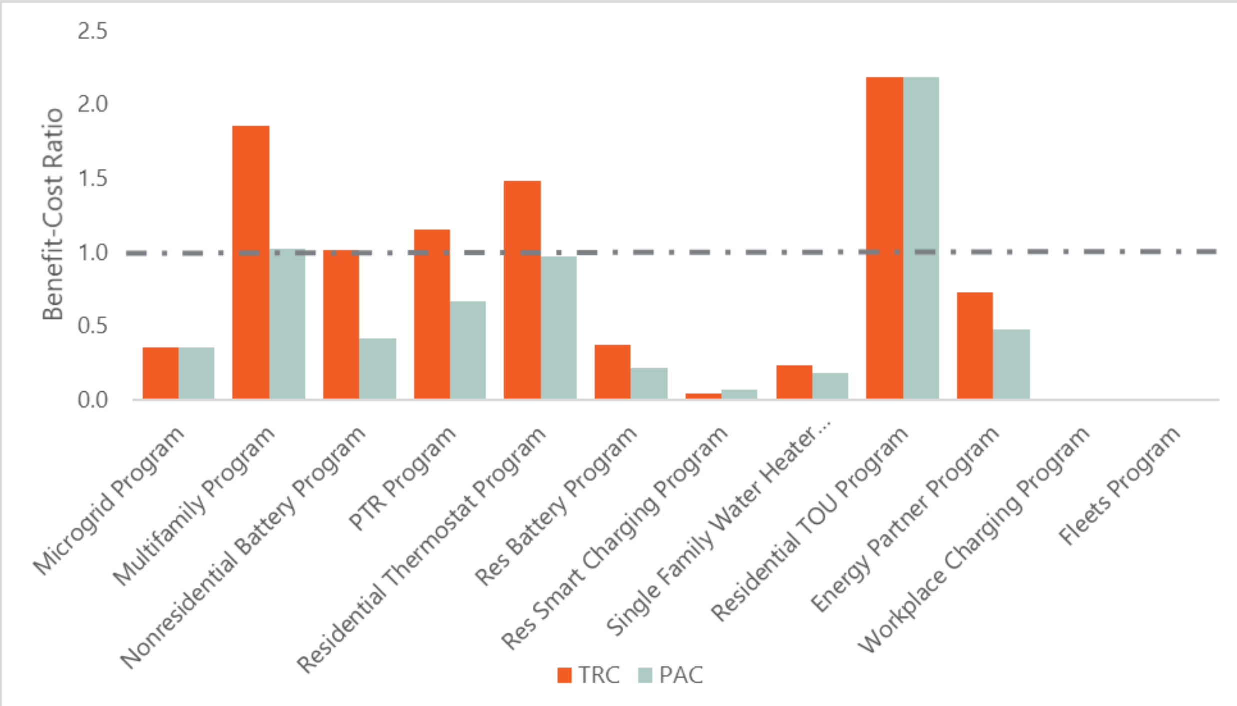
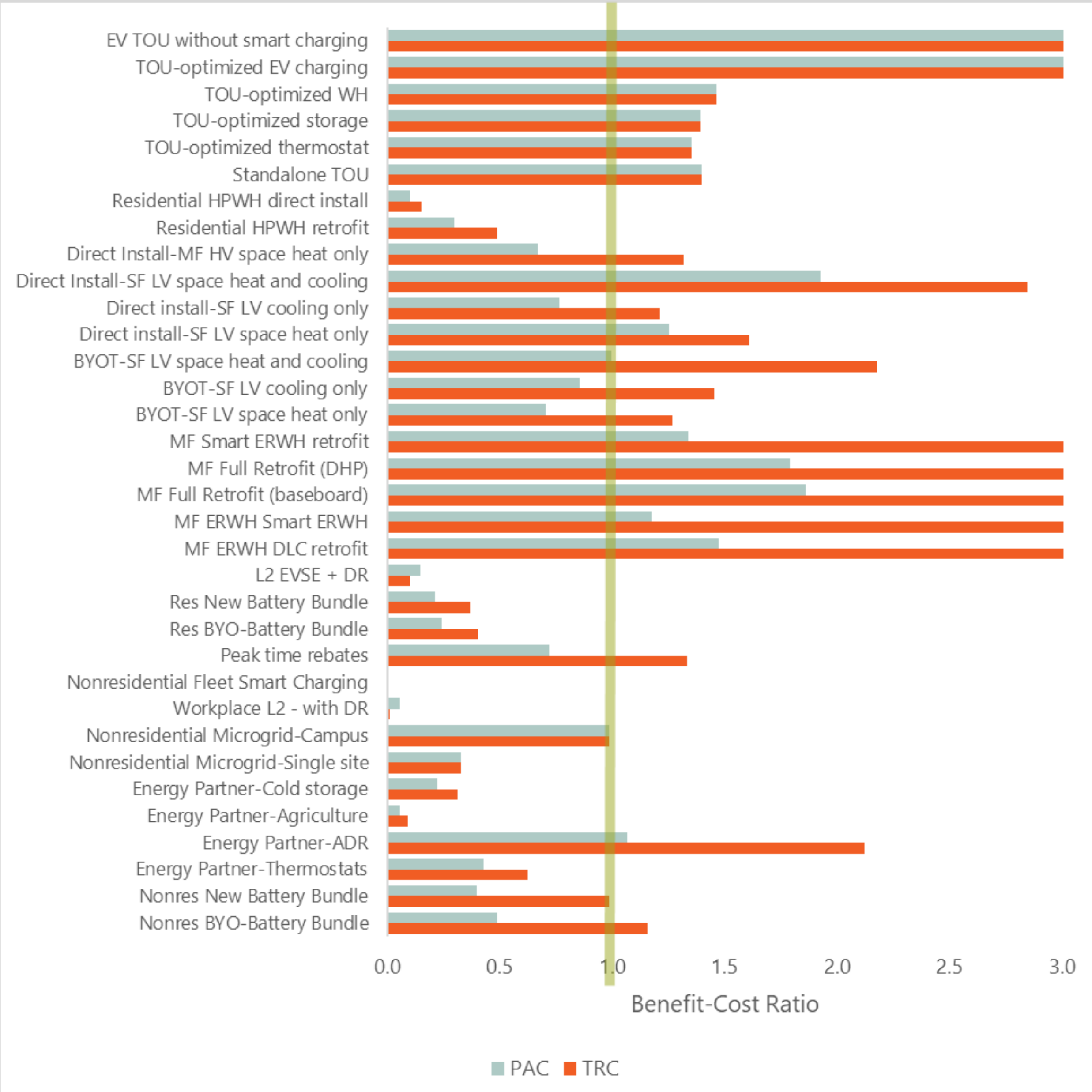


Figure 5-18 shows cost-effectiveness at the measure bundle level. Interestingly, due to its high ELCC and dual season availability, we find that BYO-nonresidential storage appears to be potentially cost-effective at scale. New nonresidential storage and campus microgrids are nearly cost-effective as well, with TRCs around 0.98. While we do not expect particularly high adoption (driven largely by low expected solar adoption by nonresidential customers), these measure shows promise long term particularly if costs can be brought down. We expect that further cost declines and a leaner program design for residential storage could expect the same result.

Figure 5-18 Cost-Effectiveness by Measure Bundle

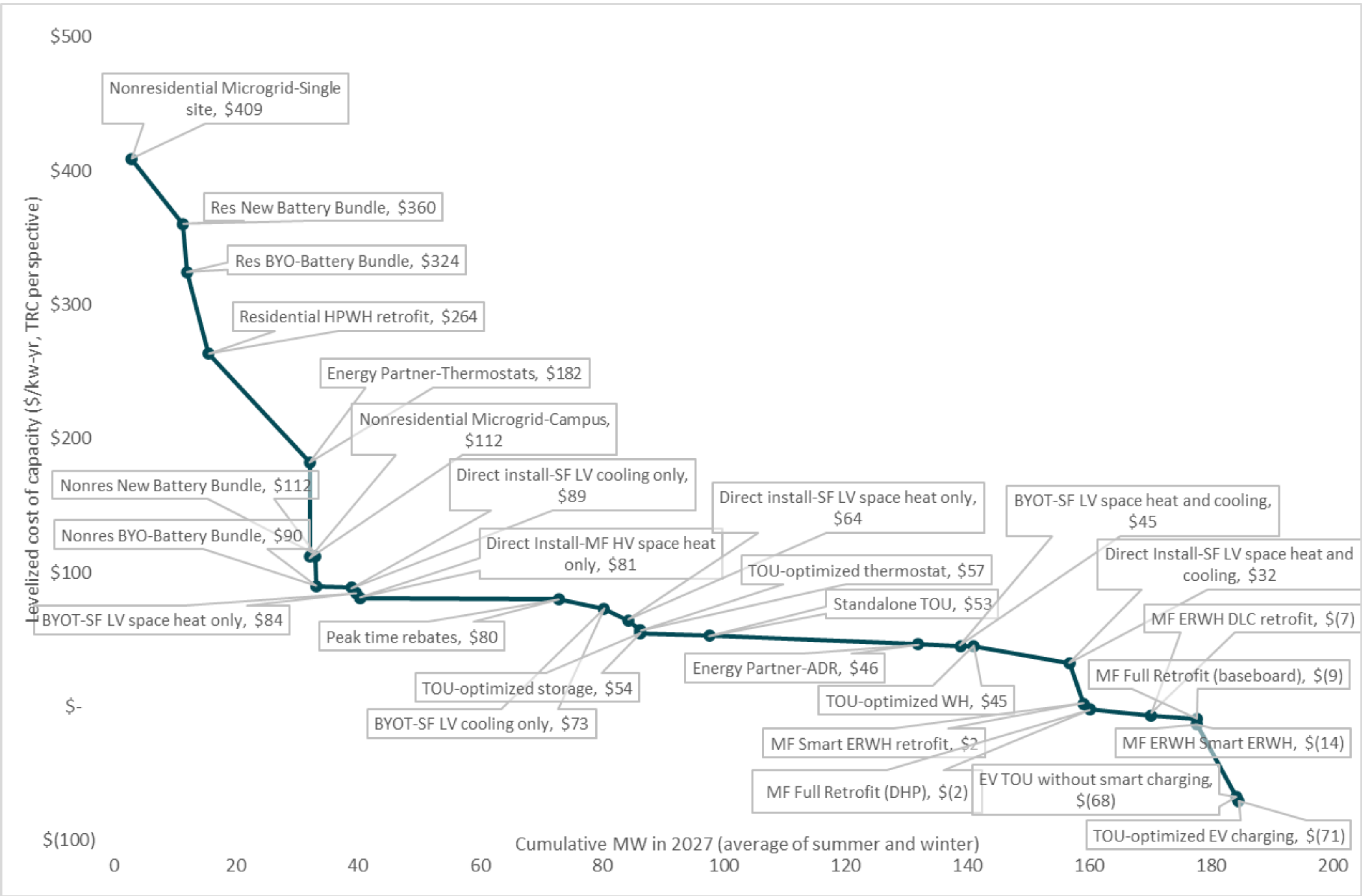


Because we model economics and impacts down to the site and annual level, we are able to develop supply curves for capacity resources at this level. Figure 5-19 shows levelized cost of capacity plotted against average 2027 peak MW impacts (average of summer and winter). Given the ability of some measures to provide services beyond generation capacity (such as energy, flexibility, and transmission capacity)[40], we find that there are several measures that in fact have

[40] The Cadeo team and PGE are engaged in ongoing discussion about cost-effectiveness methodology following the acceptance of PGE's Flex Load Plan. As such, the methodology that this study used will evolve in future iterations of this analysis.

net levelized costs below zero. Interestingly, we see an inflection point in the curve at approximately $100/kw-yr (roughly PGE's avoided cost of capacity). This inflection is driven by a set of measures that have very high costs and relatively low near-term potential.

Figure 5-19. Supply Curve of Demand Response Resources



Section 6 Conclusions

The Cadeo team developed tools and generated results in the study that provide a foundation for PGE to build upon as it embarks on its efforts to create an integrated planning framework across Distribution System, Flexible Loads, Electrification, and Integrated Resource Planning. We find that PGE has a wide array of resources at their disposal as they seek to create value for their customers on the distribution grid.

We see several trends interacting in our forecast:

- Dramatically increasing adoption of residential solar is expected to increase needs on the distribution system and encourage adoption of storage;
- Electrification of transportation will create unprecedented impacts on the energy system and present growing opportunities for flexible loads;
- Flexible loads are becoming increasingly cost-effective and there are new opportunities to integrate them with new DERs;
- DERs of all kinds create new constraints on the built infrastructure: an integrated approach to their deployment will be critical.

Actionable Insights

We see several ways in which the results of this study can be used to inform future work by PGE planning and programs staff.

1 | We find that there are likely 169 MW of summer and 134 MW of winter economic and achievable demand response by 2027 in PGE's service area, made up largely of programs they are already well into piloting. Continued focus on streamlining and scaling these programs will be critical to achieving these goals.

2 | Time of use rates, particularly when paired with increasingly prevalent enabling technologies, show tremendous promise to manage peak demands, especially as transportation electrification becomes more prevalent. Further demonstration of how these rates might be deployed more rapidly could help PGE accelerate progress toward its goals.

3 | Storage programs appear to be within the grasp of cost-effectiveness and program incentives will be critical to stimulating this market in Oregon. PGE should explore new opportunities to find cost savings in program delivery and/or capture new value streams to further improve economics.

4 | While we did not explicitly model a service area-wide program in this study, our analysis of smart water heater adoption and controls shows that there is a rapidly growing opportunity for taking a market transformation approach to water heaters. We find that PGE's multifamily water heater program is already cost-effective and expect a program utilizing CTA-2045 more broadly would be as well.

Areas for Further Research

While the research here provides a robust foundation for understanding future DER adoption, we see a few areas where further research might be warranted.

1 | We modeled panel constraints statistically in our analysis and their impact on home charging, building electrification, solar, and storage could be significant. We recommend further and possibly primary research on the existing panel configurations in PGE's service territory and possible solutions to overcome these challenges more cost-effectively.

2 | Our analysis took a relatively simple approach to DER dispatch, calling the fleet of dispatchable assets in aggregate based on a forecasted LOLP. A more integrated optimization of the fleet as a single Virtual Power Plant may more accurately reflect the full co-optimized value of these assets.

3 | Different segments of the population have lower adoption rates simply due to differences in the built infrastructure, existing equipment in place, and programs available to them. As the Cadeo team moves toward locational analysis, the bottom-up approach that we used in this study could also be used to better understand the equity impacts of DER adoption today and under different portfolios of interventions.

4 | Building electrification measures show large potential in the commercial HVAC space, as analyzed here. A deeper investigation of these emerging technologies as well as potentially industrial loads may be useful to understand where greater carbon impacts may be possible.

Next Steps

1 | The Cadeo team will work with PGE to develop locational forecasts based on this work to further advance their Distribution System Planning efforts;

2 | We have already begun the process of transferring code base, results, and inputs to PGE internal analysts to ensure that they can replicate and advance this work; and

3 | Results from this study will serve as an input to PGE's 2021 Integrated Resource Plan.

Appendix A. Electric Vehicle Adoption Estimation Methodology

The following appendix outlines our approach to modeling electric vehicle adoption across each vehicles class.

Light-Duty Vehicles

The electric light-duty vehicle (LDV) forecast relies upon Brattle's econometric electric vehicle (EV) adoption model. Leveraging an econometric approach enables allows us to identify the relative importance of the many drivers of EV adoption. The model is estimated using historical state-level, monthly independent variables from all 50 states and Washington DC between 2011 and 2019. These variables are:

- **Purchase Incentives:** the sum of state-level and national rebates or tax credits that offset the purchase price of a new BEV or PHEV.
- **EV Battery Price:** the per-kWh price of electric vehicle batteries, used to capture the declining costs of electric vehicles.
- **Relative Fuel Price:** defined as the ratio of the cost to drive 100 miles in an EV to the cost to drive 100 miles in an ICE vehicle, used to capture the importance of the varying costs of electricity and gasoline and the relative fuel savings from an EV.
- **Available Models:** the number of different plug-in hybrid EV (PHEV) and battery EV (BEV) models that are available for purchase in a given state.
- **ZEV State:** a binary variable if the state has a Zero-Emission Vehicles (ZEV) target.
- **Vehicle Miles Traveled:** state-level annual average vehicle miles traveled to capture impact of driving patterns.
- **Green Views:** the state-level score provided by the League of Conservation Voters scorecard intended to capture a state's environmental preferences.
- **Charging Rate:** a binary variable if the state has a utility that offers a charging rate.

By using the forecast values of these drivers in the econometric estimation time frame, the model produces a monthly forecast of electric vehicles (i.e., BEVs and PHEVs) in Oregon on a per million people basis that we scale to monthly sales using a forecast of Oregon's population.

While the econometric modelling approach is attractive because it allows us to decompose the impact of drivers of adoption, it is unable to account for certain key drivers of adoption that may not be readily captured in the econometric model, most importantly declining non-battery EV costs and range anxiety. We account for these drivers missing from our econometric forecast with exogenous impact forecasts:

- **Non-battery EV costs**: we employ a forecast of non-battery EV cost component declines (i.e., R&D, EV powertrain, and assembly cost declines). We then transform the battery price coefficient from the econometric model using historical battery capacity to determine the increased adoption due to non-battery cost decline.
- **Range anxiety:** we developed a framework to evaluate "chargers in range," or the total chargers an EV can encounter on its entire battery capacity. Using this framework, we can account for the impact that improvements in battery range as well as increased charging infrastructure have on addressing range anxiety and boosting adoption. We have a forecast for increases in range, while we tie the level of charging infrastructure to the amount of EVs on the road using a constant ratio. The impact of this "chargers in range" variable increases over time, but its marginal increases begins to decline as the amount of EV charging infrastructure approaches that of current ICE fueling infrastructure (i.e., gas pumps).

After incorporating the exogenous impacts to finalize our state-level forecast, we scale the Oregon EV sales forecast to the PGE service territory using the historical ratio of PGE sales to Oregon sales.

Because we calibrated our econometric model is using historical sales, it does not include the impact of LDV electric trucks because such vehicles have not yet become available. To account for these LDV electric trucks, we shift and scale our LDV EV forecast. First, we shift our LDV forecast out until we assume LDV electric trucks will fully enter the market (2023), and then we scale our forecast by the share of the current market that is LDV trucks (14%). We then add together the LDV electric truck forecast to the LDV EV forecast. Finally, to account for EV retirements, we assume a 10-year vehicle lifetime for EVs, so monthly retirements trail monthly sales by ten years.

Medium and Heavy-Duty Vehicles

While there is now significant historical and survey data to develop trajectories on personal U.S. electric light-duty vehicle adoption, similar data is not yet available on the commercial/fleet medium-duty and heavy-duty electric vehicle categories. Therefore, we have decided to leverage the "Delphi Method", which is a well-established forecasting method that relies on the expertise of a panel, for developing forecasts for medium- and heavy-duty electric vehicles.

The survey consists of two stages:

1. First, we emailed experts a list of questions to capture their vision of how MDV and HDV adoption will play out in the U.S. in the future. All vehicles are divided into six groups: weight class 2-3, class 4-6, class 7-8 regional vehicles, class 7-8 long-haul vehicles, city transit bus, and school bus. In each group, the expert was asked to provide a lower bound, an upper bound, and their best estimate for the national electric vehicle share by 2025, 2035, and 2050.
2. After analyzing the responses, we developed a consensus projection to share with all survey participants. At this stage, the experts had an opportunity to update their previous projections and provide reasoning for keeping the original forecasts or updating them.

The first phase took place in December, and we concluded the second phase in mid-January. All surveys were conducted via email. Overall, we recruited 15 experts, spanning research/non-profit organizations, government, utilities, and industry (Figure A-1). Three groups of experts provided joint responses, and there are 12 responses in total. Note that participation was anonymous.

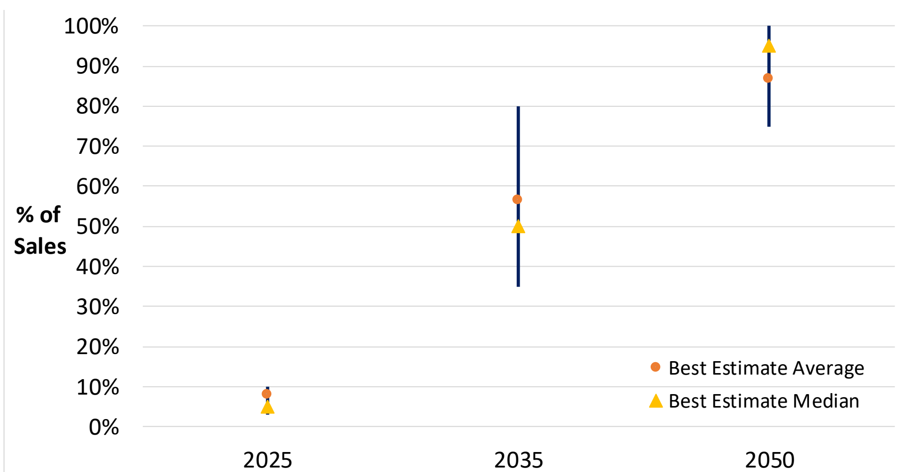
Figure A-1. Participating Experts and their Backgrounds

Research/Non-Profit
Atlas Public Policy
CTE
CTE
Electrification Coalition
NREL
Rocky Mountain Institute
Union of Concerned Scientists
Government
DOT
Utility
Duke Energy
Seattle City Light
Industry
ACT Research
American Trucking Associations
NA Council for Freight Efficiency
VEIC
VEIC

Results for all vehicle weight classes are shown in Figure A-2 through Figure A-7 below. Each figure shows the average and median of the best estimates as well as the 10th and 90th percentile values. Here are the key takeaways:

- In general, near-term adoption of MHDEV is expected to be limited. Across all classes, less than 10 percent of new MHDV sales is expected to be electric by 2025. Adoption of electric city and school buses are expected to be higher, primarily because of the advantageous total cost of ownership compared to their diesel or gasoline counterparts.
- According to the experts, adoption will increase across all vehicle classes will 2035, and will be close to universal adoption by 2050 for Class 2-6 vehicles as well as city and school buses.
- Significant uncertainty exists in deployment of class 7-8 electric vehicles.
- Participants anticipate that because of favorable policies, the adoption rate of MHDEV in Oregon will be higher than the national adoption rate. For simplicity, we will assume that the adoption rate in Oregon will be the same as the national adoption rate.[41]

Figure A-2. Forecasted National Share of Class 2-3 Electric Vehicles



[41] We did not elicit responses for Oregon-specific adoption because the majority of experts focus on national developments and trends.

Figure A-3. Forecasted National Share of Class 4-6 Electric Vehicles

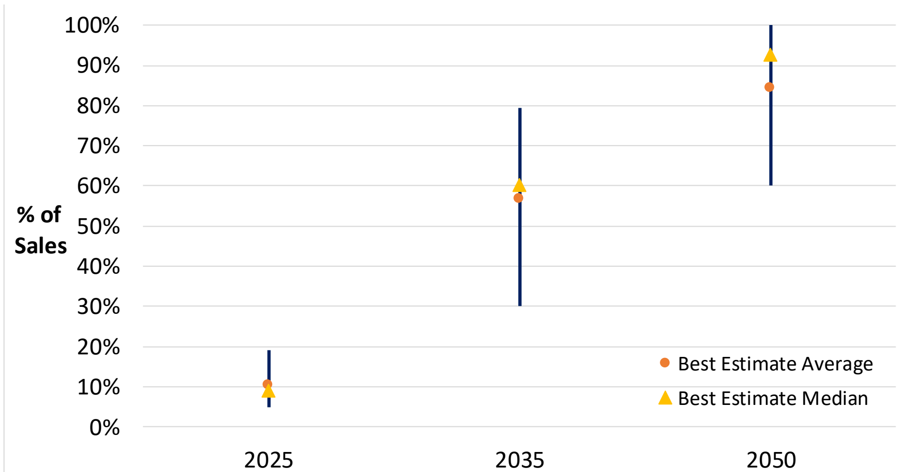


Figure A-4. Forecasted National Share of Class 7-8 Regional Electric Vehicles

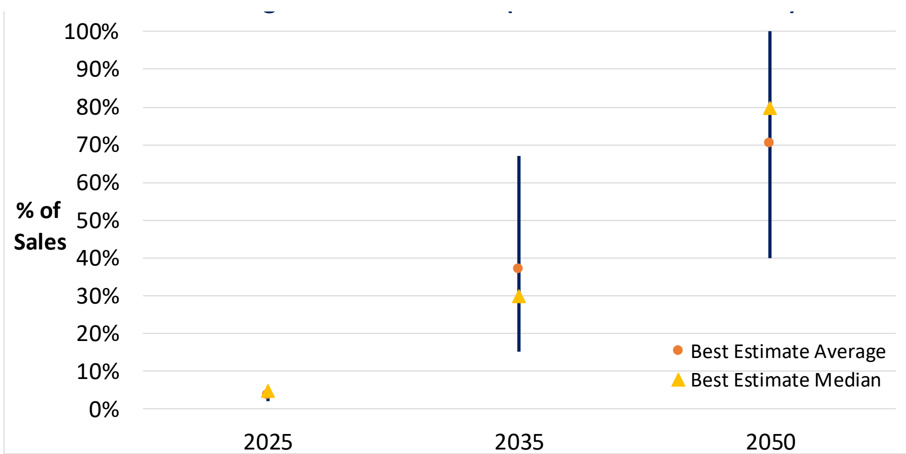


Figure A-5. Forecasted National Share of Class 7-8 Long-Haul Electric Vehicles

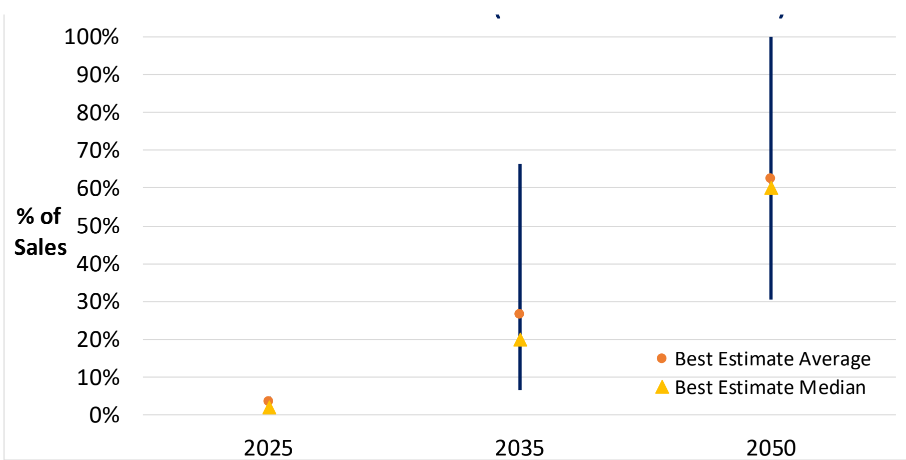


Figure A-6. Forecasted National Share of Electric City Bus

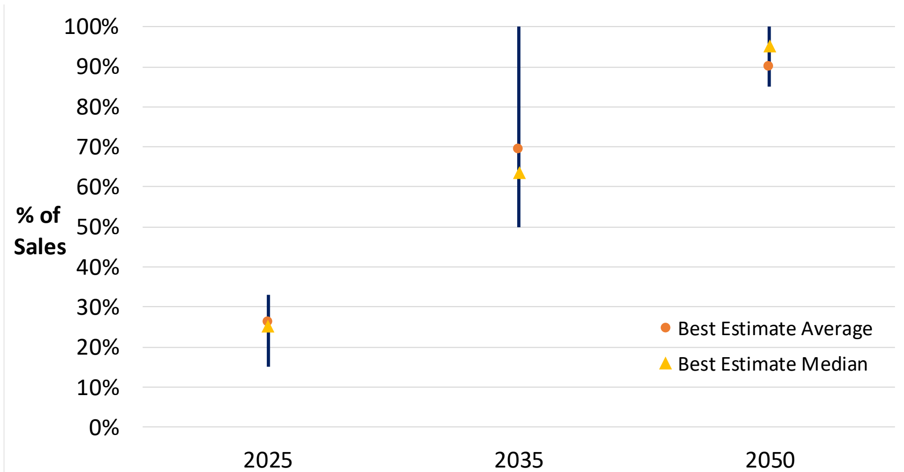
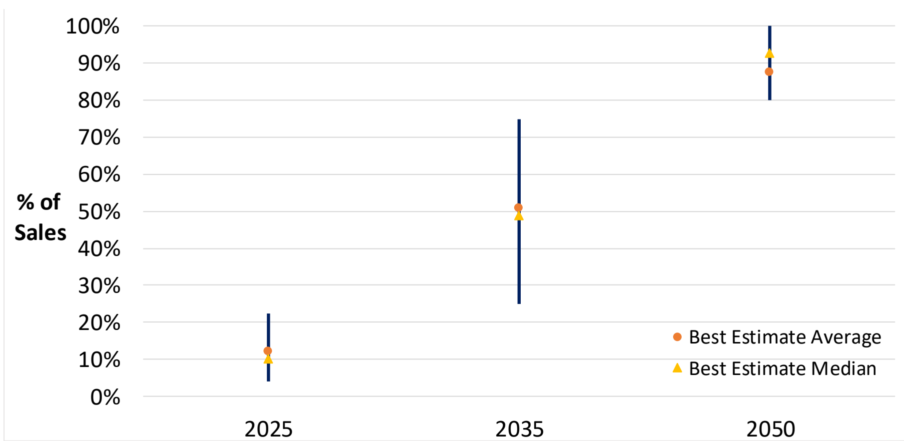


Figure A-7. Forecasted National Share of Electric School Bus



Historical MHDV Sales

We obtained historical registration data for MHDVs in Oregon from IHS Markit. The dataset covers the number of registered vehicles from 2017 to September 2020 for vehicle weight classes 2-8. Figure A-8. below provides a summary of the registration data.

Next, we determine the total number of future registered across all classes. We first estimate the average annual growth rate of vehicle registration for each class between 2017 and 2019. The 2020 data was partial and subject to Covid-19 pandemic impacts, therefore was excluded from the analysis. For example, the average annual increase in registration for class 2-3 vehicles increased from 952,940 in 2017 to 1,026,264 in 2019, an average increase of 3.85 percent.[42] Figure A-9. below provides a summary of the average increase in annual registered vehicles by class. We then estimate the total number of registered vehicles for each class to 2050 using the corresponding annual growth rate, using 2019 as the base year.

We define the number of new vehicle sales in a particular year as the difference in total registered vehicles between that year and the following year.[43]

Figure A-8. Number of Total Registered MHDVs in Oregon (2017 to September 2020)

Class	2017	2018	2019	2020
Commercial Vehicles (Class 2-3)	952,940	993,994	1,026,264	1,032,400
All Commercial Vehicles (Class 4-6)	63,908	65,711	66,945	65,225
Regional Trucks (Class 7-8)	1,077	1,208	1,252	1,237
Long Haul Trucks (Class 7-8)	50,741	54,582	56,578	57,437
School Bus (All Classes)	3,681	3,939	4,103	3,942
City Transit Bus (All Classes)	1,299	1,327	1,616	1,592

Notes: City and school buses were removed from their respective classes. Regional trucks include fire Trucks, Incomplete Vehicles with Strip Chassis, Step Van Vehicles and Glider Vehicles. Long haul trucks include straight Truck Vehicles, Cab Chassis Vehicles, Motor Home Vehicles and Tractor Truck Vehicles. Unknown vehicles are excluded.

Figure A-9. Average Increase in Annual Registered MHDVs IN Oregon (2017-2019)

Class	Annual Registration Increase
Commercial (Class 2-3)	3.85%
Commercial (Class 4-6)	2.35%
Regional Trucks (Class 7-8)	8.12%
Long Haul Trucks (Class 7-8)	5.75%
School Bus (Class 7-8)	5.73%
City Transit Bus (Class 7-8)	2.16%

Notes: Increase for city bus is between 2017-2018

42 For city bus, there was a significant increase of 22 percent from 2018 to 2019, possibly from a major one-time purchase. For this reason, we used the 2017-2018 annual increase of 2.2 percent instead.

43 For instance, the number of projected total registered vehicles for class 2-3 increases from 1,287,150 in 2025 to 1,336,670 in 2026, so the total new sales in 2025 is 49,520.

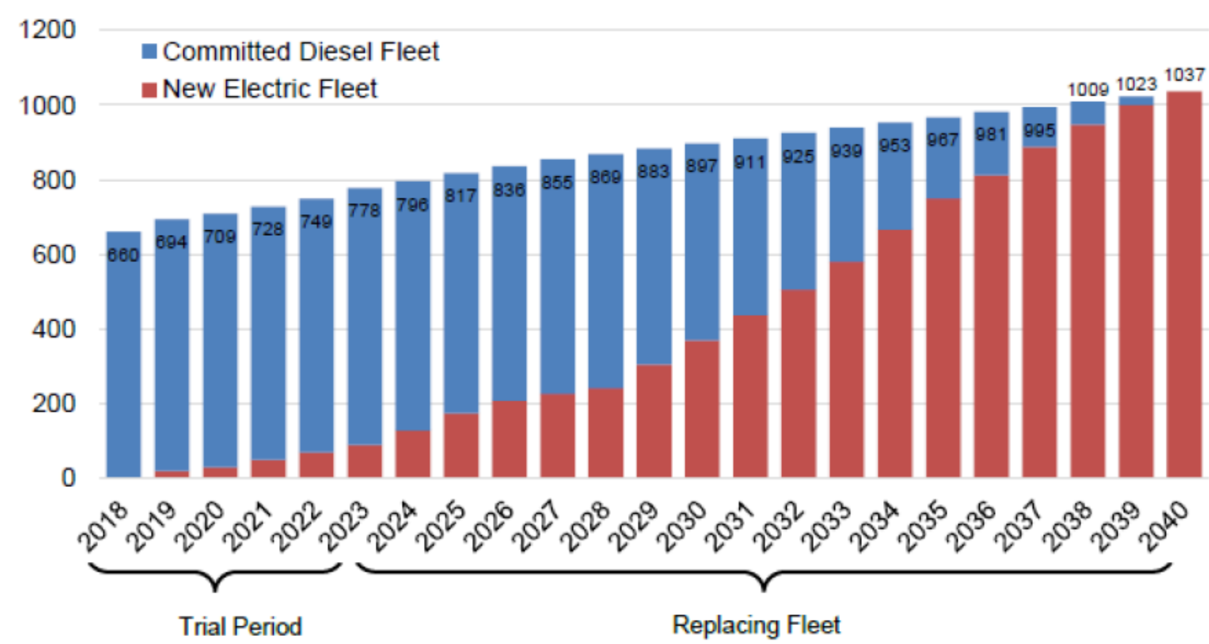
Future MHDEV Sales

The number of electric vehicles in a particular year is the product of the adoption rate (obtained from the expert survey) and the number of new vehicle sales in that year. To obtain the adoption rate for the intervening years, we scale the adoption rates obtained from the expert survey linearly.

We model adoption of electric city buses based on information from TriMet, the mass transit agency in the Portland area. We rely on the agency's planned progression of electric fleet to replace diesel fleet by end of 2040 (seeFigure A-10). About half of the agency's fleet will be electric by 2031, and the transition away from diesel buses will be complete by 2040. We assume that the total number of registered city buses in the rest of Oregon at the same rate as TriMet's growth. The share of electric buses in the rest of Oregon is the same as that share in the TriMet/Portland area.

Figure A-10 below shows the 2025 results. For instance, there will be 49,520 class 2-3 vehicles sold in 2025. Eight percent of the new vehicle sales will be electric (3,827 vehicles), bringing the total number of class 2-3 electric vehicles to 14,758. Note that we assume no retirements. We estimate the same adoption rates for 2035 and 2050. In addition, we consider a high adoption scenario and a low adoption scenario using the 90th and 10th percentile adoption rates from the expert survey.

Figure A-10. TriMet's Electric Bus Adoption Plan



Note: We do not have the underlying data, so the exact number of electric buses is estimated. We will update the model once we receive the underlying data.